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Mélina LONDON

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Composition du jury

Isabelle MEJEAN Sciences-Po Paris	Rapporteure
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Banu DEMIR Bilkent University	Examinatrice
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Patrick PINTUS Aix-Marseille Université	Directeur de thèse
Julien MARCILLY	Directeur de thèse en entreprise

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Affidavit

I, undersigned, Mélina London, hereby declare that the work presented in this manuscript is my own work, carried out under the scientific direction of Patrick Pintus, in accordance with the principles of honesty, integrity and responsibility inherent to the research mission. The research work and the writing of this manuscript have been carried out in compliance with both the french national charter for Research Integrity and the Aix-Marseille University charter on the fight against plagiarism.

This work has not been submitted previously either in this country or in another country in the same or in a similar version to any other examination body.

Paris, 15/03/2022

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Liste de publications et participation aux conférences

Participation aux conférences et écoles d'été au cours de la période de thèse:

1. 2021: CREST PhD Seminar, AFSE Annual Conference, GDRE, EconomiX Conference in International Economics, Young Economist Symposium 2021
2. 2020: Innovation Lab Seminar – College de France Workshop, AMSE PhD Seminar, Sciences Po PhD seminar, GSIE Lunch Seminar
3. 2019: AMSE PhD Seminar

Résumé

Dans cette thèse, je construis et j'exploite une base de données originale pour explorer les réseaux d'entreprises et le financement du commerce. Je montre que pour évaluer les vulnérabilités d'une entreprise, il est nécessaire d'étudier les fragilités de ses partenaires. Dans les deux premiers chapitres, j'analyse la propagation des chocs au sein d'un réseau donné. Dans le premier chapitre, je cartographie un réseau de relations prédictives entre la santé financière de chaque secteur. Je mets en avant la corrélation de ce réseau prédictif avec la structure de production dans les économies étudiées. Dans le deuxième chapitre, j'explore davantage la propagation des chocs au sein du réseau et j'étudie l'effet des changements de la politique monétaire américaine sur le crédit commercial vers les marchés émergents. Je constate que le crédit commercial est un canal de transmission supplémentaire de la politique monétaire américaine et un substitut à d'autres types de financement pour les importateurs émergents. Plus précisément, le resserrement monétaire américain augmente la demande de crédit commercial des importateurs émergents, qui l'utilisent comme substitut à d'autres outils de financement, eux-mêmes contraints. Dans le même temps, il restreint la capacité des fournisseurs américains à accorder des crédits commerciaux à leurs clients, en contraignant leur liquidité. Dans le troisième chapitre, je me concentre sur la transformation des réseaux après un choc. J'étudie comment les catastrophes naturelles dans les pays partenaires induisent un remodelage durable des réseaux commerciaux des plus grands exportateurs plutôt qu'une destruction permanente du commerce.

Mots clés: Macroéconomie internationale, Réseaux, Commerce, Crédit commercial

Abstract

In this dissertation, I build and exploit an original database to fill the gap and explore firm-level networks and trade financing. I show that a proper assessment of a firm's vulnerabilities requires accounting for its partners' fragilities. In the two first chapters, I analyse shock propagation within a given network. In the first chapter, I map a network of predictive relationships across the financial health of several sectors. I highlight the correlation between these predictive relationships and the input-output production structure in the studied economies. In the second chapter, I further explore the propagation of shocks within the network and study the effect of changes in US monetary policy on trade credit flows towards emerging markets (EM). I find trade credit to be an additional pass-through channel of US monetary policy and a substitute to other types of financing for EM importers. Specifically, US monetary tightening increases EM importers' demand for trade credit, used as a substitute to other financing tools, themselves restrained. At the same time, it restricts US suppliers' ability to extend trade credit to their EM customers, acting as a liquidity squeeze. In the third chapter, I focus on the network transformation following a shock. I study how natural disasters in partner countries induce a durable reshaping of the largest exporters' trade networks rather than a permanent destruction of trade.

Keywords: International macroeconomics, Networks, Trade, Trade credit

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Table of Contents

Affidavit 2

Liste de publications et participation aux conférences 3

Résumé 4

Abstract 5

Remerciements 6

Table of Contents 8

List of Figures 11

List of Tables 13

1 General Introduction 15

1.1 Trade financing 16

1.1.1 Sources of trade financing 16

1.1.2 Trade credit insurance 17

1.1.3 Building a proprietary database to study trade credit financing . 18

1.2 Literature: Trade financing, trade credit and networks 22

1.2.1 Trade and financing needs 22

1.2.2 Determinants of trade credit 24

1.2.3 Production network 25

1.2.4 Financial network 26

1.3 Organization of the dissertation 26

2 Cross-Sector Interactions in Western Europe: Lessons From Trade Credit Data 29

2.1 Introduction 31

2.2 Empirical Strategy 34

2.2.1 Methodology 35

2.2.2 Trade credit and firms' financial health 38

2.3 Data and Pre-estimation Treatment 39

2.4 Results 41

2.4.1 A network of cross-sector interactions to enhance sector-level monitoring 42

2.4.2 Exploring mechanisms: sector-level shock propagation 47

2.5 Robustness Tests . . . 53
2.5.1 Coface risk management . . . 53
2.5.2 Multiple testing procedures . . . 53
2.6 Conclusion . . . 55

Appendices **56**
2.A Post-Double Estimation Procedure: Add-Ons to the New Framework . 56
2.A.1 Lasso estimation . . . 56
2.B Sector codes . . . 57
2.C Principal component analysis on macroeconomic indicators . . . 58
2.D Network of significant predictive relationships over the period 2013-2019 58
2.E Logistic regression– negative predictive relationships over the period 2013-2019 . . . 62
2.F Distribution of selected sectors by country . . . 63

3 US Monetary Policy Spillovers To Emerging Markets: The Trade Credit Channel **64**
3.1 Introduction . . . 66
3.2 Literature Review . . . 68
3.2.1 US monetary policy and emerging markets . . . 68
3.2.2 Trade credit: complement or substitute in the business cycle . . 70
3.3 Data . . . 72
3.3.1 Trade credit . . . 72
3.3.2 Identifying monetary policy shocks . . . 75
3.4 Empirical Strategy . . . 78
3.4.1 A first glance at the global effect . . . 78
3.4.2 Exploring heterogeneity . . . 80
3.5 Results . . . 82
3.5.1 Trade credit: a pass-through channel of US monetary policy to EMEs . . . 82
3.5.2 Quality: A demand-driven funding effect . . . 83
3.5.3 US suppliers: financial constraints on the supplier side dominate 84
3.5.4 USD trade credit: an exchange rate channel . . . 86
3.6 Robustness tests . . . 87
3.6.1 Alternative specifications . . . 87
3.6.2 Alternative policy indicators . . . 89
3.7 Conclusion . . . 91

Appendices **94**
3.A Descriptive Statistics on Monetary Policy Announcements . . . 94
3.B Disentangling “Pure" Monetary Policy and “Informational" Shocks . . 94
3.C Descriptive Statistics for Alternative Policy Indicators . . . 95
3.D Sample for Goods and Services . . . 96
3.E Data Sources . . . 97

4 Trade Networks and Natural Disasters: Diversion, not Destruction **98**
4.1 Introduction 100
4.2 Data and Methodology 103
4.2.1 Data 103
4.2.2 Empirical Strategy 110
4.3 Results 112
4.3.1 Main Results 112
4.3.2 Natural disasters decrease the quality of the supplier's networks of buyers 118
4.3.3 The role of supplier heterogeneity 120
4.3.4 Net Supplier Effect: A Restructuring of the Network 123
4.4 Robustness 127
4.4.1 The effect is not explained by buyers defaulting on their trade credit 127
4.4.2 The effect is not explained by credit insurance rationing 127
4.4.3 Absence of anticipatory effects per ratings category 128
4.5 Mechanisms 128
4.6 Conclusion 131

Appendices **132**
4.A Definition of events 132
4.A.1 Timing baseline event: worst disaster in the country 132
4.A.2 Timing alternative event: first big disaster in the country 133
4.A.3 Main results with first big disasters 135
4.A.4 Main results excluding the never treated, first big disaster 136
4.A.5 Main results with top quartile disasters 136
4.B Disaster Types 137
4.B.1 Definition 137
4.B.2 Heterogeneity in Types of Disaster 138
4.B.3 Trade in Goods - Extensive Margin 139
4.B.4 Ex-Ante Rating Category 140
4.C Notation 140
4.D Variable Description 141
4.E End-Use 143

5 General Conclusion **143**

List of Figures

1.1 Density functions for overall and export net turnover 21
1.2 Density functions for intra & extra-EU exports 22
1.3 Trade receivables and Coface trade credit exposure 22

2.1 Cross-Sector Information to Add Predictive Power 43
2.2 Full Network of Significant Cross-Sector Interactions 44
2.3 Aggregate Sector Distribution - Inward & Outward Links 46
2.4 Inward and Outward Link Distribution 47
2.5 Centrality in Production and Granger-Causality Networks 51
2.6 Inward and Outward Links in Positive Network 52
2.C.1 Principal Components Analysis From 2007 to 2019 58
2.D.1 Full Network of Significant Cross-Sector Granger Causalities Over the Period 2013-2019 59
2.D.2 Network of Significant Cross-Sector Links with Positive Cumulated Amplitude – Period 2013-2019 60
2.D.3 Network of Significant Cross-Sector Links with Negative Cumulated Amplitude – Period 2013-2019 61

3.1 Buyers' Rating and Quality Categories in Mexico 76
3.3 Buyers' Rating and Quality Categories in Turkey 76
3.A.1 Monetary Policy Surprises 94
3.B.1 Change in the 2-year Nominal Treasury Yield and the S&P 500Iindex around FOMC Announcements in pp 95

4.1 Trade Credit to Customs Data Coverage 106
4.2 Natural Disasters 109
4.3 Geographical Distribution of Natural Disasters Events 109
4.4 Effect of Natural Disasters on Exposure 113
4.5 Extensive and Intensive margin 115
4.7 Long run effect (yearly data) 116
4.8 Effect of Natural Disaster on the Distribution of Buyers per Supplier-Destination 117
4.10 Effects of Natural Disasters on the Export of Goods 119
4.12 Effect of Natural Disasters on Buyer Quality after 2 Years 120
4.13 Effect of Natural Disasters on the ex-ante Distribution of Buyer Quality after 2 years 121
4.14 Effect of Natural Disasters conditional on the supplier size (k=2) 122
4.16 Effect of Natural Disasters conditional on supplier output specificity (k=2) 123

4.17 Effect of Natural Disasters conditional on supplier output specificity and size (k=2) 124
4.18 Long Run Effects of Natural Disasters on Supplier-level Trade 125
4.20 Effects of Natural Disasters after 2 years conditional on Supplier Size . 126
4.22 Effect on Default 127
4.24 Supplier vs. Insurer Effect 128
4.26 Effect of Natural Disasters on Buyer Quality 2 Years prior to the disaster 129
4.A.1 Timing of selected events 132
4.A.2 Natural Disasters 133
4.A.3 Timing of alternative events 134
4.A.4 Effect of Natural Disasters on the Number of Buyers - First big disaster 135
4.A.6 Effect of Natural Disasters on the Number of Buyers - Excluding never treated 136
4.A.7 Effect of Natural Disasters on the Number of Buyers - Top quartile events 137
4.B.1 Heterogeneity in Types of Disasters 138
4.B.2 Trade in goods extensive margin 139
4.B.3 Effect of Natural Disasters per ex-ante rating category 140

List of Tables

1.1 Summary statistics on Coface database for year 2018 21

2.1 Descriptive Statistics—Coface Trade Credit Data 40
2.2 Percentage of Explained Variance - By Sectors 45
2.3 Post-Crisis Period—Amplitude of Interactions—Significant Links . . . 48
2.4 Logistic regressions - Input-Ouput Flows and Positive Predictive Relationships 50
2.5 Kendall Correlation Test - Granger-Causing Effect and Input-Ouput Flows 50
2.6 Logistic regressions - Input-Ouput Flows and Positive Predictive Relationships - Benjamini-Yekutili Correction for Multiple Testing 54
2.B.1 Sector codes 57
2.E.1 Logistic regressions - Input-Ouput Flows and Negative Predictive Relationships 62
2.F.1 Selected Sectors By Country 63

3.1 Descriptive Statistics On Import Sample by Suppliers' Origin for Mexico 74
3.2 Descriptive Statistics on Import Sample by Suppliers' Origin for Turkey 75
3.3 Descriptive Statistics on Import by Currency for Mexico 75
3.4 Descriptive Statistics on Import Sample by Currency for Turkey 75
3.5 Descriptive Statistics for US Monetary Policy shocks (in pp) 78
3.6 Trade Credit in Mexico and US MP Surprises - Baseline 83
3.7 Trade credit in Turkey and US MP Surprises - Baseline 84
3.8 Mexico : Quality 85
3.9 Turkey : Quality 86
3.10 Mexico : Trade Credit from US Suppliers 87
3.11 Mexico : Currency Type 88
3.12 Turkey : Currency Type 89
3.13 Trade Credit in Mexico and US MP - Controlling for Empirical Choices 90
3.14 Trade Credit in Turkey and US MP - Controlling for Empirical Choices . 91
3.15 Different Measures of Surprises : Mexico 92
3.16 Different Measures of Surprises : Turkey 93
3.C.1 Descriptive stat. for US Monetary Policy shocks with alternative indicators 96
3.D.1 Descriptive Statistics by Suppliers' Origin for Mexico 96
3.D.2 Descriptive Statistics by Suppliers' Origin for Turkey 96
3.E.1 Description of the variables 97

4.1 Sample Descriptive Statistics - Trade & Trade Credit Data 104
4.2 Sample Descriptive Statistics - Natural Disasters 108

4.3 Sample 108
4.B.1 Disaster Types 137
4.E.1 End-Use classification 143

1 General Introduction

Contents

1.1 Trade financing 16
1.1.1 Sources of trade financing 16
1.1.2 Trade credit insurance 17
1.1.3 Building a proprietary database to study trade credit financing . 18
1.2 Literature: Trade financing, trade credit and networks 22
1.2.1 Trade and financing needs 22
1.2.2 Determinants of trade credit 24
1.2.3 Production network 25
1.2.4 Financial network 26
1.3 Organization of the dissertation 26

The common thread in this dissertation is the study of networks. The identification of networks refers to the existence of production, financial or trade links, which relate firms and sectors to one another. Because of such links, firms, sectors and countries become interdependent and interlocated. Recent news have provided examples of such interdependencies. Looking on the production side, the early stages of the COVID-19 crisis highlighted supply shock propagation patterns among global value chains that structure our globalized economies. When the disease was only confined to China, disruptions in Chinese factories already created disturbances in production in countries still unscathed. This can be explained by the interpedendance of production processes and China's centrality in the global manufacturing system. As another example, the supply shortages during the recovery in 2021-early 2022 only stressed such production interdependencies. With too few electronic chips produced by the Taiwanese giant TSMC (Taiwan Semiconductor Manufacturing Company), some car makers in Europe and in the US were missing key inputs and had to close some plants[1]. However, besides those production links also exist financial interactions across firms. They can be indirect, through intermediates like banks, that use some firms' assets to finance others' liabilities. They can also be direct between two firms financing one another. An example of the latter are the chains of defaults observed with the bankrupcy of the tourism agency Thomas Cook in September 2019 that created ripple effects among all its suppliers, leading some of them to insolvency. Their balance-sheets were interdependant, with one's assets being liabilities for the other.

[1]See NY Times article A Tiny Part's Big Ripple: Global Chip Shortage Hobbles the Auto Industry

In such types of events, from the aggregate, precise mechanisms are invisible, and the understanding of interplaying channels of impact is clouded. Thus, there has been an increasing agreement on the need for a deep analysis of such inter-firm links to better identify firms' real exposure to shocks. It is clear that such network effects need to be included in firms' assessment of vulnerabilities but remain the question of how to do it. To answer it, lies the question of identifying such networks. While the literature has started to study production networks and their consequences at the country and sector level for the recent years, the identification of the same mecanisms for financial interactions is very recent and still sparse. This is even more the case when focusing on firm-level financial interactions for which data are very rare, clouding the picture. Therefore, in this dissertation, I address this need for a clear mapping of network effects, linking production and financial interactions. I build and exploit an original database on firm-to-firm trade credit to study a specific type of network at the crossroad of financial, trade and production flows. I show how those firm-level interconnections allow shocks to propagate and describe how acknowledging such propagation channels can help better monitor firms' and sectors' vulnerabilities.
I do this building on a new database constructed with data from a trade credit insurer named Coface. I will now provide more details on trade credit and trade credit insurance in the context of trade financing. Then, I will describe the literature on which this dissertation builds. I will follow by describing further the detailed contribution of this work.

1.1 Trade financing

1.1.1 Sources of trade financing

To allow firms to trade, financing requirements can be quite high. In the case of global value chains, financing needs increase in a non linear way with the length of the supply chains as described by Bruno et al. (2018), raising even more such requirements. International trade also involves higher commercial risk than domestic trade. Firms have several financing tools to choose from to face such capital needs. Either the buyer bears the costs of the trade, or the supplier does, or they request bank intermediation. In this dissertation, when I refer to the supplier, I mean the firm producing the good or service and selling it to another firm. Differently, the buyer is the firm that receives the good or service on the other side.
A first option is to use bank intermediation through letters of credit, factoring of invoices, or invoice discounting, among others. With letters of credit, the bank guaranteees the supplier that the buyer's payment for the purchase will be received on time and for the correct amount. In case the buyer is unable to pay, the bank will cover the due amount. A second option are cash-in-advance terms, where the buyer finances the purchase of the good without requesting intermediation. This ensures to the supplier the payment of the good or service prior to the shipment. In this case the buyer bears the risk in case of damages to the shipment. A third option are open-account

terms, called trade credit terms in this dissertation. In this latter case, the supplier pays for the production of the good or service and allows the buyer to pay after the delivery. In this context, the supplier bears all the risk of non payment while those terms are the most advantageous for the buyer. In their 2015 paper, Antras and Foley study the use of those different payment terms and the relationship with the legal system quality in the buyer's country. In their specific case of a poultry exporter, in line with ICISA[2] numbers, 42.4% of trade are done under cash-in-advance terms, 41.3% under trade credit terms, while the rest is bank intermediated with 5% with letters of credit. They show that suppliers tend to choose cash-in-advance terms when there are only weak contract enforcement tools in the buyer's country. Letters of credits, that are quite costly, are chosen when banks in the buyer's country have a better access to information than the supplier. Finally, the choice of trade credit terms is often dictated by the level of competition in the sector. Indeed, offering trade credit allows the supplier to attract more buyers (see Demir and Javorcik (2018)). The size of each counterpart will be key to set the terms of contracts that favor the biggest of the two, while the access to capital on the supplier's side will be another main determinant. Schmidt-Eisenlohr (2013) models the choice of the trade payment contract as a trade-off between financing requirements and the risk of the transaction. Cash-in-advance terms will be prefered when there is weak contract enforcement and low financing costs in the buyers' country. Countries with strong contract enforcement will be preferably supplied using Open-account terms if financing costs are low enough in the supplying country. Letters of credit, which requires extra fees, will be favored for trade between two countries with weak contract enforcement.
In this dissertation, the focus will be on trade credit. Because it finances firm-to-firm trade flows, trade credit inserts into production mechanism and global value chains. At the same time, because it involves a provision of credit from one firm to the other, it is also deeply integrated into financial dynamics. Its existence make suppliers' and buyers' interdependant, both in production and financial terms. It is this interdependance that this dissertation will explore.

1.1.2 Trade credit insurance

Under trade credit terms, the supplier takes a risk with a potential default from its buyer. In such case, the supplier comes under increasing pressure to meet its own financial constraints as trade receivables are often matched with trade payables. In some cases, it could even be pushed into bankruptcy for very large credits. Boissay (2006) highlights the existence of such chain reactions and contagion along the supply chain if some debtor defaults on its credit to its supplier. To protect itself from such chain reaction, the supplier might want to insure itself. To do so, it can suscribe to trade credit insurance from an insurer, which will reimburse the amount due in the case of default. According to Berne Union, trade credit insurers provide payment risk capital for around 13% of global cross-border trade and Europe is by far the largest

[2] International Credit Insurance & Surety Association

market for trade credit insurance with 50% of insured exports worldwide. Boissay et al. (2020), trade credit insurers cover 14% of final trade receivables, which is greater than banks' exposure. The trade credit insurance market is stronly oligopolistic with three main actors covering 60% of trade credit insured amounts. Euler Hermes covered 27% in 2019, Atradius 19% and Coface 14%[3].

To avoid moral hazard the insurer will impose several conditions. First, the supplier has to declare all its buyers under trade credit terms in order to avoid risk selection. Then, only around 90% to 95% of the trade receivable is fully covered so that the supplier still bears some of the cost in case of default from the buyer. Finally, the premium to be paid for the insurance is computed based on the supplier's history of defaults and probability of default from the buyer. It is negociated as a share of the turnover made on the buyer for which the trade receivable is insured. This is done in order to make sure the supplier is still cautious in its choice of partners even though it is insured. The premium is defined contractually and is only renegociated at the expiration of the contract, if there is a default on the insurance policy or if competitors try to win the supplier over.

According to the insurance contract, the supplier requests an amount of insurance for a specific buyer, obtains either all the amount requested, only part of it or nothing at all, depending on the insurer's risk perception on the buyer. The insurer can decrease the amount of sales insured at any time on a specific buyer, and inform the supplier that from month t only a reduced amount will be covered on any new trade credit sale. As suppliers pay their premium on realized sales (rather than anticipated sales) they may request for larger coverage than the amount actually needed. At the same time, counteracting this effect, the amount of coverage requested affects the premium paid as it affects the risk taken by Coface. Thus, the supplier faces a trade-off and does not request an infinite coverage. Coface also provides incentives to suppliers so that they limit the amount requested to their actual needs as the amount insured defines Coface's capital needs from the regulator's perspectives.

Then, every time a buyer defaults, the supplier will be directly reimbursed by the insurer up to the amount garanteed. It is in the supplier's interest to declare payment defaults as soon as the grace period expires. Hence, data compiled by the trade credit insurer on a monthly basis tend to provide an up-to-date record of payment defaults.

1.1.3 Building a proprietary database to study trade credit financing

A key contribution of this research is to provide an original database on firm-to-firm trade and financial links within an insured trade credit framework. This dataset builds on highly confidential data on firms' supply chains and inter-firm credit relationships on a monthly basis. This allows to minimize the use of proxies when studying inter-firm links. At the same time, the construction of this database provides the source, the

[3] see Coface Universal Registration Document 2020

trade credit insurer Coface, with a new perspective on its data and activity. By adopting a network view, it joins the supplier's and buyer's side, usually analyzed separately by Coface.
I will now provide a brief overview on the exact content of the database used in the three chapters of this thesis while keeping specific descriptive statistics relevant to each specific analysis for each chapter.

The dataset records a monthly stock of trade credit exposure for a pair of supplier-buyer. Exposure corresponds to the maximum amount of trade credit sales insured by Coface between a supplier and its buyer on a monthly basis. This amount does not match with the supplier's exact trade receivables for this specific client as it records the maximum amount covered by the insurer. The supplier is then free to use 100% of its insurance each month to provide trade credit to its buyer, or only part of it, or even decide to provide additional trade credit at its own risk, above the amount insured. Therefore, the data is only a proxy for trade credit sales done by a supplier to a specific buyer. Other sales can also happen using other financing tools, such as cash-in-advance or banks' intermediated tools. The supplier can also decide to insure its trade credit with one of Coface competitors. However, the database identifies precisely the identity of the supplier and its buyer. The data provides the complete set of buyers under trade credit terms given the supplier's requirement to declare all buyers under trade credit terms to avoid moral hazard and risk selection. The only exception appears when Coface decides not to cover a specific buyer. Only trade credit covered by the insurer appears in the data. Moreover, no information is available on the exact trade credit sale insured, nor the sales amount, the bill issuance date, nor the timing for reimbursement, described here as the grace period.

The data includes both domestic and international trade credit relationships with heterogenous coverage based on the history of the credit insurer in the country. As example, in France, there is a higher share of trade credit towards the export market than for the domestic one given the historical role of Coface as the former official French export credit insurance agency before its privatisation in the 90s.

Regarding general coverage of supply chains, a main limitation of this dataset is that it covers only inter-firm trade. This leaves out an important share of today's global value chains that takes place within multinational firms, between headquarters and their affiliates. Insurers do not intervene in intra-multinational trade.

In terms of variables included, at the supplier-buyer level, the data provides the monthly stock of trade credit exposure, i.e. the maximum amount of trade credit sales insured by Coface. The amount of insurance initially requested by the supplier for the specific buyer also appears in the data, to be compared with the amount insured at the end which corresponds to the trade credit exposure. The requested amount is available on a yearly basis. Then, the data also encompasses the country and sector of origin, for both buyers and suppliers. The supplier's sector is defined as the sector with the greatest insured exposure when goods or services sold encompass different sectors. For the buyer, the declared sector is used. On the buyer side, ratings are available each month, synthesizing the observed quality of the buyer from Coface's perspective using an internal scale. This scale goes from 0 to 10. A rating of 10 identifies the firms with strongest financial health and 0 the weakest one that went out of business. Several types of methodology are used to obtain this rating depending on the amount requested for insurance. Higher amounts requires more disaggregated financial data but all methodologies converge to the structured 0-to-10 ranking. The rating is reviewed from time to time, with the level of scrutiny being dependant on the amount of exposure. Then, at the buyer's level, there is also information on defaults. Suppliers notify the insurer of a potential default as soon as the buyer is late on its payment. Those defaults can happen because of full insolvency or because of temporary liquidity issues implying only a delay. Date of the notification and the reason for the default, i.e. insolvency or protracted default, are also included in the data.

Broad Descriptive Statistics

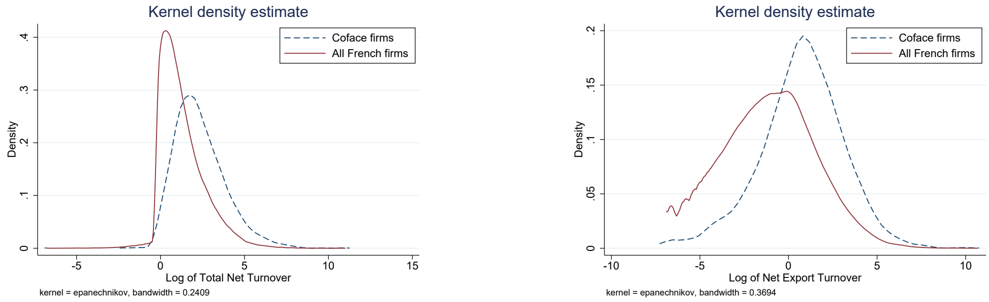
The database encompasses data from 2007 to 2019 with around 5 millions of supplier-buyer pairs each year, for a total of 780 millions observations at the monthly level. On average, each year, there are 33,476 distinct suppliers related to 1,882,027 distinct buyers, belonging to 92 supplier countries and 200 buyer countries and territories and all 38 sectors of the classification.
Table 1.1 provides the broad descriptive statistics of the main variables taking year 2018 as reference. We see that there is a much higher number of buyers than suppliers in the database. Suppliers exports to a wide set of destinations and buyers with on average 947 buyers per supplier, reflecting a very heterogenous distribution as shown by the high value of standard deviations. Defaults are also very rare events.

Regarding the characteristics of the firms' population belonging to Coface database, I will use the French case for which firms' data are easily available with FIBEN dataset and compare Coface suppliers with the overall population of French firms. It should be noted that, given the French origin of Coface, France is one of the countries in the dataset for which the insurer has the greatest coverage. For other countries, like emerging markets, the US and Asian countries, the insurer coverage will encompass a smaller share of the population of firms. Nonetheless, most features are likely to replicate across countries on the characteristics of the included suppliers.
Around 3.2% of firms registered in FIBEN data are suppliers in Coface database, mixing domestic and international trade credit flows. Among French exporters, 4.1% of them belong to Coface database. However, Coface firms represented 9.4% of produced value added across FIBEN firms in 2018, being bigger on average. This is visible from figure 1.1 in which I proxy size by net turnover. Coface firms are also exporting more. Regarding their exports, as shown in figure 1.2, there is a much greater gap in the differential with the overall population of French exporters for extra-EU exports than for intra-EU flows. This is explained by the insurance origin of the database, given that

Nb observations	53,068,956
Nb defaults	14,921
Nb suppliers	37,835
Nb buyers	1,833,995
Average monthly nb supplier-buyer pairs	4,422,413
Average nb destinations/supplier	19.6
Average nb buyers/supplier	947.3
SD nb buyers/supplier	2,127.5
Average monthly trade credit exposure/supplier (EUR)	71,132,866.0
Average nb buyer sectors/supplier	20.6
Average quality of buyers/supplier	6.0
Average monthly amount of defaults/supplier (EUR)	39,380.0
Average monthly trade credit exposure/supplier-buyer pair (EUR)	85,493.6
SD monthly trade credit exposure/supplier-buyer pair (EUR)	597,374.4

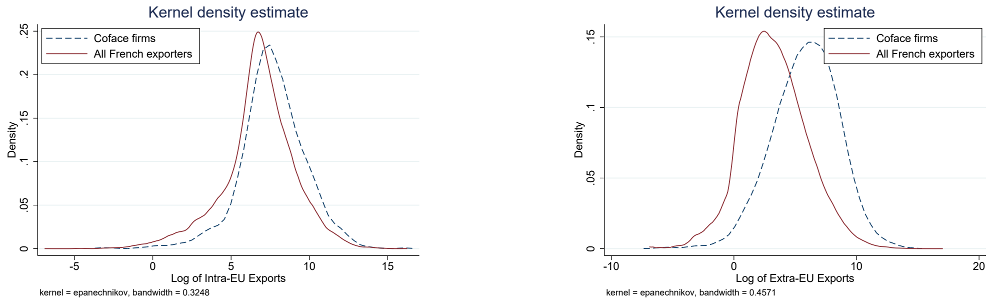
TABLE 1.1 : Summary statistics on Coface database for year 2018

for non-EU trade the risk perceived is much higher, due to legal system differences among others. Thus, firms will mostly request insurance when they trade with non-EU partners. In figure 1.3, we also see that a firm's total amount of receivables are positively and linearly correlated with the amount of trade credit exposure insured by Coface. This makes trade credit exposure a reliable proxy for overall trade credit flows for the firms in the sample, despite the fact that not all trade credit flows are insured for the reasons described above.



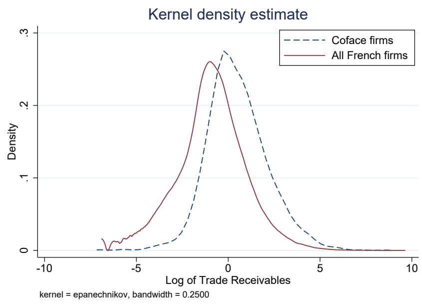
NOTE : Both densities are computed for the year 2018, taking the log of net turnover and net export turnover.

FIGURE 1.1 : Density functions for overall and export net turnover

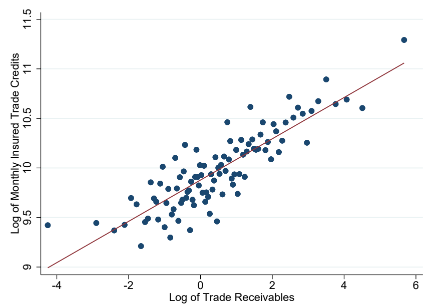


NOTE : Both densities are computed for the year 2018, taking the log of exports volumes.

FIGURE 1.2 : Density functions for intra & extra-EU exports



NOTE : Both densities are computed for the year 2018, taking the log of trade receivables.



NOTE : This describes the average value of monthly trade credit exposure for each averaged amount of trade credit receivables within each bin. The red line represents the linear relationships between both variables.

FIGURE 1.3 : Trade receivables and Coface trade credit exposure

1.2 Literature : Trade financing, trade credit and networks

This dissertation builds on several strands of the literature. As I study a trade financing tool, a first step is to look at what has been done in the literature on trade and trade financing needs. Then, I will detail more specifically the key findings regarding trade credit flows and their determinants. After this, I will focus on the ongoing work on networks, both for production and financial linkages, with trade credit flows at the intersection of both.

1.2.1 Trade and financing needs

The recent trade literature has worked towards the inclusion of financial frictions in trade theory, in order to fully explain the fall in trade observed during the great

financial crisis of 2007-2008. Amiti and Weinstein (2011) and Chor and Manova (2012) are among the first to point the fall in trade finance during the crisis as a key determinant of the decrease in trade flows during the period. Amiti and Weinstein establish a causal link between the health of banks providing trade finance and the growth in a firm's exports relative to its domestic sales. On a similar line, Chor and Manova (2012) highlight the role of the credit crunch in reducing trade finance and thus curtailing firms' production and exports in sectors most intensive in external financing. From there, the literature started to include those financial frictions in trade models. Building on Melitz (2003) model with heterogenous firms on the exporter side, Manova (2013) focuses on the importance of financial constraints in raising the productivity threshold to participate in international trade. Firms' ability to secure loans from banks, access financial markets, and the degree of pledgeability of their assets, will condition their access to the necessary financing to trade. In another paper, Manova et al. (2015) provide firm-level evidence that credit constraints restrict participation to international trade and affect the pattern of multinational activity. Using the Chinese case, they show that foreign affiliates and joint venture, which benefit from a greater access to capital, have a better export performance than domestic firms in sectors financially more vulnerables. Using again the Chinese case, Manova and Yu (2016) show that financial frictions induce most constrained firms to remain in processary trade rather than ordinary trade. Processing requires lower upfront costs than regular trade, despite the loss in value added it implies. Finally, in the case of global value chains, Bruno et al. (2018) highlight how working capital needs increase in a non linear way with the length of the supply chains.
The literature has also explored the trade impact when shocks close access to sources of financing, increasing mecanically firms' financial constraint. In their 2017 paper, Niepmann and Schmidt-Eisenlohr use data on US banks' trade finance claims to study the effect of a letter-of-credit suply shocks on US exports. They show that a fall in the provision of letters of credit lead to lower exports from the US. Given the geographical specialization of some banks and the concentration of letters of credit among few banks, shocks to individual banks can have aggregate effects and affect trade patterns to particular countries. Using a more global definition of trade finance, Korinek and Cocguic (2010) show that the restricted availability of bank-intermediated trade financing and firm to firm credit and the rise in cost have had a negative effect on trade flows during the Great Financial Crisis, albeit smaller than that of falling demand. However they do not see an effect outside of crisis periods. Complementing this study, van der Veer (2015) find evidence of a positive effect of private trade credit insurance on exports. They highlight the existence of a trade multiplier of export credit insurance on trade. Using the actual risk of trade credit insurance as an instrument for insured trade credit, Auboin and Engemann (2014) establish a causal link between insured trade credit and trade during the entire business cycle.

1.2.2 Determinants of trade credit

From this importance of trade financing, researchers have started to focus on available trade financing tools and the reasons to chose one over the other. Regarding trade credit terms, Fisman and Love (2003) describe how trade credit use is stronger in countries with relatively small and less developed financial markets. Demirguc-Kunt and Maksimobic (2001) show that trade credit is preferably used in countries with less-developed legal system. This makes it a widespread tool for financing in emerging markets. It is confirmed by Hill et al. (2017) who show that in such markets, firms with better access to financial credit use relatively less trade credit. The counter-cyclical nature of trade credit, as described by Nilsen (2002) and Burkart and Ellingsen (2004), has been mainly explored through the relationship between trade credit use and other financing tools in the banking sector. Meltzer (1960) was the first to suggest a substitution effect between trade credit and banking loans, with a redistribution happening through large liquid firms that behave as net suppliers of credits to smaller firms through their better access to bank finance. Fisman and Love (2003) and Danielson and Scott (2004) empirically document the increase in demand for trade credit from suppliers when bank loans become scarce. Molina and Preve (2012) show that firms demand more trade credit when they are in financial distress to substitute to other sources of financing. Minetti et al. (2019) highlight how firms with weaker relationships with banks will be more likely to integrate global value chains in order to borrow liquidity from their suppliers. Because of the fixed cost associated to the establishment of a trade relationship, Cuñat (2007) shows that suppliers have an interest in insuring their customers against liquidity shocks through trade credit provision, in order to continue the relationship. Garcia-Appendini and Montoriol-Garriga (2020) go further and show that, when facing high switching costs, suppliers will continue to extend trade credit to their clients approaching bankruptcies. However, this substitution effect can be mitigated in the context of systemic financial crises. Love and Zaidi (2010) examine the role of trade credit during the financial crises in Thailand, Philippines, Indonesia and Korea in the late 1990s. They find evidence against the premise that trade credit can act as a substitute to bank credit in those particular episodes. During such events, suppliers of financially constrained firms themselves suffer from negative liquidity shock, impeding the insurance mechanism normally in place. In a subsequent paper, Garcia-Appendini and Montoriol-Garriga (2013) highlight the role of suppliers' financial constraint in determining whether suppliers could perform their insurance role for their clients in times of crisis. They show that firms with high liquidity level prior to the crisis increased their level of trade credit provided to their customer during the Great Financial Crisis. The supplier's choice to extend trade credit to its buyers will also be strongly dependant on the sector's level of competitiveness. Fabbri and Klapper (2008) show that firms facing strong competition in the product market are more likely to extend trade credit and have a larger share of goods sold on credit. In another paper that studies the end of a quota system on textiles in Turkey, Demir and Javorcik show that firms respond to an increase in competitive pressures by providing trade credit and lowering prices. Garcia-Marin and Schmidt-Eisenlohr

(2020) also show that trade credit use increases with the length of the relationship between a supplier and its buyer.

1.2.3 Production network

Trade credit establishes a link between two firms, creating interactions. The literature on network has focused on the study of such links of all types and their consequences on the economy. In their 2012 paper, Acemoglu et al. opened the path for the study of production networks. In this article, they contrast Lucas (1977) view that sector shocks will average out and produce negligible aggregate effects. They show that input–output relationships across sectors act as propagation channels for localized production shocks. They emphasize on the importance of the production network structure for the dissemination of the shock and the size of the aggregate effect. The centrality of a sector is key in this diffusion. In a network that is asymmetric enough, a sectoral shock can induce aggregate fluctuations. In a later paper, Acemoglu et al. (2015) highlight the specific propagation pattern according to the type of shock affecting the sector. They show that for a demand shock, the propagation will occur upward in the supply chain. The affected sector's demand for inputs will decrease as a result of the shock. Thus, the supplying sector will have no opportunity to sell its products. This will impact its own demand for inputs produced by other sectors higher in the chain. Conversely, for a supply shock, the propagation will occur downward in the supply chain, working through the supply of inputs to other sectors. Barrot and Sauvagnat (2016) identify empirically such propagation patterns at the firm level. They use natural disasters as exogenous shocks affecting only suppliers and show that their clients, which are not directly affected by the event, will nonetheless suffer from its consequences. The amplitude of the impact is highly dependent on suppliers' specificity in the sense of flexibility in input sourcing. The more difficult it is for a client to change suppliers, the more impacted it will be in the case of a shock affecting its suppliers. In the case of the 2011 Japanese earthquake, Carvalho et al. (2021) also emphasize on the role of intermediate good substitutability. Such substitutability frames indirect horizontal propagation between two suppliers of the same client.

Boehm et al. (2019) show that the 2011 Tohoku 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 and highlighted the importance of production linkages as propagation channels. 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 a related paper, Kashiwagi et al. (2021) 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.

1.2.4 Financial network

Building on this early research on network, Bigio and La'o (2020) highlight the critical role of financial constraints in the propagation of financial shocks. Looking at US monetary policy, di Giovanni and Hale (2021) show that the majority of the response of global stock returns to US monetary policy shocks is due to global production linkages. Demir et al. (2020) provide another set of empirical evidence of such propagation using a change in the tax on imports purchased with foreign-sourced trade credit. They highlight the critical role of firms' financial constraints in this propagation. They show that low–liquidity firms amplifies the shock transmission. Altinoglu (2021) and Luo (2020) go further and modelize the interactions of firms' financial constraints through the existence of trade credit relationships across firms. In their models, the shock affects suppliers through lower demand for inputs and tighter financial constraints. The latter relates to clients defaulting on their trade credit, which adds to the budget constraints for their supplier's future production volumes. Looking specifically at positive financial shock through the European Central Bank's Corporate Sector Purchase Program, Adelino et al. (2020) show that trade credit allows for the redistribution of unconventional monetary policy to a wider set of firms than the ones eligible to the initial program. In another paper, Costello (2020) shows that trade credit also propagate banking shocks experienced by suppliers to their downstream customers.
Recent research also shed light on the role of trade credit defaults on firms' financial constraints. Using the case of France, Boissay and Gropp (2013) show that trade credit acts as insurance for buyers, which will choose to default on their trade credit when their financial constraint tightens. Rising defaults on trade credit are likely to highlight a deteriorating financial health of firms in a sector affected by a shock. When a firm defaults on its trade credit, the financial shock will propagate to the firm's suppliers. The latter are themselves likely to default on their own trade credit, disseminating it further. The chain will stop only when a "deep-pocket" supplier possesses enough treasury to compensate for its clients' defaults. Jacobson and von Schedvin (2015) focus on the role of those trade credit chains in corporate bankruptcies in Sweden and highlight how the default by a buyer on its claim when in bankruptcy causes a credit loss for its creditors, potentially inducing their own bankruptcy for large claims.

1.3 Organization of the dissertation

Building on the literature described above, the two first chapters of this dissertation analyze shock propagations and resulting interdependencies, taking the structure of inter-firm links as given. Through those links, shocks travel and propagate. When assessing firms' vulnerabilities, it is key to account for those propagation mechanisms.
Chapter 1. Because of a lack of data, the question of interdependencies in financial health has been largely unexplored. I fill this gap with a first chapter called *Cross-Sector Interactions in Western Europe : Lessons From Trade Credit Data*. I show that financial health in one industry helps to forecast financial health in another industry. I am able to map a network of predictive relationship across industries. To control for omitted

variable bias, I apply a high-dimensional VAR analysis, and isolate direct cross-sector causalities à la Granger from common exposure to macroeconomic shocks or to third sector shock. To assess financial health, I use trade credit defaults in five Western European countries between 2007 and 2019. With this, I provide a new advanced indicator to track propagation across industries and countries on a monthly basis. I show that monitoring some key sectors – among which construction, wholesale and retail, or the automotive sector – can improve the detection of financial distress in other sectors. I describe the structure of predictive relationships across industries and compare them with well-known network structures, namely production networks. I find that those financial predictive relationships correlates with the input-output structure in the five economies. This likely reflects vertical shock propagation along the value chain. Overall, the results highlight the need to take into account firms' and sectors' financial interdependencies when assessing vulnerabilities.

Chapter 2. I further explore the propagation of shocks within the network in a second chapter co-authored with Maéva Silvestrini (Banque de France, Paris-Dauphine University). In this paper, called *US Monetary Policy Spillovers To Emerging Markets : The Trade Credit Channel*, we study the effect of changes in US monetary policy on trade credit flows towards emerging markets economies (EME). While the relationship between portfolio flows to emerging markets and US monetary policy has been widely described in the literature, trade credit flows have been left out from the analysis despite their key financing role. We find trade credit to be an additional pass-through channel of US monetary policy to emerging markets and a substitute to other types of financing for EME importers. A key contribution of this paper is to make use of granular data to unravel mechanisms invisible in the aggregate. Specifically, we find that US monetary tightening exerts three distinct effects. First, it increases EM importers' demand for trade credit, used as a substitute to other financing tools themselves restrained. Second, it restricts US suppliers' ability to extend trade credit to their EME customers, thus acting as a liquidity squeeze. Finally, it also affects trade credit flows through an exchange rate channel, impacting differently USD and non-USD flows. To find this, we apply a panel data analysis using Coface proprietary database on firm-to-firm trade credit flows towards Mexican and Turkish buyers, on a monthly basis, from July 2010 to June 2019. We study the heterogeneity of the effect based on buyers' quality, suppliers' origin and currency used.

Chapter 3. Differently, the last chapter of this dissertation focuses on the network transformation following a shock. In this chapter called *Trade Networks and Natural Disasters : Diversion, not Destruction*, my co-author (Timothée Gigout, Collège de France & Banque de France) and I study how the structure of trade networks react to natural disasters. We innovate with respect to the literature by looking at a wide array of events and see how they alter the structure of the network. Previous research has mostly focus on the impact of specific disasters and the propagation of such shocks through the network. We estimate the causal effect of natural disasters in partner countries on various firm-level outcomes, describing the size, shape and quality of the French exporters' network. We pair firm-to-firm Coface data on exporters with exhaustive disaster data from EM-DAT. We apply a dynamic differences-in-differences identification strategy. We employ the de Chaisemartin and D'Haultfoeuille (2021) estimator and provide an estimate that is robust to heterogeneous treatment effects. We find evidence of large and persistent disruptions to international buyer-supplier relationships. This leads to a restructuring of the trade network of largest French exporters and a change in trade finance sources for affected countries. French suppliers decrease their trade credit sales to affected countries and do so mostly through the extensive margin by reducing their number of clients rather than exposure per client. The reduction in the number of buyers is particularly strong among those with good credit ratings, which are typically larger firms. We find a similar greater sensitivity of larger firms on the supplier side, particularly for those with strong local presence in the affected country. Such suppliers display a lower opportunity cost to switch away from the affected country without fully loosing access to this export market. It is easier for large multinationals with already a wide range of destination countries to divert the extra trade to other destinations and already-existing buyers. This mechanism is stronger for large multinationals operating in sectors with low relationship specificity. Overall, our results indicate that natural disasters mostly induce a reshaping of the trade networks of the largest exporters and a diversion of inter-firm trade finance away from affected markets rather than a permanent destruction of trade.

2 Cross-Sector Interactions in Western Europe : Lessons From Trade Credit Data

Contents

2.1 Introduction 31
2.2 Empirical Strategy 34
2.2.1 Methodology 35
2.2.1.1 A two-step methodology 36
2.2.2 Trade credit and firms' financial health 38
2.3 Data and Pre-estimation Treatment 39
2.4 Results 41
2.4.1 A network of cross-sector interactions to enhance sector-level monitoring 42
2.4.2 Exploring mechanisms: sector-level shock propagation 47
2.5 Robustness Tests 53
2.5.1 Coface risk management 53
2.5.2 Multiple testing procedures 53
2.6 Conclusion 55

Abstract :

Large-scale analyses to map interactions between financial health at the sectoral level are still scarce. To fill the gap, in this paper, I map a network of predictive relationships across the financial health of several sectors. I provide a new advanced indicator to track propagation of financial distress across industries and countries on a monthly basis. I use defaults on trade credit as a measure of firms' worsening financial conditions in a sector. To control for omitted variable bias, I apply a high-dimensional VAR analysis, and isolate direct cross-sector causalities à la Granger from common exposure to macroeconomic shocks or to third sector shock. I show that monitoring some key sectors – among which construction, wholesale and retail, or the automotive sector – can improve the detection of financial distress in other sectors. Finally, I find that those financial predictive relationships correlates with the input-output structure in the considered economies. Such structure of financial interactions reflect the propagation of financial distress along the supply chain, between suppliers and their buyers .

JEL classification : F14, F36, F44, L14

Keywords : Trade credit ; Network ; Cross-Sector Financial Interdependencies

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2.1 Introduction

On 23rd September 2019, the 178-year-old British travel agency Thomas Cook filed for bankruptcy. The international ripple effects of the event made the headlines. Worldwide hotels, airlines, catering–service firms, and a wide set of enterprises belonging to very diverse sectors, suffered from this insolvency. These knock-on effects highlighted existing interdependencies in firms' financial health. While researchers have studied propagation effects of one-time episodes through production outcomes, large–scale analyses to map existing interactions across sectors' financial health are still scarce. This applies even more when focusing on short-term interactions due to data limitation. In this paper, I take advantage of a granular proprietary dataset from a private credit insurer. I map financial interactions across sectors and countries in Western Europe and explore the related mechanisms. Financial health is analyzed through the lenses of trade credit defaults, used as an indicator across sectors and countries.
In this paper, the term "supplier" refers to the firm producing the good or service sold. The term "client" or "buyer" means the firm buying the good or service from the supplier. As a credit made by suppliers in the period between the delivery of the good or service and the actual payment of the sale by the buyer, trade credit is a specific term of payment for inter-firm trade. It is cited as one of the most important sources of short-term financing for firms around the globe (Petersen and Rajan (1997)). According to Boissay et al. (2020), the total of trade credit payables, i.e. the amount due by firms to their suppliers, equals to 20% of GDP and is comparable to the amount of outstanding corporate bonds. Defaulting on a trade credit means that a buyer fails to repay its supplier as planned, either due to temporary issues or to full insolvency. Those defaults are found to be good indicators of financial conditions in a given sector by Boissay and Gropp (2013). Data on firms' payment behaviors towards their suppliers are not easily available, as it requires firms to share key information about the identity of their clients and terms of contracts. One of this paper's key contributions is the use of a proprietary database from a trade credit insurer, which records defaults on trade credit agreements on a monthly basis in various Western European countries. This makes it possible to study defaults, and thus firms' financial soundness, in a specific sector without requiring proxies. Using this monthly indicator allows to test empirically on a larger scale the propagation of financial distress across sectors, domestically and internationally.

Following the seminal work of Acemoglu et al. (2012), the production network literature has shown that a shock to one sector could cause aggregate fluctuations because of existing production interdependencies. Because firms use the output of others as input in their production processes, a shock can propagate throughout the network, disrupting production along the supply chain. Building on this network structure, Bigio and La'o (2020) showed that a financial shock would also propagate across sectors through those production links. Barrot and Sauvagnat (2016), among others, exploited natural disasters as exogenous shocks and followed their propagation through the production network to explore amplification mechanisms. Firms' financial constraints drive such propagation processes. However, while production interdependencies can be clearly mapped through input-output data, no large-scale picture has been drawn regarding financial interactions across sectors. In this paper, I investigate empirically the existence of such interactions and try to determine whether they reflect the propagation of tighter financial conditions along production networks. If so, such interactions will prove key in monitoring processes in times when acute assessments of firms' financial soundness are strongly needed given the rising trend in non-financial corporate debt.

In this paper, I provide the first large-scale analysis of short–term predictive relationships across sectors' financial conditions, both domestically and internationally. Past data on trade credit defaults in other sectors can help predict future defaults in a sector of interest. Applying high-dimensional VAR analysis, it is possible to isolate direct cross-sector interactions from common exposure to macroeconomic shocks or to third-sector shock. From there, I also shed light on the correlation between the pattern of those predictive relationships and the input-output structure of the five Western European economies considered. The combination of these two facts allows to interpret the existence of short-term predictive relationships across sectors' financial conditions as evidence of short-term shock propagation within the production network, in line with the literature. The correlation pattern points towards direct vertical propagation along the supply chain as the key mechanism. Vertical propagation refers to the diffusion of distress from buyers to suppliers (upward), or from suppliers to buyers (downward). Results also highlight the predominance of inter-sector interdependencies, rather than intra-sector ones. The prevalence of international cross-sector interactions also reflect the usefulness of this indicator for cross-country monitoring purposes, often harder to follow with country's specific macroeconomic indicators. Some key sectors – such as construction, wholesale and retail, or the automotive sector – display a wide set of predictive relationships towards other sectors and should be primarily monitored to strengthen sector-based tracking in monitoring processes.

To achieve this, I exploit a proprietary database from Coface, one of the top-three trade credit insurers in the world, which records firms' payment defaults on insured trade credits. The data gather information on a total of 131 sectors in Germany, France, Italy, Spain and the United Kingdom between 2007 and 2019. Using such data on payment defaults, I construct a default rate indicator to reflect firms' financial conditions in each sector. This indicator is available on a monthly basis in the five countries at the sector level, without requiring the use of end-of-year balance-sheet data. Taking advantage of a new high-dimensional VAR methodology developed by Hecq et al. (2021) for financial stock analysis, it is possible to balance between over-dimensionality issues and omitted-variable bias. Thanks to the use of a two-step method involving repeated lasso selections, I single out predictive relationships across sectors' financial conditions. To do this, I highlight conditional causalities à la Granger across sectors' default rates on trade credit. I obtain conditional Granger causalities filtered from macroeconomic or third-sector effects. A directed conditional Granger-causality with positive coefficients defines a directed and positive predictive relationship from one sector to the other. It means that a past increase in defaults in the source sector will help predict a future increase in defaults in the destination sector as detailed further in section 2.2.

Related Literature

This study adds to several strands in the literature. First, it follows the work of Acemoglu and his co-authors since their seminal paper of 2012 on production networks. They show that sector-level shocks can lead to aggregate fluctuations because production relationships across sectors act as propagation channels for shocks. They emphasize on the importance of the production network structure. The centrality of a sector is key in the diffusion of the shock. In a network that is asymmetric enough, with a sector feeding a wide set of other sectors, a shock to this sector will induce aggregate fluctuations. In a later paper, Acemoglu et al. (2015) highlight the specific propagation pattern according to the type of shock affecting the sector. They show that for a demand shock, the propagation will occur upward in the supply chain. The affected sector's demand for inputs will decrease as a result of the shock. Thus, the supplying sector will have no opportunity to sell its products. This will impact its own demand for inputs produced by other sectors higher in the chain. Conversely, for a supply shock, the propagation will occur downward in the supply chain, working through the supply of inputs to other sectors. Barrot and Sauvagnat (2016), Kashiwagi et al. (2021) or Boehm et al. (2019) identify this downward propagation pattern at the firm level. Barrot and Sauvagnat use natural disasters as exogenous shocks affecting only certain suppliers and show that firms, which are not directly affected by the event, will nonetheless suffer from its consequences. The amplitude of the impact is highly dependent on suppliers' specificity in the sense of input sourcing flexibility. The harder it is for a client to change supplier, the more impacted it will be by a shock affecting its supplier. In the case of the 2011 Japanese earthquake, Carvalho et al. (2021) also emphasize on the role of intermediate good substitutability. Such substitutability frames indirect horizontal propagation between two suppliers of the same client. This paper contributes to this strand by studying another type of interactions along those input–output networks, looking at financial interdependencies and related mechanisms.

Building on this early research on network, Bigio and La'o (2020) highlight the critical role of financial constraints in this propagation mechanism. Demir et al. (2020) use a change in the tax on imports purchased with foreign-sourced trade credit in Turkey in 2011 to highlight how low–liquidity firms amplify the transmission of the shock. Altinoglu (2021) and Luo (2020) go further and modelize the interdependencies of firms' financial constraints through the existence of trade credit across firms. In their model, the shock affects suppliers through lower demand for inputs and tighter financial constraints. The latter relates to clients defaulting on their trade credit, which adds to their suppliers' budget constraint and affects future production volumes.

Using the case of France, Boissay and Gropp (2013) show that trade credit acts as insurance for buyers, which will choose to default on their trade credit when their financial constraints tighten. Rising defaults on trade credit highlight a deterioration of financial health in a sector. When a firm defaults on its trade credit, the financial shock will propagate to the firm's suppliers. The latter are themselves likely to default on their own trade credit, disseminating it further. The chain will stop only when a "deep-pocket" supplier possesses enough treasury to compensate for its clients' defaults. Jacobson and von Schedvin (2015) focus on the role of those trade credit chains in corporate bankruptcies in Sweden. They highlight how the default by a buyer on its claim when in bankruptcy causes a credit loss for its creditors, potentially pushing them to bankruptcy for large claims. Costello (2020) highlights the existence of a trade credit channel, along the trade channel, to propagate banking shocks. Suppliers that suffer from a drop in bank financing pass it to their downstream customers by reducing the amount of trade credit provided and reducing output deliveries. This paper builds on the above by developing an indicator of firms' level of financial constraint in a given sector to be able to track empirically the propagation of tighter financial conditions across sectors and countries and compare such patterns with production networks.

My indicator is similar by nature to the indicator developped by Bourgeon and Bricongne (2014). They use payment incidents on trade credit agreements with suppliers, as recorded by the Banque de France, to construct an indicator of financial stress at the firm level. Both indicators reflect realized defaults rather than potential ones as it is the case when using balance-sheet financial indicators. Besides the difference in the level of aggregation, the monthly dimension of Coface data allows my indicator to be more precise across time even though it does not cover the totality of French firms as their. The international coverage of Coface data also allows to map both cross–country and cross-sector financial interdependencies, without restrincting the analysis to one country. The rest of this paper is organized as follows : section 2.2 specifies the empirical strategy implemented and provides more information on trade credit. Section 2.3 describes the data. Section 2.4 provides further details on the results of the analysis, and section 2.5 introduces some alternative specifications.

2.2 Empirical Strategy

In this section, I start by describing the methodology used to test for financial health interactions across sector thanks to the use of a VAR model and conditional Granger-causality tests. Then, I provide background information on trade credit and the relation between defaults on those trade credit agreements and firms' financial health to construct the indicator.

2.2.1 Methodology

The central aim of this paper is to see whether I can identify interactions in sectors' financial health and detect predictive relationships among sectors' financial soundess. Such a relationship exists between two sectors when information on past values of financial health in the source sector enhances the prediction of financial conditions in the other sector. To identify such relationships, I construct a Vector Auto-Regressive model in which all sectors' financial health will be dependent on their own past financial outcomes as well as on past values in other sectors. Written in matrix form, I have the following :

$$FH_t = C + A_1 FH_{t-3} + A_2 FH_{t-6} + \epsilon_t \tag{2.1}$$

FH_t is a vector of firms' financial health in each specific country–sector at time t, while FH_{t-3} & FH_{t-6} record the same information but with one and two quarter lags. In this study, the focus is to identify interactions that would be consistent with sector-level shock propagation patterns. Thus, I want to be able to filter out any interdependency reflecting common exposure to macroeconomic fluctuations. To control for those macroeconomic shocks I include a set of macroeconomic indicators as control variables to obtain the following exogenous VAR model (VAR-X) :

$$FH_t = C + A_1 FH_{t-3} + A_2 FH_{t-6} + BZ_t + \epsilon_t \tag{2.2}$$

The matrix Z_t includes all the set of macroeconomic indicators and their respective lags as I will detail later on.
In this VAR-X model, I will define as predictive relationship the existence of a significant conditional causality à la Granger between two sectors. If the German plastics sector is said to conditionally Granger cause the German chemicals sector then information on firms' financial health in German plastics provides additional information to better predict the financial condition of firms in German chemicals. In this context, monitoring German plastics will prove useful in keeping track of German chemicals. Here, I have chosen to focus on conditional Granger-causalities in the very short term to detect short-term cross-sector signals and provide some remedy to the lack of up-to-date sector-level indicators. I want to test for the existence of such a conditional causality à la Granger for any considered pair of sectors in the studied economies, controlling for macroeconomic determinants of each sector's financial health, as well as for third-sector effects affecting both tested sectors.

This is done through the estimation of the VAR-X model in equation 2.2. It can be estimated using several ordinary least-squares estimations for each individual indicator of financial constraint. Conditional Granger-causality is tested with a Wald test to identify predictive relationships. In this equation and in the rest of the paper, when mentioning financial health in a sector, I refer to a sector within a country. In the case of a Granger test of sector p on sector s, those two sectors can belong to the same country c or to different countries c and c'. I estimate the following :

$$\begin{aligned} FH_{c,s,t} &= c + \theta_1 FH_{c,s,t-3} + \theta_2 FH_{c,s,t-6} + \beta_1 FH_{c',p,t-3} \\ &+ \beta_2 FH_{c',p,t-6} + \sum_{j=1}^{C}\sum_{i=1}^{S}\gamma_{j,i} FH_{j,i,t-3} + \sum_{j=1}^{C}\sum_{i=1}^{S}\gamma_{j,i} FH_{j,i,t-6} + \sum_{k=1}^{K}\sum_{h=1}^{12}\alpha_{k,h} Z_{k,t-h} + \eta_t, \\ &\text{with the country-sector pair j–i} \neq \text{c–s, c'–p} \end{aligned} \tag{2.3}$$

Here, financial health in sector s, country c at time t is determined by its own past values lagged by one and two quarters, country–sector $c' - p$ past values, lagged over two quarters, as well as all past measures of financial soundness in all other country-sectors — excluding country-sector c–s and c'–p — and the set Z of monthly macroeconomic indicators, lagged up to twelve months.

In this VAR-X model, testing for conditional Granger-causality takes the form of a conditional Wald test for the null hypothesis of joint non-significance of all sector $c' - p$'s coefficients, conditional on the inclusion of all of the other variables. This means testing whether $\beta_1 = \beta_2 = 0$ in the above specification. More specifically, it reduces to test whether including past values of $c' - p$ decreases the estimation error for $c - s$ compared with an estimation comprising only the other specified variables.

Solving this VAR-X model involves estimating a large number of coefficients, through the inclusion of the set of macroeconomic variables and simultaneous estimation of the ordinary least-squares for all sectors across the five countries. With only a limited number of observations, over-dimensionality quickly becomes an issue.

2.2.1.1 A two-step methodology

Therefore, to solve the model, it is necessary to achieve the correct balance between the required reduction in dimensions—to perform the estimations—and a reduction in the omitted-variable bias to capture solely cross-sector interactions. This is the aim of Belloni et al.'s (2014) *post-double-selection procedure*, later developed by Hecq et al. (2021) in a VAR framework for financial stock analysis. They developed a methodology to conduct conditional Granger-causality tests in high-dimensional frameworks, using two steps to balance the two imperatives.

Adapted to the current framework, the method first uses adaptive LASSO (least absolute shrinkage and selection operator) regressions to select the most relevant variables. It conducts the selection among the lagged indicators of financial health from all country–sectors (excluding pairs $c - s$ and $c' - p$) and lagged macroeconomic variables, to estimate financial soundness in $c - s$. Next, these selected variables will form an information set, conditional on which conditional Granger-causality between country–sectors $c' - p$ and $c - s$ is tested. This is done by performing a Wald test. The rest of this section will quickly detail the different steps of the procedure. More details can be found in section 2.A in the Appendix.

Step 1 : building an information set using lasso regressions

Following Hecq et al. (2021), the first step of the procedure is centered around the identification of the most relevant variables to form the control information set. This information set should fulfill two objectives. First, it should include all variables useful to estimate the left-hand variable, $FH_{c,s,t}$. Second, it should be complete enough to capture all third-sector effects going through the right-hand variables that could obscure the direct effect of the variable of interest, $FH_{c',p,t}$, on $FH_{c,s,t}$. According to Belloni et al. (2014), there is a non–zero probability that the lasso will not select an important variable, whose omission would later induce an omitted-variable bias. This involves constructing the information set using several adaptive lasso-type penalized estimation procedures on both the dependent variable and the lags of the Granger-causing variable[1]. I include in the information set any variable selected at least once among the several lasso estimations. The set of selected variables will form my information set I^*_{lasso}.

Step 2 : Wald Test for conditional Granger-causality

Once I^*_{lasso} is constructed, I perform a Wald test to determine the conditional Granger-causality of country–sector c'–p's FH on country–sector c-s's FH, conditional on I^*_{lasso}. For this purpose, I compare two models estimated by ordinary least-squares : a constrained model (M1) and an unconstrained model (M2).

$$M1 : FH_{c,s,t} = c + \gamma_1 FH_{c,s,t-3} + \gamma_2 FH_{c,s,t-6} + \alpha I^*_{lasso} + \upsilon_t \tag{2.4}$$

$$M2 : FH_{c,s,t} = c + \alpha I^*_{lasso} + \gamma_1 FH_{c,s,t-3} + \gamma_2 FH_{c,s,t-6} + \beta_1 FH_{c',p,t-3} + \beta_2 FH_{c',p,t-6} + \eta_t \tag{2.5}$$

Using a Wald test, I assess whether β coefficients are jointly equal to 0, that is, whether the following hypothesis (H0) holds : $\beta_1 = \beta_2 = 0$.

If I can reject the null hypothesis H0 at 5%, it means that at least one of the β coefficients is significantly different from 0. Therefore, past measures of financial health for $c' - p$ do enhance the estimate of financial health in $c - s$ at time t. They bring additional information compared with only the past values of country–sector $c - s$ and the information set variables.
The test is performed using Wald statistics corrected for autocorrelation and heteroscedasticity, using a Newey–West method when needed[2].

[1] See Appendix section 2.A.1

[2] Given the setting of the VAR model, there could be a risk of autocorrelation in residuals. To control for this possibility I run a Breush-Godfrey test. If I can reject the null hypothesis of no auto-correlation, I use Newey-West Heteroscedasticity and Auto-Correlation (HAC) robust standard errors as proposed by Wooldridge (2013) (see chapter 12) when I construct the Wald statistic.

Finally, p-values are corrected for multiple testing using the Benjamini–Hochberg procedure [3]. This is done to account for the increase in the probability of type I (false rejection of H0) and type II (false rejection of the alternative hypothesis, H1) errors when conducting this procedure for all pairs cs–$c'p$ across all country-sectors in the considered economies. Alternative correcting procedures will be exposed as robustness checks in section 2.5.
I consider as significant any conditional Granger-causality with a Benjamini–Hochberg-corrected p–value that falls below the 5% threshold.

2.2.2 Trade credit and firms' financial health

Trade credit is a specific term of payment for the sale of a good or service between two firms. 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. Trade credit is one of the main financing tools available to firms to finance trade as described by Antras and Foley (2015). Under trade credit terms, the supplier pays for the production of the good or service and allows its client to defer payment until after the delivery. According to Bureau et al. (2021), trade payables, which record the amount due by firms to their suppliers within trade credit agreements, amounted to EUR 520 billion in France in 2019, seven times higher than bank short-term financing. The payment takes place at the end of a grace period, which varies according to the supplier–buyer relationship. Using data on buyers located in North America and Europe, Klapper et al. (2012) highlight a median duration of 60 net days before payment is due by the buyer while Alfaro et al. (2021) record 86 days in average for Chilean firms, with some payment period extending to 120 days or longer in some specific cases (longer for capital goods). Such credit is highly appreciated by clients, who will tend to favor these types of partnerships. From the supplier's perspective, however, it can prove dangerous. In the case of payment default, the supplier comes under increasing pressure to meet its own financial constraints. In some cases, it could even be pushed into bankruptcy for very large credits. To protect itself from potential payment defaults from the buyer, the supplier might want to insure itself. To do so, it takes out trade credit insurance from an insurer, which will reimburse the amount due in the case of default. According to Berne Union, trade credit insurers provide payment risk capital for around 13% of global cross-border trade. Data used in this paper comes from such types of agreements from suppliers requesting insurance from one of the top-three trade credit insurers worldwide named Coface.

In this paper, default from a buyer specifically means a failure of the buyer to meet its payment obligations. It can be due to either temporary constraints on the buyer's cash flows or to full insolvency. Both cases reflect increasing financial constraints on the buyer side.
Every time a buyer defaults, the supplier will be directly reimbursed by the insurer.

[3] See Benjamini and Hochberg (1995)

It is in the supplier's interest to declare a payment default as soon as the payment period expires. Hence, data compiled by the trade credit insurer on a monthly basis tend to provide an up-to-date record of payment defaults. They are likely to mirror existing financial constraints for firms defaulting. I have chosen to identify the level of constraint through the number of defaults and not the amount. This allows me to detect widespread constraints spread over numerous firms in a sector.

An indicator of financial constraint : defaults on trade credit

As one of the key contribution of this paper, I construct a short-term indicator of firms' financial conditions in a given country–sector using trade credit defaults recorded on a monthly basis by Coface. I proxy firms' level of financial constraints for a country c and a sector s at month t with the following default rate (DR) :

$$DR_{c,s,t} = \frac{\frac{1}{3}\sum_{j=t-2}^{t} \text{Number of Defaults}_{c,s,j}}{\text{Number of Supplier–Buyer Relations}_{c,s,t-6}} * 100 \tag{2.6}$$

I divide the number of defaults recorded by the initial number of insured partnerships, to allow for comparisons across sectors and see which share of trade credits is in default. This also controls for changes in Coface's risk policy, i.e. Coface's willingness to insure trade credits for buyers in specific sectors and countries. Given the existence of a grace period between the time of the sale and the due date for payment, it is necessary to take the number of partnerships up to six months before. Taking it with such a lag allows for the integration of a majority of cases despite heterogeneity in the length of grace periods and include agreements with longer terms than the median (86 days in average for Alfaro et al. (2021)). This is also in line with the choices made by operational staff at Coface to build their own activity indicators.

Using this indicator, the model presented in equation 2.2 becomes :

$$DR_t = C + A_1 DR_{t-3} + A_2 DR_{t-6} + BZ_t + \epsilon_t \tag{2.7}$$

where DR_t is a vector of all country–sector–level payment default series across all countries at month t. DR_{t-3} and DR_{t-6} record the same series lagged respectively by one and two quarters. By taking lags over quarters, I avoid overlap across rolling means in my indicator. DR_t averages defaults over $t, t-1$ and $t-2$, while DR_{t-3} does the same over $t-3, t-4$ and $t-5$, as does DR_{t-6}, with an additional three-month lag.

2.3 Data and Pre-estimation Treatment

To conduct the empirical strategy described above, I use data from one credit insurer, named Coface, on five main Western European countries : France, Germany, Italy, Spain and the United Kingdom. In these countries, the trade credit insurance market

is developped, trade credit is a widely used trade financing tool and Coface is well positioned on the market. According to Berne Union, Europe is by far the largest market for trade credit insurance and represents 50% of insured exports worldwide. With Coface among the leaders on the insurance market in Europe, it makes the data quite representative of overall trade credit market dynamics in Western Europe.
I construct the previously-described indicator for 36 sectors in the five countries between July 2007 and December 2019 using the International Standard Industrial Classification of All Economic Activities Revision 4 for sectors (see Table 2.B.1 in the Appendix for a full description).
I have excluded all public-service sectors, as well as financial and insurance sectors, from the conditional Granger-causality analysis. However, I do include them among the pool of variables to construct the information set with lasso selections. In addition, I restrict the considered sectors to record on average at least one default every month over the whole period. This means I exclude 10% of sectors for which Coface data do not record enough events for the analysis to be representative. Finally, the analysis is performed for a total of 131 country-sector variables (see Table 2.F.1 in the Appendix for a full list of included sectors by country). Table 2.1 details the summary statistics on the number of insured trade credits, the number of defaults and the key indicator for the analysis, the default rate, at the country-sector level for each month.

TABLE 2.1 : Descriptive Statistics—Coface Trade Credit Data

Statistic	Number of trade credits	Number of defaults	Default rate indicator
N	18,252	18,252	18,252
Mean	17,112.32	27.85	0.12
St. Dev.	36,077.46	96.16	0.13
Min	387	0	0.00
Pctl(25)	3,289.8	1	0.04
Median	7,113.5	5	0.08
Pctl(75)	14,155.2	15	0.15
Max	323,728	2,472	1.21

Note : These statistics are displayed at the country-sector level on a monthly basis.

Given the VAR setup of our model, the data need to be stationary. To remove trends and seasonal patterns, Loess decomposition is applied to the time series, and the residual is kept as the variable in the analysis.

Regarding exogenous macroeconomic variables, one requirement is to use monthly indicators that allow us to control for the business cycle, not only in the five countries of interest, but also at the global level. For this reason, I have included the following :

- Industrial production indices in the five countries and at the Eurozone level, using data from Eurostat. The United States, Japan and China are also included, as well as regional-level indices for Latin America, Central Eastern Europe and East Asia, computed by the CPB (Netherlands Bureau for Economic Policy Analysis).

- Business confidence and consumer confidence surveys, which detail the balance of positive and negative answers, for the five countries, as well as at the European Union level, using data from Eurostat.
- M2 money supply indicators, which include retail deposits and cash in M4, computed as contributions to the euro basis in millions of euros for Spain, Italy, France and Germany, as well as Eurozone money supply as a whole, from Eurostat. For the United Kingdom, these are computed in millions of pounds sterling by the Bank of England.
- Interest rates on loans to non-financial corporations up to 1-year maturity, for the United Kingdom, France, Germany, Italy and Spain, as well as for the Eurozone, using European Central Bank data.
- Yield on ten-year government bonds for the five countries, the eurozone as a whole and the United States, based on OECD data.
- Brent oil prices (USD/barrel) averaged over a month from ICIS (Independent Commodity Intelligence Services) data.
- Export and import flows taken from International Monetary Fund trade statistics in millions USD for the five countries of interest.

For the same reasons as for defaults, macro series also need to be stationary, and thus Loess decomposition is also performed on these variables to remove trend and seasonality patterns. Finally, to reduce dimensionality of the system while allowing for the lasso estimation to select variables that control for the macro-financial cycle, I perform principal components analysis on this set of macroeconomic variables and select the components for which the eigenvalue is greater than 1. Figures 2.C.1a and 2.C.1b in section 2.C in appendix display the results of this analysis. The selected principal components form the matrix Z_t in the VAR-X model and are lagged up to twelve months.
I conduct the above-described analysis over the whole sample, from July 2007 and December 2019, and from July 2013 to December 2019 to have a second sample excluding periods of macroeconomic crisis.

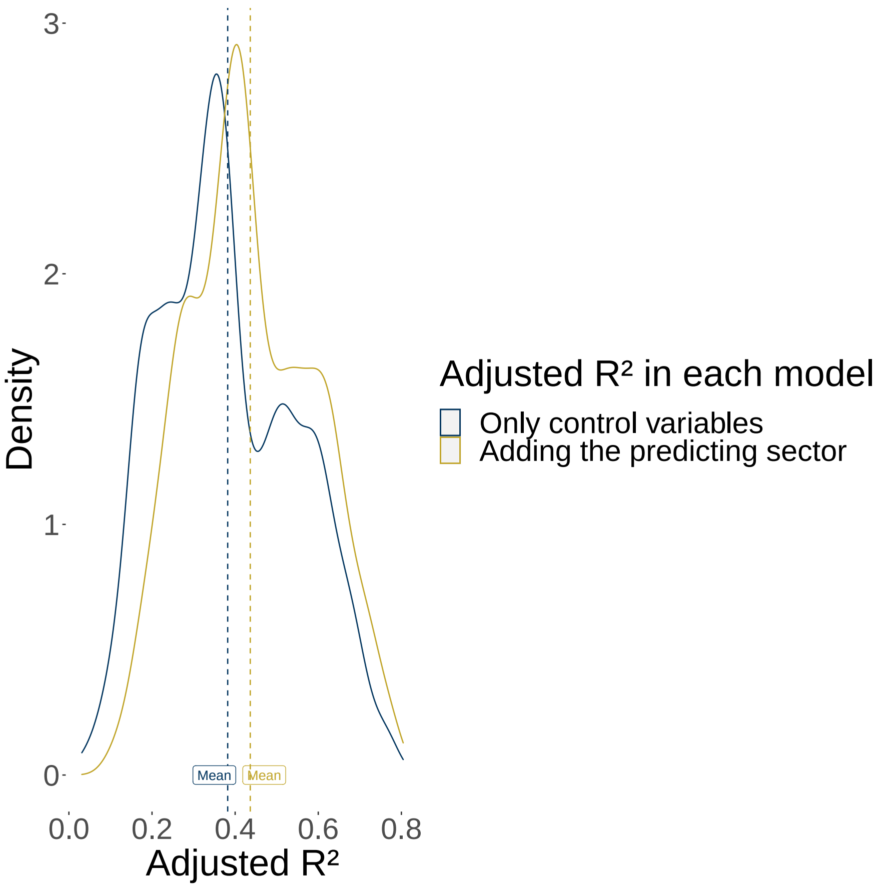
2.4 Results

In this section, I detail the two key results of the analysis. First, I describe the network of predictive relationships across sectors' financial health, cleaned from macroeconomic or third-sector omited-variable bias. This result is key to improve monitoring processes at the sector-level. Then, I describe the empirical evidence that points towards financial distress propagation along production networks, sparked by sector-level shocks, to explain the existence of such predictive relationships across sectors.

2.4.1 A network of cross-sector interactions to enhance sector-level monitoring

Conducting the procedure in section 2.2 over the period 2007-2019, I obtain a network of significant predictive relationships. Out of 13,572 potential interactions, 2,810 (21%) are deemed significant as conditional causalities à la Granger. Past outcomes in other sectors do help predict future financial developments in one sector. This holds even after controlling for trends in the macroeconomic cycle and third-sector omitted-variable bias through the use of control variables.
Figure 2.1 shows the improvement in the estimation of payment defaults at the sector level thanks to the information provided by other sectors. It represents the R^2 distributions for the sectors whose prediction is improved thanks to information from other sectors. The two distributions reflect the distribution of R^2 in equation 2.4 and 2.5, i.e. with only controls or including the Granger-causal sector, for the 2,810 significant predictive relationships. A shift to the right of the R^2 distribution is observed when adding the Granger-causal sector to the control variables. On average, 44% of the variance is explained when including past information on Granger-causing sectors.

FIGURE 2.1 : Cross-Sector Information to Add Predictive Power

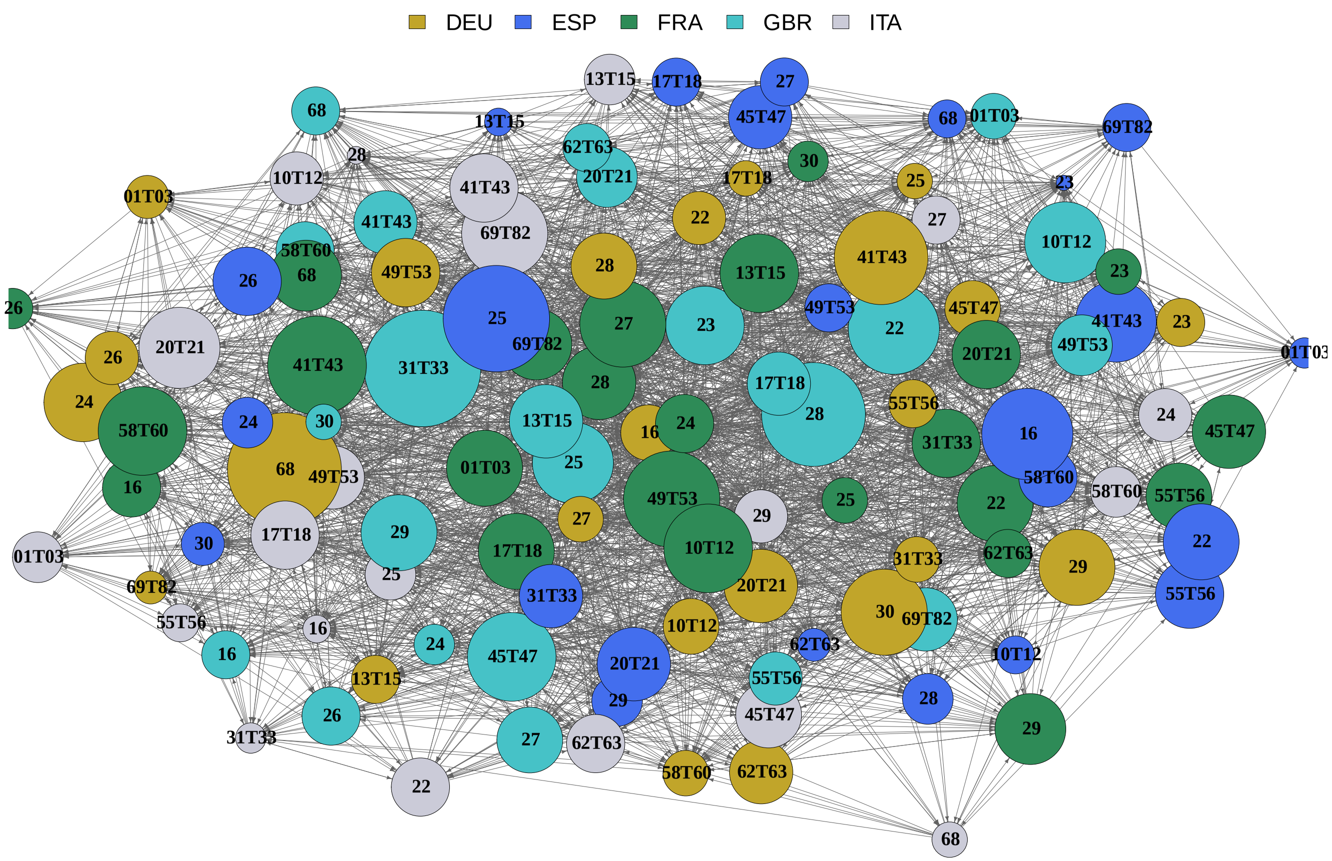


In blue, the distribution of R^2 in 2.4 and in yellow in 2.5 for the 2,810 significant predictive relationships.

Figure 2.2 maps all the significant cross-sector predictive relationships. Arrows represent the directed predictive relationships between two country-sectors symbolized as circles. The size of the circle is proportional to the number of predictive signals streaming from the sector. The number of arrows pointing towards a circle reflects the number of other sectors sending signals to improve predictions in the sector of interest. The network is characterized by a majority of inter-sector and international links. Most links are between different sectors located in different countries. International patterns first mirror market interdependencies in Western Europe among deeply integrated markets. However, the prevalence of international links (78.8% of total) among the highlighted Granger causalities also means that such international cross-sector interactions are not easily captured by common macroeconomic indicators included in the information set. This makes the indicator even more useful for cross-country monitoring purposes.

Of these links, 616 are bidirectional. This means that if my sector of interest provides useful information for another sector, the reverse also holds. This is likely due to the sector classification available in the data that is still quite aggregated.

Moreover, strong heterogeneity prevails in the interactions. Node size varies strongly



Each circle represents a sector in one country and each arrow the link from a sector toward another. The direction indicates whose past values help explain whose value at time *t*. Circle size is proportional to the number of of predictive signals sent. Are represented only links for which the p value with Benjamini–Hochberg correction falls below the 5% threshold. See the Appendix for sector codes.

FIGURE 2.2 : Full Network of Significant Cross-Sector Interactions

across sectors presented in Figure 2.2. This means that some sectors are useful in enhancing predictions for a variety of sectors. The same can be noted in the number of arrows pointing toward a sector. This suggests that for some sectors, a wide set of others can improve predictions. Thus, some sectors are more central than others in the interaction network, in the same way as some sectors have been found in the literature to be more central in production networks.

A similar heterogeneity is visible at the aggregate sector level as observed in table 2.2. As for figure 2.1, it summarizes the R^2 distribution for significant Granger-causalities at the sector level, aggregating country-sectors in the five countries. The third column synthesizes the difference in variance explained between the two models in 2.4 and 2.5. It appears that cross-sector links bring the most valuable additional information for sectors relatively less well explained by the controls, i.e. mostly the macroeconomic cycle. Payment defaults in construction, IT services or real estate can be much better predicted when accounting for cross-sector information. However, even for sectors as motor vehicles, fabricated metals or rubber and plastics, that are relatively well predicted by the macroeconomic cycle, cross-sector information do help improve predictions in payment defaults.

TABLE 2.2 : Percentage of Explained Variance - By Sectors

Sectors	R^2 for Model M1	R^2 for Model M2	Additional Variance Explained in M2
Real estate activities	26	33.21	7.21
IT and other information services	24.05	31.18	7.13
Publishing, audiovisual and broadcasting	21.38	28.49	7.12
Construction	20.68	27.59	6.91
Computer and electronic	33.53	40.39	6.86
Electrical equipment	28.38	35.02	6.64
Other business sector services	29.10	35.57	6.47
Agriculture	25.60	31.71	6.11
Wholesale and retail trade	36.21	42.28	6.06
Food products, beverages	36.09	42.07	5.97
Textiles, apparel	36.27	41.76	5.49
Transportation and storage	34.80	40.14	5.34
Other transport equipment	43.63	48.76	5.13
Accommodation and food services	37.87	42.98	5.11
Wood	36.39	41.33	4.94
Glass and other	43.63	48.48	4.85
Basic metals	47.65	52.47	4.82
Machinery andequipment	46.18	50.99	4.81
Rubber and plastic	53.22	57.92	4.70
Paper	45.06	49.63	4.58
Other manufacturing	36.65	41.10	4.45
Chemicals and pharmaceuticals	53.66	57.78	4.12
Motor vehicles	51.82	55.85	4.03
Fabricated metal	52.62	56.64	4.02

Columns 1 and 2 display the percentage of explained variance in model 2.4 and 2.5 for significant Granger causalities. Column 3 is equal to the difference between the two (in percentage points). Column 1 averages the R^2 in 2.4 – which includes only controls as covariates – for each aggregate sector. Column 2 averages the R^2 in 2.5 which also includes lagged payment defaults for the Granger causing sector.

Figure 2.3 maps each sector according to inward and outward interactions with other sectors. By inward interaction, I mean that other sectors provide information to enhance the estimation of financial conditions in my sector of interest. By outward link, I mean the information provided by my sector of interest to improve other sectors' estimates. Construction, chemicals and pharmaceuticals, rubber and plastics, wholesale and retail, transportation, and motor vehicles help predict outcomes in other sectors, whereas few sectors can help predict their own outcomes. All of these sectors should be monitored as a priority, as their own developments will provide useful information to better predict financial conditions in multiple other sectors. Conversely, some other sectors are well predicted by others. These are fabricated metal, machinery and equipment, paper, and textiles and apparel.

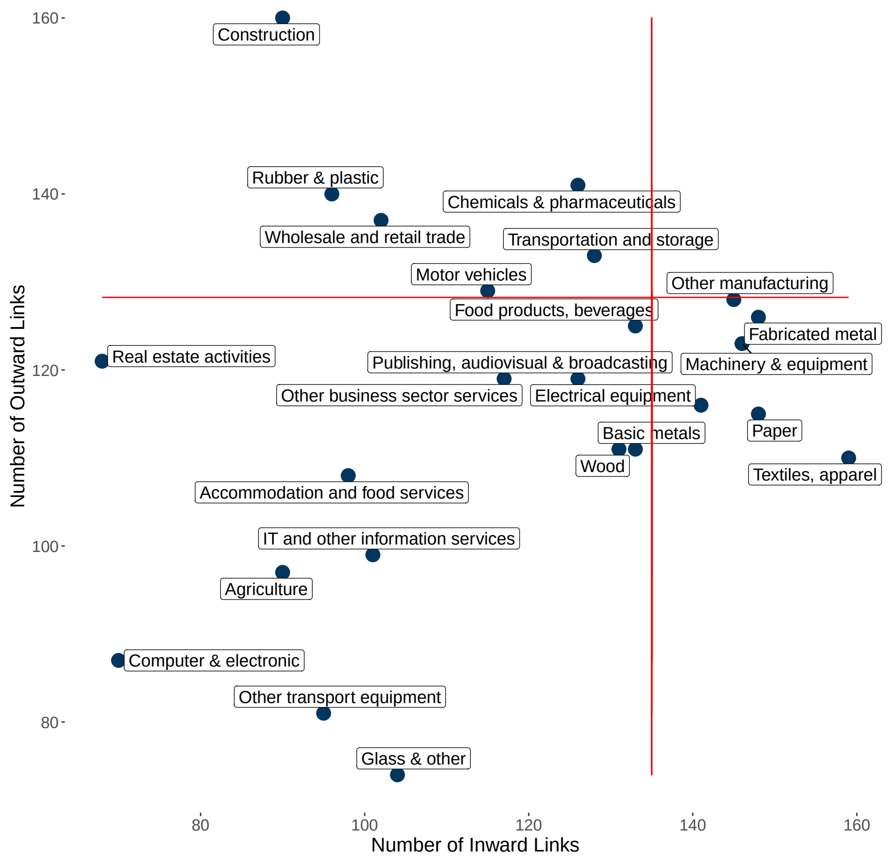
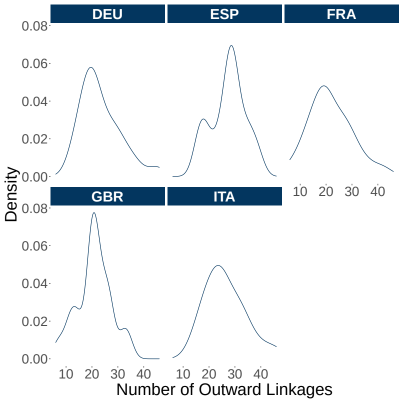
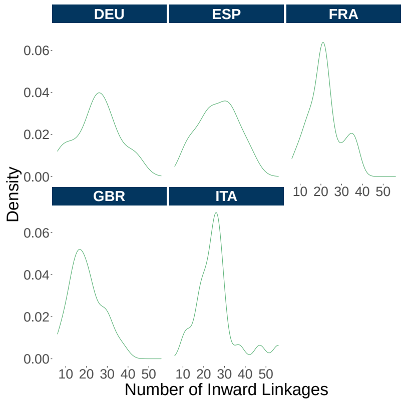


FIGURE 2.3 : Aggregate Sector Distribution - Inward & Outward Links
The x axis represents the total inward interactions for each sector, that is, the information provided by other sectors to enhance the estimation in each sector. The y axis represents the total number of outward interactions, that is, the information each sector provides to improve other sectors' estimates. Red lines indicate the third quartile for each measure.

Figures 2.4a and 2.4b display, respectively, density functions for outward and inward links, for each country in the sample. They highlight the strong heterogeneity among sectors across countries. Most sectors are sparsely connected to others, and only a few display numerous interactions. The proportion of each type differs across countries. Distribution of inward and outward links also strongly differ within the same country. From those results, it appears that sector-level dynamics prevail over country-level ones.



(a) Density function for outward links by country



(b) Density function for inward links by country

FIGURE 2.4 : Inward and Outward Link Distribution

From this first set of results, appears the usefulness of cross-sector monitoring to predict tightening in financial constraints at the sector-level. Macroeconomic indicators cannot supply all the necessary information, and developments in other sectors provides specific information that cannot be obtained from another source. In this predictive network, some sectors are central as key information senders and should be monitored in priority.
Starting from there, now comes the necessity to explore the source of such interactions and underscore the causing mechanisms.

2.4.2 Exploring mechanisms : sector-level shock propagation

In order to highlight the underlying mechanisms and structural patterns, I focus on a restricted time period, excluding times of crises in Europe in the first half of the sample with the financial and European sovereign debt crises. I conduct the exact same analysis, but this time focusing on the period spanning from 2013 to 2019. The resulting network of 1,774 links is displayed in graph 2.D.1 in appendix. In this network, I define the cumulated magnitude of the predictive relationship as the sum of coefficients β_1 and β_2 in equation (2.5) for coefficients found to be jointly significant. Taking back my previous example, positive magnitude in the predictive relationship means that an increase in payment defaults German plastics helps predicting an increase in defaults in German chemicals. Conversely, a negative magnitude means an increase in plastics helps predicting a decrease in chemicals.
Table 2.3 displays summary statistics of such predictive power magnitude for both individual lags and the cumulated one — computed as sum of the individual amplitude — for 2013–2019. On average, both individual and cumulated amplitude are positive, and more than 75% of links display a positive magnitude. However, 23% of the 1,774 significant links from 2013 to 2019 display a negative cumulated effect.

TABLE 2.3 : Post-Crisis Period—Amplitude of Interactions—Significant Links

Statistic	Coefficient First Lag	Coefficient Second Lag	Combined Effect
N	1,774	1,774	1,774
Mean	0.23	0.06	0.29
St. Dev.	0.41	0.36	0.60
Min	−1.85	−2.03	−3.88
Pctl(25)	0.06	−0.14	0.05
Median	0.22	0.05	0.27
Pctl(75)	0.42	0.25	0.57
Max	2.79	2.56	2.75

Note : The combined effect displayed in the third column is equal to the sum of the two first columns.

Mechanisms in the literature

Based on the network literature described in section 2.1, sectors are interdependent based on the production structure. Thus, if due to shock propagation, predictive relationships should follow production network. Such propagation scheme can be of two types : either vertical or horizontal.
In case of vertical propagation of shocks (see Acemoglu et al. (2015))– between suppliers and buyers – the existence of predictive relationships should be positively related to the amount of intermediate goods flowing between two sectors. In case of a supply shock, developments in the supplying sector should help predict developments in the buying sector as disruption in the production of inputs will forbid buyers to produce their own good. Therefore, the predictive relationship should be directed downward in the supply chain and of positive magnitude. In case of a demand shock, the direction of the prediction should reverse, with demand falling in the buying sector and suppliers left with surplus. Therefore, the predictive relationship should point upward the chain with again a positive magnitude.

Differently, an horizontal propagation pattern, as defined by Carvalho et al. (2021), refers to shock propagation among two suppliers of a common sector. The sign of the magnitude in the predictive relationship should depend on the type of inputs produced by the two suppliers for their common buyers. In case of complement inputs, if a shock affects one supplier, it will disrupt the production process for the buyer, therefore affecting the other supplier because of complementarity in the process. In such case, the predictive relationship between the two suppliers should be of positive magnitude. In case of substituable inputs, the common buyer is likely to switch input sourcing from one supplier to the other, and therefore one is likely to struggle while the other strives. In that case, the predictive relationship should be of negative magnitude. With horizontal propagation, the correlation with the amount of intermediate good flows between the two suppliers is more uncertain and highly dependent on the level of aggregation. For highly disaggregated sectors, the amount of intermediate good exchanged by two suppliers should be very small. However, for more aggregated sectors it is likely that supply chain for several types of goods overlap.

Verifying mechanisms in the data

To test the propagation pattern highlighted above, I split the predictive network between predictive relationships with positive and negative magnitudes. Resulting networks can be found in figures 2.D.2 and 2.D.3 in appendix.

Table 2.4 synthesizes the output of a simple logistic test. I test whether for a specific sector pair $c'p$–cs, having a significant positive predictive relationship from $c'p$ to cs is related to the amount of intermediate good flowing from $c'p$ to cs. I test this for both direct intermediate flows from $c'p$ to cs and total value added — including flows through third sectors — measured using Leontief decomposition[4]. I standardize both measures for greater comparability and interpretation of coefficients. I use intermediate consumption data from the OECD's STAN Inter-Country Input–Output database for the year 2015, the latest available year at time of writing. The coefficient in table 2.4 should be interpreted as the influence of a one-standard-deviation increase in intermediate flows sent from $c'p$ to cs on the odds of having a significant positive predictive link from cs to $c'p$. From column 1, we can see that, a one-standard-deviation increase in the intermediate-good flow from $c'p$ to cs raises the odds of having a significant positive predictive relationship from $c'p$ to cs by $exp(0.093) = 1.097$, i.e. 9.7%. From column 2, a one-standard-deviation increase in the total value added flowing from $c'p$ to cs raises the odds of having a significant predictive link from $c'p$ to cs by 1.08, i.e. by 8%. Both coefficients are significant at 1%. The effect is stronger when looking at direct intermediate good flows rather than total value added.

Beside the existence of a predictive relationship, comes its magnitude as defined above, i.e. sum of β coefficients in 2.5. Table 2.5 presents the output of correlation tests between the cumulated magnitude of the predictive effect and input–output measures for positive relationships. A Kendall correlation test is performed to allow for nonlinear relations. The first column presents the correlation coefficient and the associated p value for direct intermediate flows, while the second column refers to Leontief measure of total value added. The magnitude of the predictive relationship is positively and significantly correlated to the amount of intermediate goods flowing from one sector to the other but not to the total value added sent from source to destination.

Further than the production flow by itself, one of the key lessons taken from the network literature regarding shock propagation is that, the more central a sector, the quicker a shock affecting this sector will propagate to the rest of the network. This means that the above results of the logistic regression might be mostly driven by some key sectors that are very central to the production network. To verify such hypothesis, I test for the correlation between two measures of centrality in both production and Granger-causality networks. I measure centrality using the out-degree measure that counts the number of outward links streamming from each sector. In the production

[4] Quast and Kummirtz (2015) is used to compute the Leontieff measure of total value added.

TABLE 2.4 : Logistic regressions - Input-Ouput Flows and Positive Predictive Relationships

	Having a Significant Granger-Causality Link With Positive Net Magnitude	
	(1)	(2)
IO Direct Flow	0.0913^{***}	
	(0.0279)	
Leontief Total Value Added		0.0769^{***}
		(0.0190)
Constant	-2.1879^{***}	-2.2026^{***}
	(0.0285)	(0.0289)
N	13,572	13,572
Log Likelihood	−4,439.9240	−4,437.4780
Akaike Inf. Crit.	8,883.8480	8,878.9560

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
Those regressions are performed under the following logistic model : $log(\frac{Pr_{ps}}{1-Pr_{ps}}) = \alpha + \beta IO_{ps} + v$. Pr_{ps} is the probability of having a significant Granger-causal link from sector c'p to cs in the period 2013-2019, using BH correction, with a positive net magnitude, i.e. with the sum of β_1 et β_2 >= 0 in 2.3. IO_{ps} is a measure of input-output, either the direct flow from c'p to cs or the Leontief's measure of total value added from c'p to cs. Both IO measures are standardized and coefficients should be interpreted as the impact of a standard unit deviation on the log odds.

TABLE 2.5 : Kendall Correlation Test - Granger-Causing Effect and Input-Ouput Flows

	Direct IO - Correlation	Leontieff IO - Correlation
Positive Linkages	0.093 ***	-0.022

*** : 1% p-value , ** : 5% p-value, * : 10% p-value.
The Kendall correlation is computed between the cumulated magnitude of positive predictive relationships from sector c'p to cs (i.e. the sum of β_1 et β_2 >= 0 in 2.3) and input-output indicators. Input-ouput indicators measure either the direct intermediate good flow from c'p to cs (IO direct) or the Leontief's measure of total value added from c'p to cs (Leontieff IO). Both IO measures are standardized.

network, I weigh the out–degree using the standardized amount of intermediate goods flowing out from each sector using the same data as above. The two measures are significantly correlated with a Pearson coefficient equal to 0.34 and significant at 1%. Figure 2.5 synthesizes the link between the two measures and plots the linear relationship. When increasing by one the out-degree in the production network, the out-degree in the predictive network increases by 0.099. The more central a country–sector in the production network of the five considered European countries, the higher the number of predictive signals sent by this sector to better estimate outcomes in other sectors. Wholesale and retail, construction, other business services as well as food products and beverages largely drive such relationship as key information and intermediate-good providers as shown on figure 2.6.

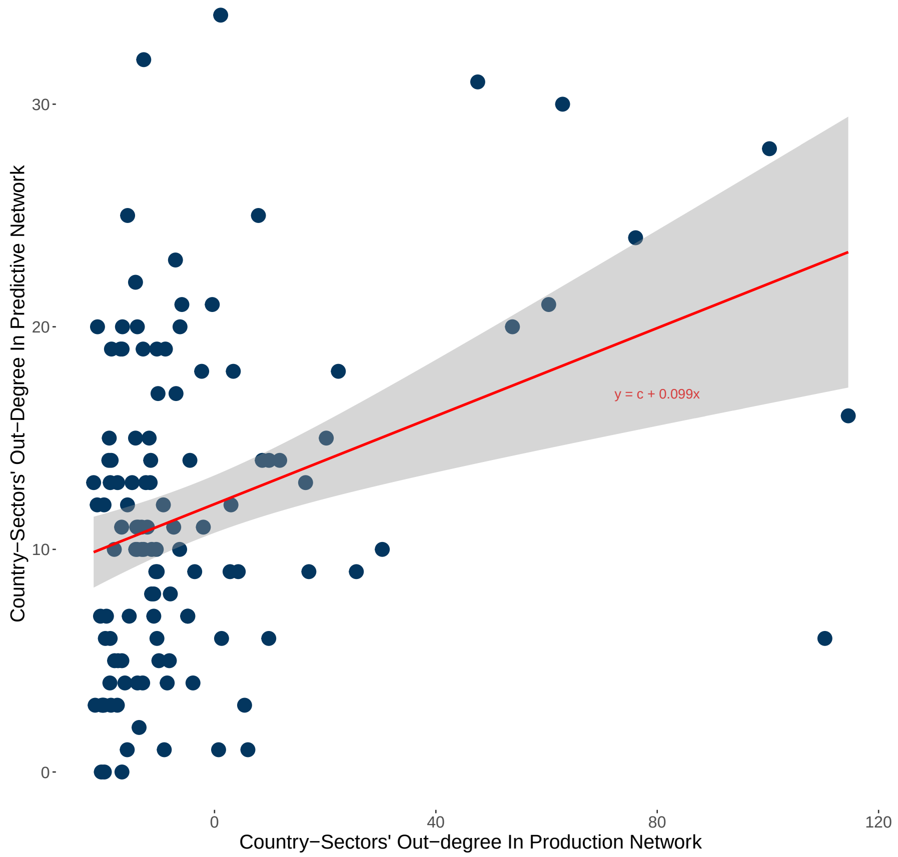


FIGURE 2.5 : Centrality in Production and Granger-Causality Networks
The x axis represents the out-degree of each country sector in the production network, weighted by the amount of intermediate goods exchanged. The y axis displays the out-degree of each country-sector in the predictive network. In blue, the linear relationship between the two measures.

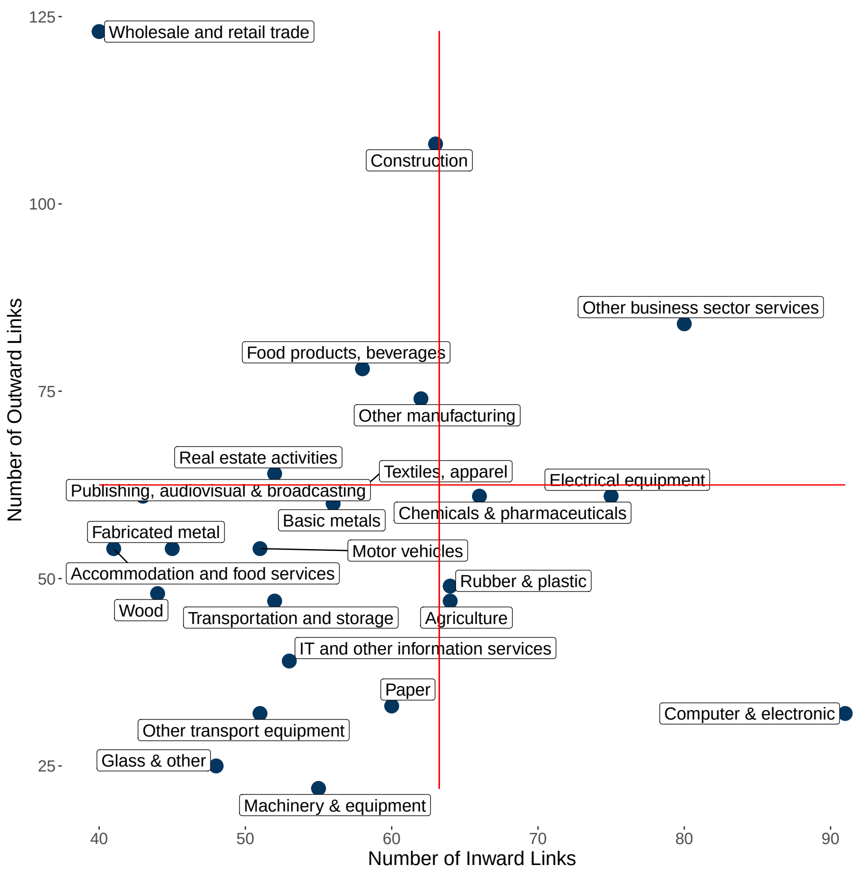


FIGURE 2.6 : Inward and Outward Links in Positive Network
The x axis represents the total number of positive predictive signals received by each sector. The y axis represents the total number of positive predictive signals sent. Red lines indicate the third quartile for each measure.

From this set of results, positive predictive relationships across sectors appear to follow a pattern that is consistent with propagation mechanisms described in the literature. Positive predictive signals reflect the vertical propagation of financial distress across sectors. The origin of such distress is likely to be at the sector-level rather than the macroeconomic one, given that the predictive relationships are detected controlling for macroeconomic shocks. As the predictive relationship goes in the same direction as intermediate good flows, with disaggregated data we could favor a supply shock propagation as the main source of such financial interdependancies. However, the aggregated level of the data used in this paper does not allow to clearly distinguish between supply and demand shock propagation. Indeed, at the current level of aggregation, intermediate flows between the two sectors are most often going both ways, with suppliers and buyers in both sectors.
Uncertainty also remains regarding mechanisms involved in negative predictive relationships. As expected, table 2.E.1 in appendix shows that the existence of negative predictive relationships is not significantly related to the amount of intermediate flows between the two sectors, nor to the total value added exchanged. Thus, as expected

from the theory such negative predictive relationships cannot reflect direct propagation between buyers and suppliers within supply chains. however, here again, data are too aggregated to confirm the horizontal propagation hypothesis between suppliers of substitutable inputs. The confirmation of these two phenomena should be left to future research.

2.5 Robustness Tests

2.5.1 Coface risk management

With 38% of the variance explained over the whole sample on average, arises the question of explaining the remaining volatility. Besides macroeconomic factors, default rates are likely to be affected by Coface's own determinants and risk management choices. Thus, I added to the specification acceptance rates at the country-sector level. This variable measures the share of total clients' request for risk coverage that Coface has actually chosen to cover. When adding this variable with twelve-month lags as exogenous regressors to the VAR-X model on the period 2010-2018 for which data are available, there is no change to the results compared with the same period with the already–described variables. Indeed, country-sector acceptance rates are never selected by the lasso selection processes, as they are deemed less significant than the macroeconomic variables. Thus, it seems that the Coface risk policy is already controlled for, thanks to the normalization performed in the construction of the indicator.

2.5.2 Multiple testing procedures

A second question lies in the choice of multiple testing corrections. The Benjamini–Hochberg method was favored as it was deemed less conservative than the Bonferroni family-wise error rate or Holm's alternative. Controlling for the false-discovery rate allows to keep false rejection of the null hypothesis low, which here means to falsely reject Granger non-causality and thus settle on a significant Granger causal link, i.e. the existence of a predictive relationhsip. Besides the Benjamini–Hochberg method, Benjamini and Yekutieli (BY) developed a more conservative methodology to control for the false-discovery rate.

When applying the BY correction instead of the Benjamini–Hochberg's one on p-values, there is a much lower number of links deemed significant. The new network of positive relationships is formed of 452 edges. However, this new output agrees with the key points of the analysis. Cross-sector interactions are useful to strengthen predictions of sector-level default rates besides macroeconomic trends. With interactions, the share of variance explained increases from 20% to 39% in the BY network. Table 2.6 displays coefficients of a logistic regression similar to the one described in Table 2.4 but applied to the BY network. Coefficients are greater. A one standard deviation increase in direct intermediate flows increases the odds of having a significant predictive link by 17.4%. A one standard deviation increase in total value added increases the odds by 11.6%. The correlation between the cumulated effect and direct intermediate flows is also again positive and significant with the new network, equal to 0.10. The relation between Granger causalities across country–sector default rates and input–output flows is confirmed for both treatments of the false discovery rate. Thus, it appears that neither the existence of predictive relationships across sectors' financial health, nor the relation between their structure and input-output network depends on the type of multiple testing correction chosen.

TABLE 2.6 : Logistic regressions - Input-Ouput Flows and Positive Predictive Relationships - Benjamini-Yekutili Correction for Multiple Testing

	Having a Significant Granger-Causality Link	
	(1)	(2)
IO Direct Flow	0.1618^{***}	
	(0.0320)	
Leontief FVAX Measure		0.1198^{***}
		(0.0219)
Constant	-3.3800^{***}	-3.4027^{***}
	(0.0482)	(0.0488)
N	13,572	13,572
Log Likelihood	−1,972.9890	−1,971.3520
Akaike Inf. Crit.	3,949.9770	3,946.7050
Notes :	Those regressions are performed under the following logistic model : $log(\frac{Pr_{ps}}{1-Pr_{ps}}) = \alpha + \beta IO_{ps} + v$. Pr_{ps} is the probability of having a significant Granger-causal link from sector c'p to cs in the period 2013-2019, using BY correction, with a positive net magnitude, i.e. with the sum of β_1 et β_2 >= 0 in 2.3. IO_{ps} is a measure of input-output, either the direct intermediate good flow from c'p to cs or the Leontief's measure of total value added from c'p to cs. Both IO measures are standardized and coefficients should be interpreted as the impact of a standard unit deviation on the log odds.	

2.6 Conclusion

This study has explored a different aspect of firms' interactions, moving away from a pure production analysis. By focusing on trade credit, I look towards a financial indicator that is deeply rooted in production strategies and involves interactions between firms' balance sheets. Taking advantage of the data of one of the top trade credit insurers, I draw key lessons on domestic and international cross-sector relationships and their use in monitoring processes. To do this, I exploit sector-level data on five Western European countries between 2007 and 2019, as well as 2013 and 2019. I use Belloni et al.'s (2014) post-double-selection procedure, adapted by Hecq et al. (2021) to a high-dimensional VAR framework. This method allows me to detect cross-sector predictive relationships through short-term conditional causalities à la Granger. Results show that most sectors are related to one or more sectors, either as sender or receiver of those predictive relationships. This emphasizes the relevance of cross-sector interactions to better predict defaults in a specific sector, once macroeconomic trends are accounted for. Such result is key to improve monitoring processes using sector-based tracking. Most often, these interactions occur on an inter-sector and international basis, rather than within a sector across countries, or between sectors within a country. This reflects the high level of integration among Western European markets but also highlights the usefulness of cross-sector interactions in international monitoring processes. Then, I show how the positive predictive signals detected reflect the propagation of financial distress among sectors, vertically along the supply chain. The methodology used allows to point towards a sector-level origin of the shocks leading to increasing financial distress, given that macroeconomic shocks are controlled for. The more central a sector in the production network, the greater the number of positive predicting signals it sends towards other sectors. The probability of detecting a positive predictive relationship sent from one sector to the other increases with the amount of intermediate goods sent by the former to the latter. A correlation also exists between the cumulated magnitude of the predictive power and the input-output indicators.

Building on this first map of international financial interactions across sectors, further research with more disaggregated data will help clearly identify the mechanisms involved in terms of negative predictions, as well as disentangle between demand or supply shock propagation as the main source of predictive signals.

Appendix

2.A Post-Double Estimation Procedure : Add-Ons to the New Framework

2.A.1 Lasso estimation

I perform the selection of variables in the information set using an adaptive lasso-type penalized estimation procedure. The adaptive lasso allows me to select the most correlated variables while setting other β coefficients to zero.
Conducting an adaptive lasso estimation involves estimating the following[5] :

$$\hat{\beta}_i = arg\min_{\beta i}(\frac{1}{T}\|y_i - X\beta_i\|_2^2 + \lambda\|w_i\beta_i\|_1) \tag{2.8}$$

with for any n-dimensional vector x, $\|x\|_q = (\sum_{j=1}^{n}|x_j|_q)^{\frac{1}{q}}$.
Here, the matrix X includes all indicators of financial constraint at t-3 and t-6 for sectors of the set R (all sectors excluding sectors $c-s$ and $c'-p$) , as well as all J macroeconomic principal components from t-1 to t-12. The y_i variable changes in each of the lasso regressions as listed below.
In penalized regression, one of the key issue involves choosing the right penalization parameter λ. Following Hecq et al. (2021), I choose λ such that it minimizes the Bayesian information criterion (BIC) while keeping the number of selected variables below a tenth of the number of observations. The BIC allows to find the right balance between restrictiveness of the lasso selection and the estimation power of the information set through the R^2.
As explained by Belloni et al. (2014), there is a non-zero probability for the lasso not to select an important variable whose omission would later induce an omitted-variable bias. Thus, to reduce such probability as much as possible, the Post-double estimation procedure involves running several lasso regression procedures, on both the dependent variable and on the Granger causing variables. In each procedure, for each cs-$c'p$ pair of sectors, I perform the three following lasso regressions taking y_i as :

- Sector $c-s$ financial health (FH) at time t (dependent variable)
- Sector $c'-p$ FH at time t-3 (first lag of the independent variable)
- Sector $c'-p$ FH at time t-6 (second lag of the independent variable)

[5] see Hecq et al. (2021)

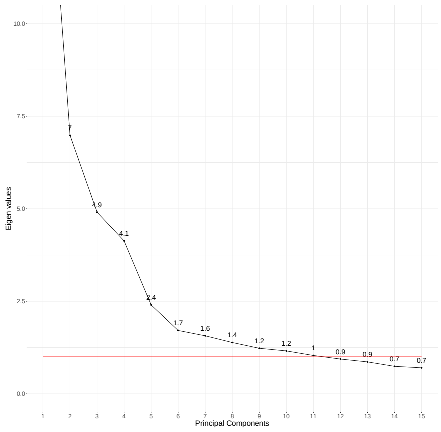
I will include as controlled variables, conditional on which I test for conditional Granger-causality, any variable selected at least once among those regressions.

2.B Sector codes

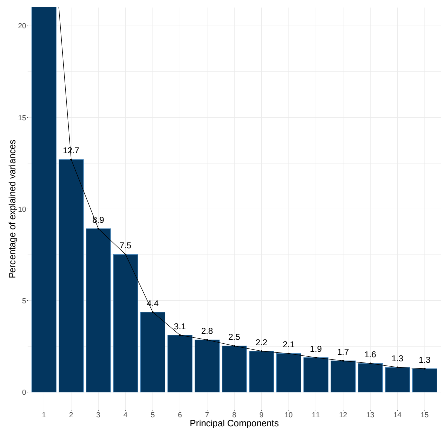
TABLE 2.B.1 : Sector codes

	Sector code	Sector description
1	01T03	Agriculture
2	05T06	Mining (energy)
3	07T08	Mining (non-energy)
4	09	Mining support (service)
5	10T12	Food products, beverages
6	13T15	Textiles, apparel
7	16	Wood
8	17T18	Paper
9	19	Coke
10	20T21	Chemicals & pharmaceuticals
11	22	Rubber & plastic
12	23	Glass & other
13	24	Basic metals
14	25	Fabricated metal
15	26	Computer & electronic
16	27	Electrical equipment
17	28	Machinery & equipment
18	29	Motor vehicles
19	30	Other transport equipment
20	31T33	Other manufacturing
21	35T39	Electricity, gas, water
22	41T43	Construction
23	45T47	Wholesale and retail trade
24	49T53	Transportation and storage
25	55T56	Accommodation and food services
26	58T60	Publishing, audiovisual & broadcasting
27	61	Telecommunications
28	62T63	IT and other information services
29	64T66	Financial and insurance activities
30	68	Real estate activities
31	69T82	Other business sector services
32	84	Public admin. and defence
33	85	Education
34	86T88	Human health and social work
35	90T96	Arts, entertainment, recreation and other service activities
36	97T98	Private households with employed persons

2.C Principal component analysis on macroeconomic indicators



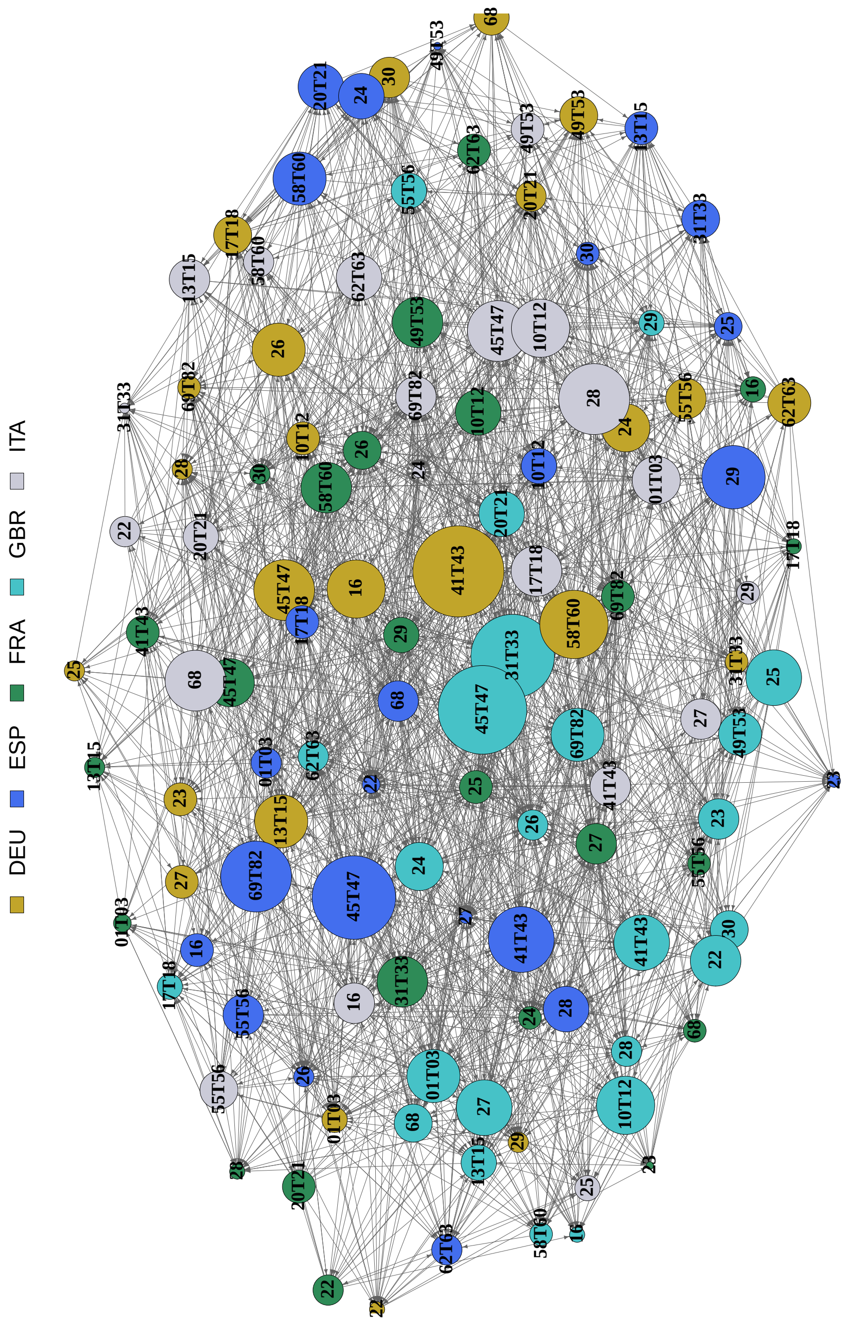
(a) Eigen Values for each Principal Component
Are selected principal components with an eigen value greater than 1, corresponding to the horizontal red line.



(b) Share of Variance Explained by each Principal Component

FIGURE 2.C.1 : Principal Components Analysis From 2007 to 2019

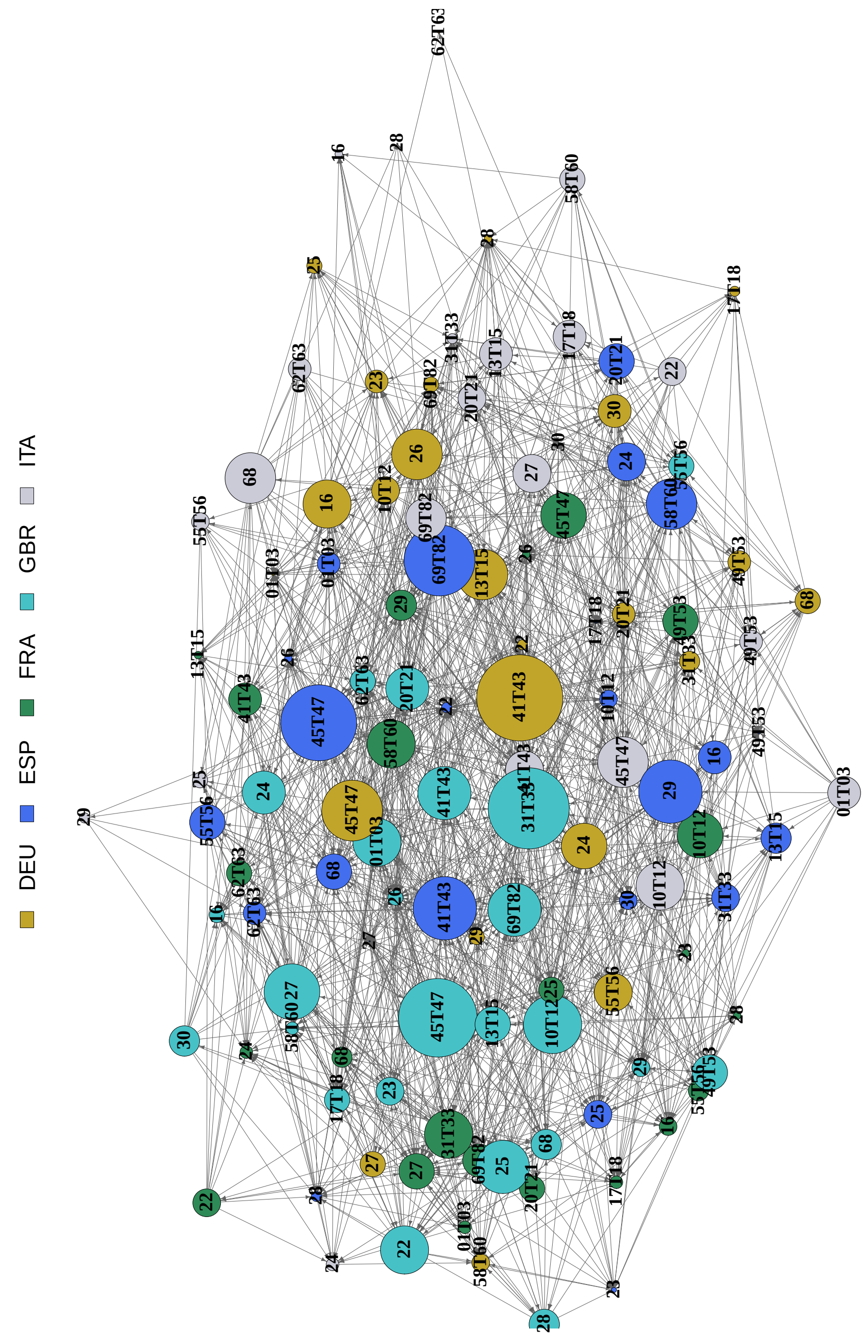
2.D Network of significant predictive relationships over the period 2013-2019



Each circle represents a sector in one country and each arrow the link from one sector toward another. The direction indicates whose past values help explain whose value at time t. Circle size is proportional to the number of links directed toward other sectors.

Represented are links only for which the cumulated effect is negative. See appendix section 2.B.1 for sector codes.

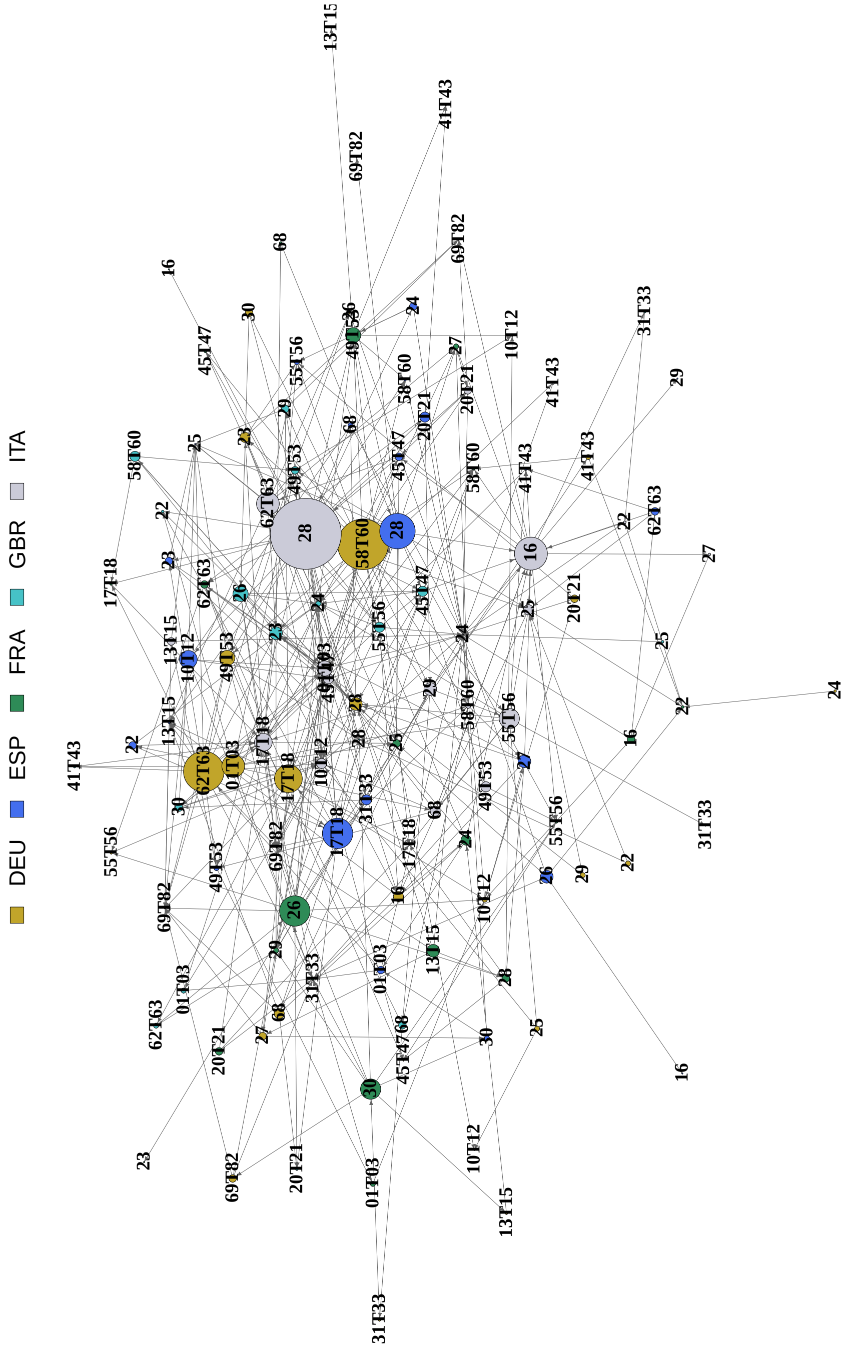
FIGURE 2.D.1 : Full Network of Significant Cross-Sector Granger Causalities Over the Period 2013-2019



Each circle represents a sector in one country and each arrow the link from one sector toward another. The direction indicates whose past values help explain whose value at time t. Circle size is proportional to the number of links directed toward other sectors.

Represented are links only for which the cumulated effect is positive. See section in 2.B.1 in appendix for sector codes.

FIGURE 2.D.2 : Network of Significant Cross-Sector Links with Positive Cumulated Amplitude – Period 2013-2019



Each circle represents a sector in one country and each arrow the link from one sector toward another. The direction indicates whose past values help explain whose value at time *t*. Circle size is proportional to the number of links directed toward other sectors. Represented are links only for which the cumulated effect is negative. See next appendix section for sector codes.

FIGURE 2.D.3 : Network of Significant Cross-Sector Links with Negative Cumulated Amplitude – Period 2013-2019

2.E Logistic regression– negative predictive relationships over the period 2013-2019

TABLE 2.E.1 : Logistic regressions - Input-Ouput Flows and Negative Predictive Relationships

	Having a Significant Granger-Causality Link With Negative Net Magnitude	
	(1)	(2)
IO Direct Flow	−0.1202	
	(0.1087)	
Leontief Total Value Added		−0.0721
		(0.0728)
Constant	−3.4913***	−3.4779***
	(0.0508)	(0.0516)
N	13,572	13,572
Log Likelihood	−1,809.9170	−1,810.1050
Akaike Inf. Crit.	3,623.8340	3,624.2100

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
Note : Those regressions are performed under the following logistic model : $log(\frac{Pr_{ps}}{1-Pr_{ps}}) = \alpha + \beta IO_{ps} + \upsilon$. Pr_{ps} is the probability of having a significant Granger-causal link from sector c'p to cs in the period 2013-2019, using BH correction, with a negative net magnitude, i.e. with the sum of β_1 et $\beta_2 < 0$ in 2.3. IO_{sp} is a measure of input-output, either the direct flow from c'p to cs or the Leontief's measure of total value added from c'p to cs. Both IO measures are standardized and coefficients should be interpreted as the impact of a standard unit deviation on the log odds.

2.F Distribution of selected sectors by country

TABLE 2.F.1 : Selected Sectors By Country

Country	Number of sectors	Included sectors
DEU	24	Accommodation and food services, Agriculture, Basic metals, Chemicals & pharmaceuticals, Computer & electronic, Construction, Electrical equipment, Fabricated metal, Food products, beverages, Glass & other, IT and other information services, Machinery & equipment, Motor vehicles, Other business sector services, Other manufacturing, Other transport equipment, Paper, Publishing, audiovisual & broadcasting, Real estate activities, Rubber & plastic, Textiles, apparel, Transportation and storage, Wholesale and retail trade, Wood
ESP	24	Accommodation and food services, Agriculture, Basic metals, Chemicals & pharmaceuticals, Computer & electronic, Construction, Electrical equipment, Fabricated metal, Food products, beverages, Glass & other, IT and other information services, Machinery & equipment, Motor vehicles, Other business sector services, Other manufacturing, Other transport equipment, Paper, Publishing, audiovisual & broadcasting, Real estate activities, Rubber & plastic, Textiles, apparel, Transportation and storage, Wholesale and retail trade, Wood
FRA	24	Accommodation and food services, Agriculture, Basic metals, Chemicals & pharmaceuticals, Computer & electronic, Construction, Electrical equipment, Fabricated metal, Food products, beverages, Glass & other, IT and other information services, Machinery & equipment, Motor vehicles, Other business sector services, Other manufacturing, Other transport equipment, Paper, Publishing, audiovisual & broadcasting, Real estate activities, Rubber & plastic, Textiles, apparel, Transportation and storage, Wholesale and retail trade, Wood
GBR	21	Accommodation and food services, Agriculture, Basic metals, Chemicals & pharmaceuticals, Construction, Electrical equipment, Fabricated metal, Food products, beverages, IT and other information services, Machinery & equipment, Motor vehicles, Other business sector services, Other manufacturing, Paper, Publishing, audiovisual & broadcasting, Real estate activities, Rubber & plastic, Textiles, apparel, Transportation and storage, Wholesale and retail trade, Wood
ITA	24	Accommodation and food services, Agriculture, Basic metals, Chemicals & pharmaceuticals, Computer & electronic, Construction, Electrical equipment, Fabricated metal, Food products, beverages, Glass & other, IT and other information services, Machinery & equipment, Motor vehicles, Other business sector services, Other manufacturing, Other transport equipment, Paper, Publishing, audiovisual & broadcasting, Real estate activities, Rubber & plastic, Textiles, apparel, Transportation and storage, Wholesale and retail trade, Wood

3 US Monetary Policy Spillovers To Emerging Markets : The Trade Credit Channel

Chapter co-authored with Maéva Silvestrini

Contents

3.1 Introduction 66
3.2 Literature Review 68
  3.2.1 US monetary policy and emerging markets 68
  3.2.2 Trade credit: complement or substitute in the business cycle . . 70
3.3 Data 72
  3.3.1 Trade credit 72
  3.3.2 Identifying monetary policy shocks 75
3.4 Empirical Strategy 78
  3.4.1 A first glance at the global effect 78
  3.4.2 Exploring heterogeneity 80
    3.4.2.1 Buyers' Quality 80
    3.4.2.2 US versus non-US suppliers 81
    3.4.2.3 A specific role for the global currency? 81
3.5 Results 82
  3.5.1 Trade credit: a pass-through channel of US monetary policy to EMEs 82
  3.5.2 Quality: A demand-driven funding effect 83
  3.5.3 US suppliers: financial constraints on the supplier side dominate 84
  3.5.4 USD trade credit: an exchange rate channel 86
3.6 Robustness tests 87
  3.6.1 Alternative specifications 87
  3.6.2 Alternative policy indicators 89
3.7 Conclusion 91

Abstract :

We analyze the effect of exogenous US monetary policy shocks on trade credit flows towards emerging markets. We use a proprietary database on firm-to-firm trade credit flows. We find trade credit to be an additional pass-through channel of US monetary policy to emerging markets and a substitute to other types of financing for EM importers. Using the granularity of the data, we distinguish between different mechanisms. Specifically, US monetary tightening exerts three distinct effects. First, it increases EM importers' demand for trade credit, used as a substitute to other financing tools themselves restrained. Second, it restricts US suppliers' ability to extend trade credit to their EM customers, thus acting as a liquidity squeeze. Finally, it also affects trade credit flows through an exchange rate channel, impacting differently USD and non-USD flows.

JEL classification : E52,F14, F40 , F44, L14

Keywords : US Monetary Policy ; Spillovers ; Capital flows ; Emerging Market ; Trade credit.

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3.1 Introduction

Emerging economies' trade dependence toward the US now frames any forecast and analysis on those markets. From a financial perspective, abrupt capital flow reversals are one of the main spillovers from US monetary policy (MP) on emerging markets, feeding emerging central banks' concerns over the Fed's decisions. At the intersection of these two types of flows, real and financial, lies trade credit, used to finance trade. In this paper, we study the effect of US MP shocks on those inter-firm credit flows, sent from foreign suppliers towards emerging buyers. We take advantage of granular data to disentangle between different channels of impact, that we can not distinguish in the aggregate. We highlight an additional spillover channel of US MP shocks towards emerging markets through trade credit flows.

Trade credit takes the form of a credit made by the supplier to its client or buyer by paying for the production of the good, delivering it and allowing the buyer to pay at the end of a grace period. This type of inter-firm financing is a key component of global value chains (GVC), "gluing" together buyers' and suppliers' balance sheets as Kalemli-Özcan et al. (2014) describe. Because of a greater comparative advantage of suppliers over banks to provide credits when financial information are scarce, suppliers' trade credit is widely used in emerging economies where financial markets are less developed as highlighted in Demirguc-Kunt and Maksimobic (2001). The literature has shown that trade credit flows are counter-cyclical, used by firms as substitute when other sources of financing dry out (banking loans mostly, see Nilsen (2002)). However, Love et al. (2007) and Garcia-Appendini and Montoriol-Garriga (2013) show that in cases of large crisis affecting suppliers, the latter will not be able to play this role of liquidity providers. In these specific conditions, trade credit can also be affected by the economic downturn, drying up as other financing sources do, as a complement rather than a substitute. Changes in the US monetary policy represent a global shock to emerging markets, through movements in capital flows and lower external demand. Therefore, in this paper, we study the impact of US monetary policy changes on trade credit flows towards emerging markets.

Several hypothesis can be made to frame such impact. Changes in the US monetary policy first represent domestic shock for US firms. Thus, an unexpected tightening in the Fed's monetary policy will increase firms' financial constraint in the US as interest rate on banking loans will increase. This is likely to reduce US suppliers' ability to extend trade credit to their buyers domestically and abroad. This would be a *supply effect through a funding channel*, playing for trade credit flows from US suppliers. Then, US suppliers could also produce less because of the economic downturn created by the monetary tightening, thus exporting less. This would be a *supply effect through a trade channel*. Moreover, a tightening in US MP can also translate into capital outflows from emerging markets towards the US as observed in May-June 2013 during the so-called *'Taper Tantrum'* episode. This is likely to cause a deterioration of the economic outlook in emerging markets. Regarding trade credit, it could mean two things depending on the channel at play. This could translate into lower trade credit amounts because of lower demand from buyers in the emerging market, thus a *demand effect through the trade channel*. Differently, it could also translate into higher amounts because of higher demand for funds, to substitute from other sources that become more scarce, thus a *demand effect through the funding channel*. Finally, a US MP tightening could also have global effects through the appreciation of the global dollar index,[1] through a *dollar exchange rate channel*. The appreciation of the global dollar index following the tightening in US MP could trigger valuation effects in firms' balance-sheets in emerging markets. This would worsen their reimbursement capacity and lower suppliers' propensity to provide them credit, a supply-driven effect through the exchange rate channel.

A key contribution of this paper is to use granular data on trade credit flows to unravel mechanisms, distinguishing between quality of buyers, origin of suppliers and currency used. We contribute to the literature on US MP impact on emerging markets (see section 3.2.1) by identifying an additional channel of impact through trade credit flows denominated in USD and those provided by US suppliers. We also contribute to the trade credit literature (see section 3.2.2) by studying the propagation of a new type of financial shocks, here US MP, along firms' trade credit networks. We also bring together the buyer's and the supplier's side in one framework and show how the buyers' demand for trade credit as a substitute financing can be limited by financial conditions on the supplier side.

To do this, we conduct a panel data analysis on trade credit amounts at the firm level. We use an original proprietary database from one of the top three trade credit insurers worldwide, named Coface. It records firm-to-firm trade credit flows from foreign suppliers to buyers in two emerging markets, Mexico and Turkey, on a monthly basis, from July 2010 to June 2019. We chose to focus on those two emerging markets for three reasons. First, both present a high share of manufacturing [2] and a high degree of trade openness,[3] two key components for GVC participation within which trade credit financing takes place. Second, this implies they both display a large use of trade credit as a source of trade financing. 76% of Mexican firms used trade credit from their suppliers in 2019.[4] In Turkey, trade credit amounted to 13.8% of firms' liabilities.[5] Finally, Coface data are also more comprehensive in these two countries. We use the panel characteristics of our data to estimate the effects of US MP shocks in each country separately while controlling for unobservables at the supplier-buyer level. We also

[1] See papers by Bruno and Shin

[2] Between 15 and 19% of the total value added to GDP has been generated by the manufacturing sector during the last decade in Mexico and Turkey. This share is larger than for other emerging economies such as Brazil (around 10%), Chile (10%) or South Africa (13%) (source : World Bank's statistics).

[3] Trade openness before the pandemic (in 2019) reached 78% in Mexico and 63% in Turkey, compared to 28% in Brazil, 57% in Chile or 59% in South Africa (source : World Bank's statistics.

[4] See *Evolución del Financiamiento a las Empresas durante el Trimestre Octubre – Diciembre de 2019*, Banco de Mexico

[5] Turkish Central Bank Data, see Sahin (2019)

control for alternate determinants of trade credit flows at the global and at the country levels, such as the country's economic outlook, exchange rates or import flows to account for a potential trade channel. We avoid potential endogeneity bias by studying the effect of unexpected changes in pure US monetary policy, which are not already priced by the market. We measure such monetary surprise with high-frequency data surrounding US Federal Open Market Committee (FOMC) announcements.
We find a positive and significant impact of a tightening in US MP on the amount of trade credit provided by foreign suppliers to buyers in Mexico and Turkey. This effect is robust in both countries to valuation effects and to changes in Coface risk strategy, to the inclusion of import flows and to a set of country-level controls, as well as to supplier-buyer fixed effects. Distinguishing across financial qualities of buyers, we find a positive effect for low quality buyers, i.e. more financially-constrained, compared to good and medium ones. This is in line with an increase in buyers' demand for trade credit through a funding channel as the access to other sources of funding is restrained. When focusing on the Mexican case and distinguishing between US and non-US suppliers with an interaction term, we find an overall negative effect for trade credit flows from US suppliers. This is consistent with an effect on the supply side through a tighter financial constraint weighing on suppliers following the increase in interest rates. For US supplied trade credit, the supply effect dominates the demand one. Finally, using the information on the currency used, we identify a different effect for USD trade credit flows towards emerging buyers compared to other currency flows. This reveals an additional pass-through channel of US MP shocks via the USD exchange rate.

The rest of this article is organized as follows. Section 3.2 reviews the related literature. Section 3.3 details the data and the identification strategy to have an exogenous shock. Section 3.4 describes the empirical specifications used. Section 3.5 presents the results and section 3.6 some robustness tests, before concluding in section 3.7.

3.2 Literature Review

3.2.1 US monetary policy and emerging markets

This paper is at the crossroads of several strands of literature. First, it relates to papers that study the spillover effects of US monetary policies on emerging economies. We contribute to this literature by analysing the response of one largely ignored macroeconomic variable, namely trade credit, in emerging economies. More precisely, while papers generally intend to analyse the consequences of US monetary policy shocks on portfolio or banking flows, we focus instead on the reaction of trade credit flows, an alternate source of funding for firms. We also use the granularity in our data to identify an additional pass-trough channel through USD trade credit flows.
Since the seminal paper by Calvo et al. (1993), the notion has emerged that expansionary US monetary policy plays a major role in driving capital flows to emerging

market economies (EMEs thereafter). This issue has received renewed interest since the introduction of unconventional monetary policies (UMP) following the 2007 crisis and the "Taper Tantrum" episode of May 2013, as large and volatile capital flow movements were indeed observed at that time -particularly in EMEs- following the change in anticipations of investors regarding the Large Scale Asset Purchases (LSAP) in the US. (Mishra et al. (2014), Aizenman et al. (2014), Ahmed et al. (2017), Lim et al. (2014)).[6]
Recent papers generally intend to measure the movements in capital flows that have been triggered by these unconventional US monetary decisions. They broadly conclude that these policies did alter the magnitude of such flows and (or) their composition, especially for flows to (and from) emerging economies (Fratzscher et al. (2018), Koepke (2018), Ahmed and Zlate (2014), Rai and Suchanek (2014), Tillmann (2016), Dahlhaus and Vasishtha (2014), Anaya et al. (2017)). For instance, Fratzscher et al. (2018) focus on the Fed's LSAP announcements and actual balance sheet changes to study the international spillovers of US unconventional policies on both advanced and emerging markets. They show that Fed policies resulted in large rebalancing towards non-US assets ; magnifying the pro-cyclicality of flows, especially to EMEs. Most of these studies focus on the impact on portfolio flows, with some of them even restricting their analysis to bond and equity from mutual funds (Fratzscher et al. (2018), Lo Duca (2012), Dahlhaus and Vasishtha (2014), Friedrich and Guérin (2020), Bhattarai et al. (2021)). In the recent period, some authors have put their attention on banking flows, trying to measure how US monetary policy affects cross-border bank lending. For instance, Bruno and Shin (2015a) find that a contractionary shock to US monetary policy leads to a decrease in cross-border banking capital flows and a decline in the leverage of international banks. Avdjiev et al. (2019) show that the relationship between the federal funds rate and cross-border bank lending is time-varying and depends on whether the main drivers of fluctuations in the federal funds rate are related to changes in US macroeconomic fundamentals or to changes in the US monetary policy stance. Using a unique dataset at the loan level in Mexico, Morais et al. (2019) find that an expansion in foreign monetary policies increases the supply of credit of foreign banks to Mexican firms, which in turn implies strong real economic effects.

Besides this capital flow channel, the literature has also identified the US dollar exchange rate as a propagation channel of US monetary shocks to EMEs. Indeed, an increase of the US interest rate tends to trigger an appreciation of the dollar (Eichenbaum and Evans (1995), Bruno and Shin (2015a)), which can have international spillover effects through various channels. First, a US dollar appreciation is likely to affect the real economy through its effect on competitiveness (and therefore on trade) : according to this *trade competitiveness channel*, a decrease of the domestic currency

[6] This has fuelled the debate on the determinants of these large reversals of flows, or "Sudden Stop" episodes. Some papers study their deleterious consequences, while others have emphasized on their determinants, looking at the well-known "push" and "pull" factors (see Koepke (2019) for a literature review on the subject. Contrary to these papers, we do not restrict our question on "Sudden Stop" episodes and study the reaction of trade credit following more frequent US monetary policy shocks.

tends to increase competitiveness and therefore trade (and mechanically trade credit). However, global value chains (GVCs) tend to dampen this effect as depreciation of the domestic currency also increases the cost of imported inputs : hence, the larger an economy's import content of exports, the smaller the impact on export volumes of a depreciation. (Ahmed et al. (2017)).
Besides, as put on evidence by Gopinath and Stein (2018) and Boz et al. (2019), the *invoicing currency* also matters for competitiveness. Thus, when the US dollar is used as an invoicing currency for trade, the volume of trade between two countries (neither of whom is the US) may in fact experience a decline following the USD appreciation, because of the competitive implications of dollar invoicing.
Finally, the dollar exchange rate affects real outcomes not only through competitiveness, but also through fluctuations in credit supply : Bruno and Shin (2015a) identify a *risk-taking channel* of exchange rates, where a stronger dollar is associated with tighter dollar credit conditions. Indeed, an appreciation of the dollar triggers a valuation mismatch that weakens those borrowers' balance sheets, increasing the tail risk for creditors and therefore reducing the supply of credit. Bruno and Shin (2019) complement this analysis by showing that after an appreciation of the US dollar, banks with high reliance on dollar wholesale funding reduce more the supply of credit more to a firm relative to banks with low wholesale dollar funding exposures for the same firm. Relatedly, Bruno et al. (2018) underline the importance of the US dollar in GVCs. A stronger dollar tightens credit conditions and reduces the growth rate of both the amount of trade payables and receivables. The decrease in receivables growth will be stronger for firms more dependant on external financing. Finally, some authors have tried to weigh up the relative impact of these two opposing competitiveness and financial channels. According to Bruno and Shin (2019), the financial channel outweighs the competitiveness gains for the firms more reliant on dollar funding. Degasperi et al. (2020) also highlight the predominance of financial channels in the global transmission of US monetary shocks to real variables. The common message of these papers is that a stronger dollar global index may actually serve to dampen trade volumes, rather than stimulate them. This is in line with the observation made by Boissay et al. (2020) according to which historically, global trade finance volumes reported by central banks to the BIS have co-moved negatively with the dollar.

3.2.2 Trade credit : complement or substitute in the business cycle

Our work is also closely related to the literature on trade credit as financing tools available to firms as well as a source of linkages across firms.
We contribute to the literature that questions the counter-cyclical use of trade credit and their complement or substitute relationship with other financing tools. By looking at the effects of US monetary policies, we broaden the scope of the analysis to other types of shocks and relationships to non-banking financing tools through capital flows.
Some researchers have explored the country determinants of trade credit use. For

instance, Fisman and Love (2003) describe a stronger trade credit use in countries with relatively small and less developed financial markets. Demirguc-Kunt and Maksimobic (2001) show that the use of trade credit is higher in countries with less-developed legal system making it a widespread tool for financing in emerging markets. This more intensive use of trade credit financing by firms in emerging markets is confirmed by Hill et al. (2017) who show that in such markets, firms with better access to financial credit use relatively less trade credit. The counter-cyclical nature of trade credit, as described by Nilsen (2002) and Burkart and Ellingsen (2004), has been mainly explored through the relationship between trade credit use and other financing tools, mainly the banking sector. Meltzer (1960) was the first to suggest a substitution effect between trade credit and banking loans, with a redistribution happening through large liquid firms that behave as net suppliers of credits to smaller firms through their better access to bank finance. Fisman and Love (2003) and Danielson and Scott (2004) empirically document the increase in demand for trade credit when bank loans become scarce. Molina and Preve (2012) show that firms demand more trade credit when they are in financial distress to substitute to other sources of financing. Minetti et al. (2019) highlight how firms with restricted access to banking loans tend to participate more to global value chains to benefit from trade credit from their suppliers. Hill et al. (2017) also find that trade credit financing is chosen by firms that have more restricted access to financial credit.

We complement these last papers by showing that more financially constrained buyers will request higher trade credit amounts from their supplier in response to US monetary shocks compared to less-financially constrained one.

From the supplier's side, Cuñat (2007) shows that suppliers have an interest in insuring their customers against liquidity shocks through trade credit provision because of the fixed cost associated to the establishment of a trade relationship. Providing such trade credit terms will ensure the continuity of the relationship. Garcia-Appendini and Montoriol-Garriga (2020) go further and show that, when facing high switching costs, suppliers will continue to extend trade credit to their clients approaching bankruptcies. However, this substitution effect can be mitigated in the context of systemic financial crises. Love and Zaidi (2010) examine the role of trade credit during the financial crises in Thailand, Philippines, Indonesia and Korea in the late 1990s. They find evidence against the premise that trade credit can act as a substitute to bank credit in those particular episodes. During such events, suppliers of financially constrained firms themselves suffer from negative liquidity shock, impeding the insurance mechanism normally in place. Studying a different type of financial shock, Swanson (2019) favors the complement hypothesis with trade credit flowing out of emerging markets affected by a sudden stop episode. In another paper, Garcia-Appendini and Montoriol-Garriga (2013) highlight the role of suppliers' financial constraint in determining whether suppliers could perform their insurance role for their clients in times of crisis. They show that firms with high liquidity level prior to the crisis increased their level of trade credit provided to their customers during the Great Financial Crisis.

We complement their study by showing how, outside of crisis periods, changes to credit conditions in the supplier's country affect the amount of trade credit provided to emerging market buyers.

This paper is also close to the literature studying how trade credit, as inter-firm link, creates a channel for shock propagation. We contribute to this literature by studying empirically a specific type of financial shock, widespread for emerging markets, US monetary policy surprises. Expanding the production network literature started by Acemoglu et al. (2012), Altinoglu (2020), Luo (2020) model the propagation of financial shocks through trade credit links. Demir et al. (2020) provide empirical proof of such propagation using a change in the tax on imports purchased with foreign-sourced trade credit. Looking specifically at positive financial shock through the European Central Bank's Corporate Sector Purchase Program, Adelino et al. (2020) show that trade credit allow for the redistribution of unconventional monetary policy to a wider set of firms than the ones eligible to the initial program. Looking at US monetary policy, di Giovanni and Hale (2021) show that the majority of the response of global stock returns to US monetary policy shocks is due to global production linkages through changes in customers' demand propagating upstream. We complement their study showing that trade credit flows, as inter-firm financial linkages, are an additional channel of impact of US monetary shocks.

3.3 Data

3.3.1 Trade credit

In this article, we introduce a novel proprietary database on firm-to-firm trade credit flows from one of the top-three trade credit insurers worldwide, named Coface. Trade credit is a specific financing tool for inter-firm trade in goods or services. Under trade credit terms, suppliers pay for the production of the good or service and allow buyers to defer payment until the end of a grace period defined contractually. This grace period can go from 1 month to 2 years, with a median usually around 2 or 3 months (60 net days for Klapper et al. (2012) and 86 days in Chile according to Alfaro et al. (2021)). However, there is strong heterogeneity depending on the sector, with much longer terms for capital goods, as well as on the length of the relationship. Offering such financing terms is very attractive for buyers as opposed to cash-in-advance options for which they have to provide the necessary financing before selling the product. It also allows to save on fees requested by banks in cases of bank intermediation through letters of credit. Trade credit is therefore a way for suppliers to be more competitive as shown in Demir and Javorcik (2018). However, doing such credits bears a risk for suppliers in case the buyer defaults on its credit and fails to repay the supplier. To protect themselves from such a risk, suppliers might request insurance from trade credit insurers such as Coface. Coface will reimburse the supplier of the due amount in case of default from the buyer in exchange of an insurance premium. The data we use correspond to the monthly maximum amount of insured trade credit sales from foreign suppliers towards Mexican and Turkish firms that import from those suppliers. The variable is a stock and the data do not provide information on the exact sale nor on the payment timing nor on the grace period. A supplier might use each month the full amount of insured trade credit flows to trade with its buyer, but it can also use only part of it. The use of the coverage is not recorded in the data and strongly varies between suppliers. Most of its insurance premium is indeed computed as a percentage of the realized sales rather than the amount of insurance obtained. However, the amount of insurance requested will still matter in the negotiation to set the exact percentage of the premium. Moreover, the supplier is required by Coface to declare all its buyers under trade credit terms in the market insured (domestic or export). However, if Coface refuses to insure sales towards a specific buyer, then the supplier can get insurance with another insurer, or provide trade credit terms at its own risk, or trade with the buyer under cash-in-advance terms. Such alternative terms of trade will not appear in the data.

We decided to focus on firms in Mexico and Turkey for several reasons. First, both countries are large emerging markets, with high trade openness and a high manufacturing share. Second, trade credit use is widespread in both markets. According to a report by Banco de Mexico, 76% of firms in Mexico used credit from their suppliers as financing tools in the fourth quarter of 2019, before the pandemic crisis.[7] This share reached 81% in the manufacturing sector over the same period.[8] Regarding Turkey, according to the 2016 company accounts of the Central Bank Republic of Turkey, trade credit received from suppliers (trade payables) accounts for 13.8% of firms' liabilities, while bank loans make up 32.2% and other financial liabilities including financial leasing, bond, equities and commercial paper constitute only 4.1% of all sources. trade credit extended by firms (trade receivables) also represent 16% of Turkish firms' assets.[9] Finally, Coface data are quite comprehensive in those countries compared to other emerging economies.

Our level of observation is the supplier-buyer pair at month t, with buyers in Mexico and Turkey and suppliers in a foreign country. For each pair, we have the amount of insured trade credit sales converted to US dollars,[10] on a monthly basis between July 2010 and December 2019. Sectors of buyers and suppliers are recorded following the NACE Rev.2 classification, covering both goods and services. The database also contains the supplier's origin country as well as the currency of the trade credit. Finally, Coface also produces rating on buyers for which it provides insurance on a monthly basis. These ratings are based on a combination of fiscal data, experts opinions and external ratings. They mirror Coface perception of payment default risk on this buyer and follow a 0 to 10 scale. A rating of 0 is the lowest possible, for firms that halted their activity, 1 is for very weak firms in financial terms while 10 reflects undoubted

[7] See *Evolución del Financiamiento a las Empresas durante el Trimestre Octubre – Diciembre de 2019*, Banco de Mexico

[8] It concerned around 80% of the firms in the service and trade sector and 31% of the firms in the rest of the economy. Banco de Mexico data.

[9] Turkish Central Bank Data, see Sahin (2019)

[10] Converted using a fixed exchange rate equal to the average rate over the 2010-2019 period for each currency

performance solidity.
When including import data as detailed in section 3.4, we restrict our sample to goods and reduce the time window to 2013-2019 in the Turkish case. Tables 3.D.1 and 3.D.2 present the descriptive statistics on trade credit flows from foreign suppliers to buyers based in Mexico and Turkey used in our baseline estimation with trade in goods. Section 3.D provides the descriptive statistics on the sample encompassing goods and services. Descriptive statistics are provided by origin of suppliers - US, Euro zone, UK and other sources - as well as for the entire sample. The statistics are provided for supplier-buyer pairs per period. To control for potential valuation effects, we take trade credit flows denominated in their currency. Then, we convert these amounts into US dollar using a fixed exchange rate. This exchange rate is computed as the mean over the sample period. We will control for the effect of such choice in section 3.6.
From table 3.D.1, we see that, in Mexico, trade credit flows from US and Euro zone suppliers represent respectively 37.2% and 50.4% of the sample. Medians are quite comparable across sub-samples of suppliers, however the distribution of trade credit amounts is even more skewed for US suppliers than for the rest of the sample. We will use the co-existence of US and non US suppliers in the analysis. Looking at table 3.D.2, we see a similar median and a comparable mean, as well as a distribution also very skewed. Our sample in Turkey is dominated by trade credit flows from Euro zone suppliers which represent 78.1% of the total.
As a comparison, looking at trade in goods in 2019, Eurozone suppliers represent around 22% of Turkish imports, and the US 5.6%,[11]. In the case of Mexico, the US amounted to 45% of total Mexican imports and main Eurozone partners to 9%.[12] Despite the fact that our trade credit data also cover trade in services in addition to the trade in goods solely used for the trade statistics, there is a bias in the data in favor of European suppliers due to the origin of the French insurer and the large share of the European market in trade credit insurance (Europe represents 50% of insured trade credit worldwide according to Berne Union). Nonetheless, we see that the difference in terms of partners' importance between the two countries are mirrored in the trade credit data, with a much greater share of the US in Mexico.

Trade credit (000s USD)	Origin of suppliers	Nber of obs.	Median	Mean	Standard Deviation	Share (%)
	Eurozone	286824	61.2	242.0	964.3	50.4
	Other	58236	100.0	347.4	1034.2	10.2
	UK	12178	51.1	178.9	674.4	2.1
	US	211990	75.0	328.2	1346.9	37.2
	all	569228	61.2	283.5	1125.0	

TABLE 3.1 : Descriptive Statistics On Import Sample by Suppliers' Origin for Mexico

Then, tables 3.3 and 3.4 present the descriptive statistics based on the currency used. First, in both countries, the share of locally denominated trade credit is close to 0. This likely reflects both suppliers' and Coface decision to avoid taking a foreign

[11] WITS data see Turkey
[12] WITS data, see Mexico

Trade credit (000s USD)	Origin of suppliers	Nber of obs.	Median	Mean	Standard Deviation	Share (%)
	Eurozone	518923	61.2	201.8	888.7	78.1
	Other	111422	30.0	178.6	1576.3	16.8
	UK	22390	43.8	141.1	520.2	33.7
	US	11179	50.0	250.3	866.3	1.6
	all	663914	50.0	196.7	1027.8	

TABLE 3.2 : Descriptive Statistics on Import Sample by Suppliers' Origin for Turkey

currency risk by providing local currency trade credit. This is also highly related to the country we are considering, as Turkey is one of the emerging countries that has experienced the most volatile exchange rate in the last decade. Then, we see that in Mexico, the sample is almost equally divided in trade credit flows in euros and US dollars. Comparing the shares with the ones presented in table 3.1, we see that some Eurozone suppliers decided to provide trade credit in USD, reflecting the role of the dollar as the global currency. We also see a quite big difference between the share of US suppliers and the use of USD trade credit in Turkey in table 3.4, despite the fact that the euro largely dominates.

Trade credit (000s USD)	Currency used	Nber of obs.	Median	Mean	Standard Deviation	Share (%)
	British pound	10162	43.8	96.7	555.9	1.8
	Euro	285117	61.2	199.7	781.1	49.9
	Mexican Peso	789	847.0	3088.4	4622.5	0.1
	Other	10399	52.9	234.8	627.6	1.8
	USD	264744	95.0	373.9	1387.1	46.3
	all	571211	61.2	283.3	1121.3	

TABLE 3.3 : Descriptive Statistics on Import by Currency for Mexico

Trade credit (000s USD)	Currency used	Nber of obs.	Median	Mean	Standard Deviation	Share (%)
	British pound	17195	43.8	103.0	259.8	2.5
	Euro	542075	61.2	188.8	826.3	81.2
	Other	18601	42.3	222.1	1161.5	2.8
	USD	87146	30.0	261.9	1879.0	13.1
	all	665017	50.0	197.1	1029.3	

TABLE 3.4 : Descriptive Statistics on Import Sample by Currency for Turkey

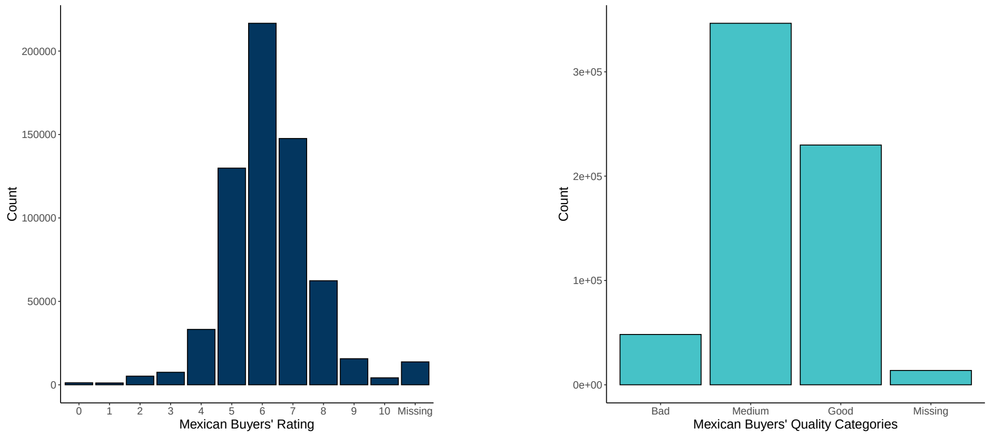
Finally, figures 3.1 & 3.3 present the distribution of buyers' ratings in each country sample, as well as the three quality categories built on the basis of these ratings. Based on discussions with operational staffs, ratings from 10 to 7 are considered as good, while 5 and 6 are medium, and ratings equal to 5 or below are considered as bad. Comparing the composition of both sample we see a predominance of good buyers in the Turkish sample, while medium buyers dominate in Mexico.

3.3.2 Identifying monetary policy shocks

In this part we describe our identification of monetary policy shocks. We follow Bernanke (1986)'s definition according to which "the shocks should be *primitive exoge-*

FIGURE 3.1 : Buyers' Rating and Quality Categories in Mexico

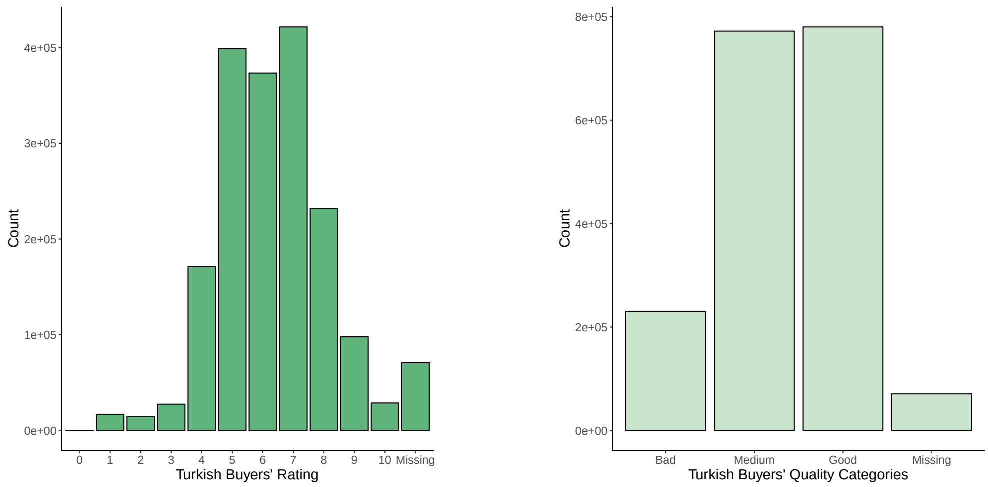
(a) Ratings (b) Quality Categories



NOTE : Ratings reflecting Coface perception of the firm's financial soundness. Ratings from 7 to 10 are considered as good buyers, 5 and 6 are medium quality buyers while ratings equal to and below 5 are bad quality buyers.

FIGURE 3.3 : Buyers' Rating and Quality Categories in Turkey

(a) Ratings (b) Quality Categories



NOTE : Ratings reflecting Coface perception of the firm's financial soundness. Ratings from 7 to 10 are considered as good buyers, 5 and 6 are medium quality buyers while ratings equal to and below 5 are bad quality buyers.

nous forces that are uncorrelated with each other and they should be economically meaningful." In this regard, they should also represent either *unanticipated* movements in exogenous variables or news about future movements in exogenous variables. This condition is not guaranteed when using "raw" measures of monetary policy, such as policy rates. Indeed, raw changes in the monetary policy target are contaminated by noise in the form of expected rate changes. Thus, we follow the extensive academic

literature on unanticipated measures of monetary policy surprises, constructed using high-frequency financial market information.[13] Closer to us in spirit are the authors who use these high-frequency surprises to identify responses of low-frequency macroeconomic variables in VAR or Local Projections frameworks,[14] as well as in panel or OLS frameworks (Bussière et al. (2021)). Unanticipated measures of MP surprises are derived from changes in a policy indicator in a short period (generally 30 minutes) surrounding FOMC policy announcements and capture the 'surprise' component of policy. Indeed, the rate at the start of the window reflects anticipated monetary policy prior to the meeting. Assuming that the only substantive macroeconomic 'news' within the announcement window pertains to monetary policy, the difference between both components would capture unanticipated monetary policy shocks. This will allow us to capture a shock not already priced by the market and accounted for in trade credit flows.
To choose an interest rate able to capture news about the expected medium-term path during a period for which we were at the zero-lower bound, we follow Hanson and Stein (2015), Swanson and Williams (2014) and Gilchrist et al. (2015) among others. We select the 2-year Nominal Treasury yield,[15] based on their arguments that the Federal Reserve's forward guidance strategy operates with a roughly two-year horizon. We show in section 3.6 that our results are robust to other policy indicators, using both shorter and longer-term surprise indicators, with changes in the 1-year ahead futures on the 3-month Eurodollar deposits (one of the instrument used by Gürkaynak et al. (2005)), as well as changes in the 5 and 10-year Nominal Treasury yields.
Finally, to be even more confident on the exogeneity nature of our shock, we control for the Fed's private information about the future state of the economy, which might be driving its policy changes. We therefore use state of the art of the literature and purge our monetary policy shocks from potential informational shocks, which are supposed to reflect this Central Bank's private information. We finally end up with an unanticipated and exogenous measure of pure monetary policy shocks (see Appendix 3.B for further details).

We use an updated version of the Gürkaynak et al. (2005) dataset, provided to us by R.Gurkaynak. Data are available until June 2019. Combined with the availability of our trade credit dataset and country controls, we get a final sample from July 2010 to June 2019.
Over the 72 FOMC announcements, 54 are seen as "pure" monetary policy announcements. Two thirds of them are negative surprises,[16] identifying as a more accommoda-

[13] See Kuttner (2001) ; Gürkaynak et al. (2021) ; Gertler and Karadi (2015) ; Jarociński and Karadi (2020))

[14] See Bauer and Neely (2014), Gertler and Karadi (2015) ; Jarociński and Karadi (2020) ; Miranda-Agrippino and Ricco (2021) ; Pinchetti and Szczepaniak (2021) or Coman and Lloyd (2022) among others

[15] More precisely, we use on-the-run Treasury securities, which are - for each maturity- the ones being most recently auctioned by the U.S. Treasury. These securities are more actively traded in the secondary market than their off-the-run counterpart.

[16] More precisely, 31 surprises have negative values, while 7 equal zero, meaning no change in the 2-year Treasury yield during the narrow window surrounding the announcements.

ting monetary policy stance than expected, as shown in 3.5. Graph 3.A.1 in Appendix displays these changes depending on the date of the FOMC announcements.

Jul. 2010 - Jun. 2019	**Nber**	**Min**	**Mean**	**Median**	**Max**
All announcements	72	-0.0992	-0.0071	-0.0039	0.0608
"Pure" Monetary Policy Ann.	54	-0.0949	-0.0087	-0.0040	0.0608

TABLE 3.5 : Descriptive Statistics for US Monetary Policy shocks (in pp)

3.4 Empirical Strategy

3.4.1 A first glance at the global effect

We start the empirical analysis in this paper by exploring some global effects before entering into an analysis of the heterogeneity of the effect allowed by the disaggregated nature of our data.

We want to estimate the effect of unexpected changes in the US monetary policy on the amount of trade credit provided by foreign suppliers to buyers in two emerging markets, Mexico and Turkey. Trade credit are specific in that they link financial and real flows as they finance trade. In this paper, we seek to study trade credit from a financial perspective, trying to see whether it behaves as a complement or substitute to other types of financing in emerging markets following unexpected changes in US monetary policy. For this purpose, we need to isolate this funding effect from the trade channel. To this aim, when estimating the below equation we include imports by Mexican and Turkish firms, besides controls at the supplying country-month and buying country-month as well as at month levels globally.

We estimate the following equation for each supplier-buyer pair $s-b$ in their respective countries f and j at month t in two distinct samples for Mexican and Turkish buyers :

$$\begin{aligned} TC_{s,b,t} = & \alpha_{s,b} + \beta \times \texttt{US Monetary Surprise}_{t-k} + \lambda \times \texttt{Import}_{n,j,t} + \nu S_{f,t} \\ & + \delta \times \texttt{Indus.Prod.}_{j,t} + \gamma X_{j,t} + \mu Z_t + \epsilon_{s,b,t} \end{aligned} \tag{3.1}$$

$TC_{s,b,t}$ refers to the amount of trade credit for the supplier-buyer pair $s-b$ at month t. $\texttt{US Monetary Surprise}_{t-k}$ refers to our measure of pure monetary policy surprises, defined as the percentage point change in the 2-year Nominal Treasury yield around FOMC announcements, cleaned from information effect. The key coefficient of interest in this paper is β. It represents the impact of unexpected changes in US monetary policy on trade credit provision towards emerging markets. We start by considering all lags from k=0 to k=6 months in order to capture the effect of the shock in the short-term. A lag of three means the shock occured three periods before we measure the amount of trade credit and all controls. Given that a trade credit expires usually in a 60-to-90 days period (median of 86 days in Chile as described by Alfaro et al. (2021)), we focus on the effect on a short time window of two quarters following the shock.

To test the counter-cyclical nature of trade credit in both emerging countries, we include the industrial production index in the buyer country j. We expect δ_1 to be negative if the demand for trade credit increases when there is an economic downturn. This would support the substitution role of trade credit to other sources of financing that typically dry up during economic downturn. If, on the contrary, δ_1 is positive, this would mean that the trade effect dominates, with trade credit flows declining when import contracts with a fall in activity in the country.
We also include the amount of goods imports by Mexican and Turkish firms in the buyer's sector n at month t, $Import_{n,j,t}$ to control for a potential trade channel. If the monetary policy effect we observe with β_1 were mainly driven by a response in trade flows, we should have a decrease in the value and significance of our β_1 coefficient when including buyer's sector imports. Import data are obtained from the Mexican Statistical office from January 2010 to December 2019 using the HS 2017 sector classification and converted to NACE Rev.2 sectors. We loose about 40% of the sample when adding trade flows as we restrict to trade credit for trade in goods and exclude services. We loose an additional 3% because of partial correspondence between the two sector classifications at our level of aggregation. For Turkey, we use data from the Turkish Statistical office using ISIC Rev. 4 classification converted to NACE Rev.2 sectors, from January 2013 to December 2019. In the Turkish case, we lose 55% of the sample by restricting the sample to goods and reducing the time window and. In appendix 3.D, we repeat the estimation on the full sample with goods and services.
To properly identify our effect, we need to control for other potential determinants of trade credit at the supplier-buyer, country and global levels. Therefore, we account for micro-level specificities by including supplier-buyer pair fixed effects, $\alpha_{s,b}$, that will control for determinants such as the length of the relationship. Then, we include a set of macroeconomic controls on a monthly basis to reflect the economic outlook in the emerging countries that could weigh on buyers' demand for trade credit. We include the key lending rate from the emerging market's central bank rate, the amount of foreign currency reserves in the emerging country, the real effective exchange rate, the volatility in the local currency against the USD,[17] and inflation at t. We also account for a potential effect of Coface risk aversion by including the three-month lagged ratio of insurance requested and obtained by suppliers in the emerging market. All of the indicators are grouped in vector $X_{j,t}$, the controls at the buyer country level.
Moreover, we control for other sources of variations on the supplier side by including the industrial production indices in the US and in the Eurozone, the two main source regions. We group these two indicators in vector $S_{f,t}$, the controls at the supplier country level.
Then, we control for alternate sources of variations affecting emerging countries at the global level. We account for global factors using the Emerging markets bond index (EMBI) spread and for other changes in monetary policies looking at unexpected changes in ECB monetary surprises as reflected by movements in the one-year OIS yield following Altavilla et al. (2019). We group all those indicators in vector Z_t, the

[17] Volatility is measure using the standard deviation computed on a twelve-month window.

controls at the global level.
Section 3.E in the appendix provides the description of all indicators and their sources.

3.4.2 Exploring heterogeneity

Based on this first estimation of the effect, a key contribution of this paper is to make use of the disaggregated nature of the data to disentangle the different mechanisms at play. First, we look at the difference in the effect across qualities of buyers. Then, we continue by taking advantage of the existence of trade credit from both US and non-US to disentangle between demand and supply mechanisms. Finally, we look at the specificity of trade credit denominated in USD, the global currency, compared to other foreign currency.

3.4.2.1 Buyers' Quality

First, we look at the difference in the effect based on the quality of the buyer. According to the literature, firms that are most financially constrained are the one requesting more trade credit to face adverse shocks. Minetti et al. (2019) show that firms more exposed to bank credit rationing and with weaker relationships with banks are more likely to participate in supply chains to overcome liquidity shortages through trade credit from their suppliers. If this were to be true in our analysis, it would point towards a demand-driven mechanism through request for funding from most financially constrained buyers.
To verify this we construct three categories of buyers, "Good", "Medium" and "Bad", using Coface internal rating. Rating from 10 to 7 are considered as good, 6 and 5 as medium and 4 to 0 as bad. Such ratings are available on a monthly basis to reflect the buyer's level of financial vulnerabilities.
Based on equation 3.1, we estimate the following equation, adding an extra categorical variable for buyer's quality, for Mexico and Turkey, in interaction with our policy shock variable :

$$\begin{aligned} TC_{s,b,t} = & \alpha_{s,b} + \beta_1 \times \texttt{US MP Surprise}_{t-3} + \omega_1 \times \texttt{US MP Surprise}_{t-3} \times \texttt{Quality}_{j,t} \\ & + \beta_2 \texttt{Quality}_{j,t} + \lambda_1 \times \texttt{Import}_{n,j,t} + \nu S_{f,t} + \delta_1 \times \texttt{Indus.Prod.}_{j,t} + \gamma X_{j,t} \\ & + \mu Z_t + \epsilon_{s,b,t} \end{aligned} \tag{3.2}$$

$Quality_{j,t}$ is a categorical variable reflecting the buyer's level of financial vulnerabilities. The key coefficient of interest here is ω_1 that synthesizes the effect of FED pure monetary policy surprises on trade credit flows towards the different categories of buyers.

3.4.2.2 US versus non-US suppliers

Second, we investigate a potential difference in response between trade credit from US and non-US suppliers– mainly Euro zone suppliers as shown in table 3.D.1 – in Mexico. The data on Turkey do not allow such distinction. If our effect were solely demand driven, then, we should see no difference between US and non-US suppliers.[18] Conversely, if our effect were to be also driven by a *supply effect*, we would expect a negative or non-significant response for US suppliers as their financial constraint tightens when interest rates increase, which decrease their ability to provide trade credit to their buyers.

To test this hypothesis, we interact the monetary policy surprise variable with a dummy equals to 1 if the foreign provider comes from the US and 0 otherwise.
We estimate the following modified equation 3.1 for Mexico :

$$\begin{aligned} TC_{s,b,t} = &\alpha_{s,b} + \beta_1 \times \texttt{US MP Surprise}_{t-k} + \beta_2 \times \texttt{US MP Surprise}_{t-k} \times \mathbb{1}_{\mathbb{US\$supplier}} \\ &+ \beta_2 \mathbb{1}_{\mathbb{US\$supplier}} + \lambda_1 \times \texttt{Import}_{n,j,t} + \nu S_{f,t} + \delta_1 \times \texttt{Indus.Prod.}_{j,t} \\ &+ \gamma X_{j,t} + \mu Z_t + \epsilon_{s,b,t} \end{aligned} \tag{3.3}$$

The key coefficient of interest here is β_2 that synthesizes the effect of FED pure monetary policy surprises on trade credit flows provided by US suppliers compared to non-US ones. The overall effect of Fed monetary policy shocks is the sum of β_1 and β_2.

3.4.2.3 A specific role for the global currency ?

Then, we take advantage of the use of different currencies by non-US suppliers to investigate whether the US dollar, as the global currency, plays a specific role in such demand for funds, leaving aside the effect coming through US suppliers. From the literature, we would expect a difference in the response of USD trade credit flows and other currency flows (here mostly euro flows) given the prevalence of the US dollar in global trade. To verify this, we interact the monetary policy surprise variable with a dummy equals to 1 if the trade credit is in US dollar and 0 otherwise. We estimate the following equation :

$$\begin{aligned} TC_{s,b,t} = &\alpha_{s,b} + \beta_1 \times \texttt{US MP Surprise}_{t-k} + \phi_1 \times \texttt{US MP Surprise}_{t-k} \times \mathbb{1}_{\mathbb{US\$D}} \\ &+ \beta_2 \mathbb{1}_{\mathbb{US\$D}} + \lambda_1 \times \texttt{Import}_{n,j,t} + \nu S_{f,t} + \delta_1 \times \texttt{Indus. Prod.}_{j,t} + \gamma X_{j,t} \\ &+ \mu Z_t + \epsilon_{s,b,t} \end{aligned} \tag{3.4}$$

The key coefficient of interest here is ϕ_1 that synthesizes the effect of FED pure monetary policy surprises on trade credit flows in US Dollars compared to non-USD flows

[18] Notice that US suppliers could also decrease their trade credit to clients in non-emerging markets, which would themselves decrease their trade credit to emerging market buyers. This could mitigate the differences between US and non-US suppliers, but remains in our view a second-order effect.

(mostly EUR). From the literature, the expected sign of ϕ_1 is ambiguous. Following Bruno and Shin (2015a), we could expect a negative ϕ_1 if buyers in emerging markets were experiencing value mismatch in their balance-sheet, which would deteriorate their financial conditions and increase the risk to lend in USD to those buyers. Depending on suppliers' bargaining power, we could also expect a positive ϕ_1, with suppliers favoring trade credit terms in USD to benefit from the expected appreciation of the dollar. A positive sign could also be expected if bigger suppliers outside the US were the ones supplying more USD trade credit as described in Gopinath and Itskhoki (2021). Indeed such suppliers are likely to be able to respond to the increase in demand given that they are less financially constrained than smaller ones. Finally, emerging buyers trading in USD could also want to protect themselves from currency mismatch and want trade credit in the same currency to avoid currency risk. We will try to disentangle between those different explanations with the estimation of equation 3.4.

3.5 Results

3.5.1 Trade credit : a pass-through channel of US monetary policy to EMEs

Tables 3.6 and 3.7 synthesize the results of the estimation of equation 3.1 for Mexico and Turkey respectively. Each column presents the result of the estimation with a different lag for the FOMC monetary surprise variable, from lag 0 to lag 6. In the Mexican case, we see a positive and significant effect at 1% of a surprise change in US monetary policy starting from lag 3 and lasting until lag 6. We interpret the coefficient for lag 3 as follow : A one percentage point change in the 2-year-bond yield around a FOMC announcement that took place 3 months ago leads to a USD 99,000 increase in the average trade credit provided by a foreign supplier to a Mexican buyer. However, we see from table 3.5 that the maximum surprise tightening is about 0.06 percentage point, around 16 times smaller than the 1 percentage point mentionned. Therefore the maximum unexpected tightening will lead to a 99,000/16=6,000 increase in the average trade credit, which is 10% of the median.
In the Turkish case, in table 3.7, there is a positive effect significant from lag 1 to lag 6. A one percentage point change in the 2-year-bond yield around a FOMC announcement that took place 3 months ago leads to a USD 77,800 increase in the average trade credit between a supplier and a Turkish buyer. The maximum US MP surprise leads to a 77,800/16=4,800 increase in the average trade credit, which is 9.7% of the median trade credit. Given the size of the standard errors, there is a strong heterogeneity in the effect, in line with the skewed regression highlighted in section 3.3.1. The positive effects in a 3-to-6-month window following the surprise change in monetary policy is robust to the inclusion of all the mentioned controls. We also see that the effect of US policy changes is mainly happening through the financial channel of trade credit as the coefficient is significant despite the inclusion of sector-level trade flows. In order to compensate for the fact that including imports restrict the data to flows in goods,

we do the same estimation in section 3.6 in the first column of tables 3.13 & 3.14, on the sample covering goods and services. We confirm our results on a wider sample, mainly through the financial component of trade credit rather than the trade part. We also control in robustness on the possibility that, by having a lag greater than the six weeks between two FOMC meeting, we might capture the effect of several shocks. Coefficients for lag three are robust to the inclusion of previous lags as visible in the third column of tables 3.13 & 3.14.
Finally, the counter-cyclical use of trade credit flows is also visible from the negative coefficient associated with industrial production at t in each specification, both for Mexico and Turkey.
Therefore, an unexpected tightening in the US monetary policy increases with some delay the amount of trade credit provided to Mexican and Turkish buyers. For the rest of the paper, we will focus on the effect with a three-month lag, given that for both countries it is the lag with higher coefficient and the first most significant one. This is also in line with what we see in the literature on the delays of transmission of international monetary policy shocks on banking flows (as shown for Mexico by Morais et al. (2019)).

TABLE 3.6 : Trade Credit in Mexico and US MP Surprises - Baseline

	Trade Credit in Thousands USD						
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
FOMC MP Surprise - Lagged	12.19	−7.05	−37.01*	99.70***	41.06**	44.14***	10.13
	(22.96)	(9.23)	(21.13)	(25.75)	(18.92)	(12.16)	(20.01)
Mexican Industrial Production	−2.08*	−2.08*	−1.90	−2.18*	−2.05*	−2.03*	−2.07*
	(1.12)	(1.12)	(1.17)	(1.12)	(1.12)	(1.11)	(1.11)
Mexican Sector Imports (Billion USD)	−0.17	−0.17	−0.17	−0.03	−0.18	−0.18	−0.16
	(1.78)	(1.78)	(1.76)	(1.79)	(1.76)	(1.79)	(1.78)
Fixed effects supplier-buyer	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Global controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	547,993	547,993	547,993	547,993	547,993	547,993	547,993
Adjusted R^2	0.75	0.75	0.75	0.75	0.75	0.75	0.75
Residual Std. Error	543.61	543.61	543.61	543.60	543.61	543.61	543.61

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.1 in the Mexican case, with alternative lags for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level.

3.5.2 Quality : A demand-driven funding effect

As described above, we first try to disentangle the mechanisms in the positive effect highlighted in section 3.4.1 by studying the heterogeneity in terms of buyer's quality. Tables 3.8 & 3.9 synthesize the results for the estimation of equation 3.2 in the Mexican

TABLE 3.7 : Trade credit in Turkey and US MP Surprises - Baseline

	Trade Credit in Thousands USD						
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
FOMC MP Surprise - Lagged	19.75*	52.98***	−24.28	77.88***	63.75***	34.80*	46.80***
	(12.00)	(16.58)	(15.78)	(21.55)	(18.96)	(18.35)	(10.78)
Turkish Industrial Production	−1.00***	−1.02***	−1.01***	−0.96***	−1.02***	−1.00***	−1.02***
	(0.18)	(0.18)	(0.18)	(0.17)	(0.18)	(0.18)	(0.18)
Turkish Sector Imports (Billion USD)	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fixed effects supplier-buyer	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Global controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	664,339	664,339	664,339	664,339	664,339	664,339	664,339
Adjusted R^2	0.83	0.83	0.83	0.83	0.83	0.83	0.83
Residual Std. Error	422.61	422.61	422.61	422.60	422.61	422.61	422.61

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.1 in the Turkish case, with alternative lags for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level.

and Turkish cases. For our maximum surprise, the effect for low-quality buyers in Mexico and Turkey will be an increase in trade credit amount by 574.8/16=35,000 USD and 133.3/16=8,300 USD respectively. When comparing with the other categories, we see that the interaction terms are negative for good buyers in both cases, while the interaction for medium quality buyer is no significant in Turkey. This means that the increase in trade credit is higher for low-quality buyers than for good and medium buyers in response to an exogenous tightening in US monetary policy. Most of the positive effect is explained by the impact on low-quality buyers. We also see that, independently from the response to the monetary policy changes, good and medium buyers receive more trade credit in average than bad buyers. This result is consistent with the fact that from the supplier's view, it is more cautious to provide trade credit terms to the healthiest firms. It is even more the case in this setup where data are provided by an insurer, willing to limit the risk of default it insures.
This result on quality points towards a demand-driven effect through the use of trade credit as a substitute to other sources of financing tools when firms in emerging markets face increasing funding constraints. This is consistent with Nilsen (2002)), Burkart and Ellingsen (2004), or Molina and Preve (2012) among others.

3.5.3 US suppliers : financial constraints on the supplier side dominate

We go further in exploring the mechanisms associated with this rise in trade credit provision following a tightening in US monetary policy and take advantage of the

TABLE 3.8 : Mexico : Quality

	Trade Credit in Thousands USD
MP Surprise - 3-month lag	574.81***
	(172.69)
MP Surprise - 3-month lag * Good quality buyer	−487.73***
	(181.10)
MP Surprise - 3-month lag * Medium quality buyer	−537.98***
	(177.46)
Mexican Sector Imports (Billion USD)	−0.49
	(1.51)
Good quality buyer	137.45***
	(37.56)
Medium quality buyer	97.66***
	(28.58)
Mexican Industrial Production	−2.56**
	(1.20)
Fixed effects supplier-buyer	Yes
Buyer country controls	Yes
Global controls	Yes
Supplier country controls	Yes
N	547,227
Adjusted R^2	0.75
Residual Std. Error	543.41

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.2 in the Mexican case, with a 3-month lag for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level. The reference category is the "low-quality" buyers, to be compared with medium and good buyer categories.

coexistence of a high share of US and non-US suppliers in the Mexican sample. We introduce an interaction term to see whether our effect is different for US and non-US suppliers as described in equation 3.3. The interaction term is negative and significant and exceeds the value of the coefficient associated with the monetary surprise alone. This means that when looking at trade credit provided by US suppliers, a 1% increase in the 2-year-bond yield leads to a 171-180=9,000 decrease in the average amount of trade credit provided to emerging buyers. Coming back to our maximum increase, we have an increase of USD 560. This quite negligible effect results from two counteracting channels. First, there is a demand-driven mechanism through higher funding needs on the buyer side as described in section 3.5.2. However, for US suppliers, trade credit flows act as a direct pass-through channel of the monetary shock. This highlights a supply channel through a reduction in trade credit supply due to higher financial constraint on the US supplier side.

TABLE 3.9 : Turkey : Quality

	Trade Credit in Thousands USD
MP Surprise - 3-month lag	133.27***
	(47.58)
MP Surprise - 3-month lag * Good quality buyer	−158.96*
	(82.46)
MP Surprise - 3-month lag * Medium quality buyer	−2.63
	(45.34)
Turkish Sector Imports (Billion USD)	0.02***
	(0.01)
Good quality buyer	81.34***
	(12.39)
Medium quality buyer	60.66***
	(10.48)
Turkish Industrial Production	−0.83***
	(0.17)
Fixed effects supplier-buyer	Yes
Buyer country controls	Yes
Global controls	Yes
Supplier country controls	Yes
N	664,119
Adjusted R^2	0.83
Residual Std. Error	422.33

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.2 in the Turkish case, with a 3-month lag for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level. The reference category is the "low-quality" buyers, to be compared with medium and good buyer categories.

3.5.4 USD trade credit : an exchange rate channel

We now focus on the specific case of USD trade credit from non-US suppliers in order to see whether we verify empirically the specific role of US dollar as global currency in the trade credit context. We restrict the analysis to non-US suppliers (mostly Eurozone according to tables 3.1 & 3.2) to isolate the effect through the currency denomination and the effect through suppliers' financial constraint. We report the coefficients associated with the estimation of equation 3.4 in the Mexican case in table 3.11, and the ones in the Turkish case in table 3.12. In the Mexican case, we find a positive and significant effect in the Mexican case for the interaction term. This means that USD trade credit flows from non-US suppliers increase more in response to an exogenous US monetary tightening than non-USD flows. The other term for US monetary policy even becomes non significant, implying that the whole effect goes through USD trade credit flows. Coming back to our maximum MP surprise, it creates an increase by 512/16=32,000 USD. This verifies the pass-through via the currency denomination in

TABLE 3.10 : Mexico : Trade Credit from US Suppliers

	Trade Credit in Thousands USD
MP Surprise - 3-month lag	171.31***
	(35.80)
MP Surprise - 3-month lag * US supplier	−180.17***
	(43.22)
Mexican Sector Imports (Billion USD)	−0.04
	(1.79)
Dummy US suppliers	181.29***
	(68.30)
Mexican Industrial Production	−2.19*
	(1.12)
Fixed effects supplier-buyer	Yes
Buyer country controls	Yes
Global controls	Yes
Supplier country controls	Yes
N	547,993
Adjusted R^2	0.75
Residual Std. Error	543.60

Notes : ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.3 in the Mexican case, with a 3-month lag for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level. The interaction term interacts a dummy variable equal to 1 if the supplier is from the US and the US MP surprise.

USD as the global currency.
For Turkey however, the interaction term is not significant. Given this difference across the two countries, this would point towards composition effect across the two countries' sample. It could be that suppliers of Mexican buyers are bigger than the ones supplying Turkey and therefore less financially constrained. It could also be that given the higher share of USD trade, Mexican buyers will tend to request more USD trade credit to match the currency used. However, those are only hypothesis and we will leave the exact identification of involved mechanisms to future research.
The key take-away from this last result, is the additional pass-through USD currency denomination can represent, in line with the literature on the dominant currency.

3.6 Robustness tests

3.6.1 Alternative specifications

As first robustness tests, we conduct several concurring estimations to confirm our main results are not driven by empirical choices. We use the simple estimation with three month lag described in equation 3.1. In the first column of tables 3.13 & 3.14, we

TABLE 3.11 : Mexico : Currency Type

	Trade Credit in Thousands USD
MP Surprise - 3-month lag	47.04
	(37.26)
MP Surprise - 3-month lag *USD Trade Credit	512.73**
	(252.52)
Mexican Sector Imports (Billion USD)	−0.10
	(2.42)
USD Trade Credit	379.94*
	(220.40)
Mexican Industrial Production	−4.27***
	(1.30)
Fixed effects supplier-buyer	Yes
Buyer country controls	Yes
Global controls	Yes
Supplier country controls	Yes
N	342,840
Adjusted R^2	0.68
Residual Std. Error	533.00
Notes :	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.4 in the Mexican case, with a 3-month lag for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level. The interaction term interacts a dummy variable equal to 1 if the trade credit is denominated in USD and the US MP surprises.

do the estimation on a wider sample of trade credit flows encompassing goods and services, excluding the import variable. We see nearly no difference in the coefficient for Mexico, given the fact that the import variable was not significant. For Turkey, the coefficient is slightly smaller but still highly significant. Therefore, our result is not restricted for trade credit financing trade in goods.

In the second column, we check that our result is not driven by a valuation effect due to our choice for currency conversion. While in our baseline specification, trade credit amounts are converted to USD using the average foreign exchange rate of the currency used against the USD over the whole period, in the second column we use the contemporaneous exchange rate to convert the amount. Our coefficient for the three-month lag of the US MP surprise remains significant and positive in both cases. In Turkey, there is a greater difference between both coefficients, potentially reflecting the difference in currency structure in the two country samples.

In the third column, we control that our key effect at the three-month lag is not in fact a sum of smaller effects of previous lags, potentially contradicting one another. We include all the lags from 0 to 3, all together in the estimation. We avoid multicollinearity issues as our shocks are independent by nature given that they measure the surprise of the market following a policy decision. We see that in both cases our coefficient

TABLE 3.12 : Turkey : Currency Type

	Trade Credit in Thousands USD
MP Surprise - 3-month lag	56.30***
	(19.59)
MP Surprise - 3-month lag *USD Trade Credit	182.91
	(168.60)
Turkish Sector Imports (Billion USD)	0.02***
	(0.01)
USD Trade Credit	117.98
	(222.64)
Turkish Industrial Production	−0.96***
	(0.16)
Fixed effects supplier-buyer	Yes
Buyer country controls	Yes
Global controls	Yes
Supplier country controls	Yes
N	653,831
Adjusted R^2	0.83
Residual Std. Error	423.53
Notes :	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

NOTE :The coefficients reported correspond to the estimation of equation 3.4 in the Turkish case, with a 3-month lag for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level. The interaction term interacts a dummy variable equal to 1 if the trade credit is denominated in USD and the US MP surprises.

for the third lag remains strongly significant and within a similar magnitude. We can note that in the Turkish case, earlier lags are significant, as visible already on table 3.7 but the third lag remains the one most significant. Thus, potentially, there is also some heterogeneity in the timing of the effect along the different mechanisms we highlighted, also explained by differences in composition in both samples.

3.6.2 Alternative policy indicators

In our baseline analysis, we chose to identify unexpected shocks in US monetary policy using movements in the two-year Nominal Treasury yield, due to the specificity of the period we analyze, mainly a period of unconventional monetary policy with interest rates close to zero. As a robustness check, we do the same analysis as in tables 3.6 and 3.7 for Mexico and Turkey, with a lag of three months, but we change our referential indicator to measure the surprise following the FOMC announcement. Table 3.C.1 in appendix 3.C displays statistics on these alternative indicator of surprises. In the first column in tables 3.15 & 3.16, we use changes in yield around the FOMC announcement for the one-year ahead future on the three-month eurodollar deposits, a measure of shock we lag by three months. In the second and third columns, we look at a longer-

TABLE 3.13 : Trade Credit in Mexico and US MP - Controlling for Empirical Choices

	Trade Credit in Thousands USD Goods and Services Sample	Trade Credit in Thousands USD Converted at contemp. FX	Trade Credit in Thousands USD Combining several lags
	(1)	(2)	(3)
FOMC MP Surprise			15.28
			(24.47)
FOMC MP Surprise - 1-month lag			5.47
			(16.86)
FOMC MP Surprise - 2-month lag			−16.33
			(26.09)
FOMC MP Surprise - 3-month lag	102.92***	101.53***	97.87***
	(14.86)	(26.05)	(29.34)
Mexican Industrial Production	−1.75**	−2.08*	−2.10*
	(0.69)	(1.14)	(1.21)
Mexican Imports		0.75	−0.03
		(1.59)	(1.79)
Fixed effects supplier-buyer	Yes	Yes	Yes
Buyer country controls	Yes	Yes	Yes
Global controls	Yes	Yes	Yes
Supplier country controls	Yes	Yes	Yes
N	983,449	547,993	547,993
Adjusted R^2	0.74	0.74	0.75
Residual Std. Error	484.30	569.20	543.61

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The first column reports the coefficients from the estimation of equation 3.1 for the goods & services sample described in appendix 3.D, without the imports variable. The second column reports the coefficients for the estimation of equation 3.1 using contemporaneous exchange rate instead of a fixed exchange rate to convert the dependant variable. The third column corresponds to equation equation 3.1 adding the USD-EUR exchange rate as control when converting at the average exchange rate. The fourth column reports the coefficients for equation equation 3.1 when the four first lags are estimated in the same equation. Standard errors are clustered at the buyer's sector level.

term indicators, with changes around the FOMC announcement on five and ten-year Nominal Treasury bond yield, with a three-month lag also. We see that despite some changes in magnitude of our effect, all the coefficients are positive and significant, for both countries. It is interesting to note that coefficients vary in a similar way in both countries depending on the indicators used and are close in magnitude. Therefore, we can confirm that 3-month lagged shocks in US monetary policy remain significant independently of the indicator used to capture the unexpected changes. In all cases, it leads to an increase in trade credit provided to Mexican an Turkish firms from foreign suppliers.

TABLE 3.14 : Trade Credit in Turkey and US MP - Controlling for Empirical Choices

	Trade Credit in Thousands USD Goods and Services Sample	Trade Credit in Thousands USD Converted at contemp. FX	Trade Credit in Thousands USD Combining several lags
	(1)	(2)	(3)
FOMC MP Surprise			25.72*
			(14.83)
FOMC MP Surprise - 1-month lag			63.56***
			(24.29)
FOMC MP Surprise - 2-month lag			4.45
			(24.94)
FOMC MP Surprise - 3-month lag	61.06***	103.61***	83.87***
	(11.31)	(24.73)	(26.68)
Turkish Industrial Production	−0.98***	−1.06***	−0.98***
	(0.14)	(0.19)	(0.17)
Turkish Imports		0.03***	0.02***
		(0.01)	(0.01)
Fixed effects supplier-buyer	Yes	Yes	Yes
Buyer country controls	Yes	Yes	Yes
Global controls	Yes	Yes	Yes
Supplier country controls	Yes	Yes	Yes
N	1,354,360	664,339	664,339
Adjusted R^2	0.84	0.82	0.83
Residual Std. Error	402.85	441.02	422.60

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The first column reports the coefficients from the estimation of equation 3.1 for the goods & services sample described in appendix 3.D, without the imports variable. The second column reports the coefficients for the estimation of equation 3.1 using contemporaneous exchange rate instead of a fixed exchange rate to convert the dependant variable. The third column corresponds to equation equation 3.1 adding the USD-EUR exchange rate as control when converting at the average exchange rate. The fourth column reports the coefficients for equation equation 3.1 when the four first lags are estimated in the same equation. Standard errors are clustered at the buyer's sector level.

3.7 Conclusion

In this article, we identify an additional pass-through of US monetary policy to emerging markets through the amount of trade credit provided from abroad to buyers located in emerging economies. To do so, we use a panel data analysis on proprietary firm-to-firm data from a trade credit insurer, Coface. We show that with a quarter lag, trade credit flows towards Mexican and Turkish buyers increase after an unexpected tightening in US monetary policy. This effect is robust to a set of macroeconomic controls, to the inclusion of import flows, as well as to the control of supplier-buyer pairs' specificities and changes in Coface risk strategy. The effect is also quite similar across both countries albeit slightly bigger in Mexico, due to its higher exposure to the US outlook. Distinguishing between categories of buyers' quality, we show that it is for the most financially constrained buyers that the increase is higher. This means

TABLE 3.15 : Different Measures of Surprises : Mexico

	Trade Credit in Thousands USD		
	(1)	(2)	(3)
MP Surprise (1-year) - 3-month lag	82.93***		
	(20.30)		
MP Surprise (5-year) - 3-month lag		58.49***	
		(17.09)	
MP Surprise (10-year) - 3-month lag			75.62***
			(27.82)
Mexican Industrial Production	−2.36**	−2.14*	−1.88*
	(1.16)	(1.12)	(1.12)
Mexican Sector Imports (Billion USD)	−0.02	−0.08	−0.08
	(1.80)	(1.78)	(1.77)
Fixed effects supplier-buyer	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes
Global-level controls	Yes	Yes	Yes
Supplier country controls	Yes	Yes	Yes
N	547,993	547,993	547,993
Adjusted R^2	0.75	0.75	0.75
Residual Std. Error (df = 531088)	543.60	543.61	543.61

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.1 in the Mexican case with k=3 months, using alternative indicators for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level.

that following an unexpected change in US MP, trade credit from abroad increases to substitute to other financing sources that dry out. Thus, we have a *demand-driven effect through the funding channel*. Using the existence of US and non-US suppliers in the Mexican case, we also identify a counteracting *supply-driven effect through the funding channel* that dominates. We find that trade credit coming from US suppliers decreases overall following an unexpected tightening in US monetary policy. This constraint on suppliers' credit conditions restrict their ability to respond to their buyers' higher demand for trade credit. Finally, using the granularity of the data on the currency used, we show that in the Mexican case, the positive effect for non-US suppliers mainly transit through the USD exchange rate channel. However, we leave to future research the identification of involved mechanisms through this channel as it requires controlling for specific composition effects in both country samples. Besides the effect of exogenous US monetary shocks on trade credit flows from foreign suppliers, future works could also explore the effects for domestic trade credit flows and see whether domestic suppliers continue to extend trade credit terms to their buyers despite changes in credit conditions in the country. The asymmetry of the policy shock that we assume could also be questioned in future works to distinguish the effect of a tightening with the effect of expansionary policies.

TABLE 3.16 : Different Measures of Surprises : Turkey

	Trade Credit in Thousands USD		
	(1)	(2)	(3)
MP Surprise (1-year) - 3-month lag	100.18^{***}		
	(26.71)		
MP Surprise (5-year) - 3-month lag		55.03^{***}	
		(18.29)	
MP Surprise (10-year) - 3-month lag			61.22^{***}
			(23.18)
Turkish Industrial Production	-0.97^{***}	-0.98^{***}	-0.98^{***}
	(0.17)	(0.18)	(0.18)
Turkish Sector Imports (Billion USD)	0.02^{***}	0.02^{***}	0.02^{***}
	(0.01)	(0.01)	(0.01)
Fixed effects supplier-buyer	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes
Global-level controls	Yes	Yes	Yes
Supplier country controls	Yes	Yes	Yes
N	664,339	664,339	664,339
Adjusted R^2	0.83	0.83	0.83
Residual Std. Error (df = 643064)	422.60	422.60	422.61

Notes : ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

NOTE : The coefficients reported correspond to the estimation of equation 3.1 in the Turkish case with k=3 months, using alternative indicators for the US Monetary Policy surprises. Standard errors are clustered at the buyer's sector level.

Appendix

3.A Descriptive Statistics on Monetary Policy Announcements

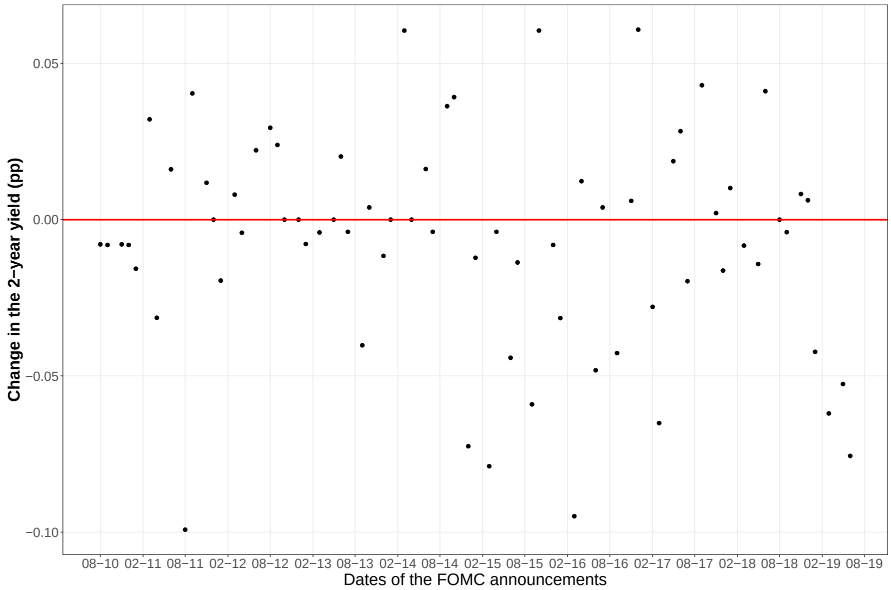


FIGURE 3.A.1 : Monetary Policy Surprises

NOTE : Surprises are computed through changes in the 2-year Nominal Treasury yields surrounding FOMC announcements and are then aggregated to the monthly frequency.

3.B Disentangling "Pure" Monetary Policy and "Informational" Shocks

The identifying assumption underlying the HFI approach is that the variations measured in a narrow window surrounding the announcements are predominantly due to the news provided by these announcements. However, part of these variations may instead be due to changes in the private information held by the Central Bank on the economic outlook. (Nakamura and Steinsson (2018) and Jarociński and Karadi (2020)). To disentangle both shocks, we follow Cieslak and Schrimpf (2019) and Jarociński and Karadi (2020) among others and rely on the high-frequency co-movement of interest rates and stock prices : in case of a "pure" restrictive monetary policy shock, the contraction of the economy is associated with lower share prices (lower present value of future returns due to higher discount rates and lower future economic performance due to monetary tightening) ; hence a negative co-movement between interest rates and stock prices. Conversely, in case of an informational shock, this tightening monetary policy is seen as good news (better economic situation than expected) and is therefore associated with an increase in stock prices ; hence a positive co-movement. We therefore use these sign restrictions to identify both types of shocks : only surprises with a negative co-movement between interest rate and stock prices are considered as "pure" monetary policy shocks. Others are seen as informational shocks and are therefore excluded from our sample. [19]

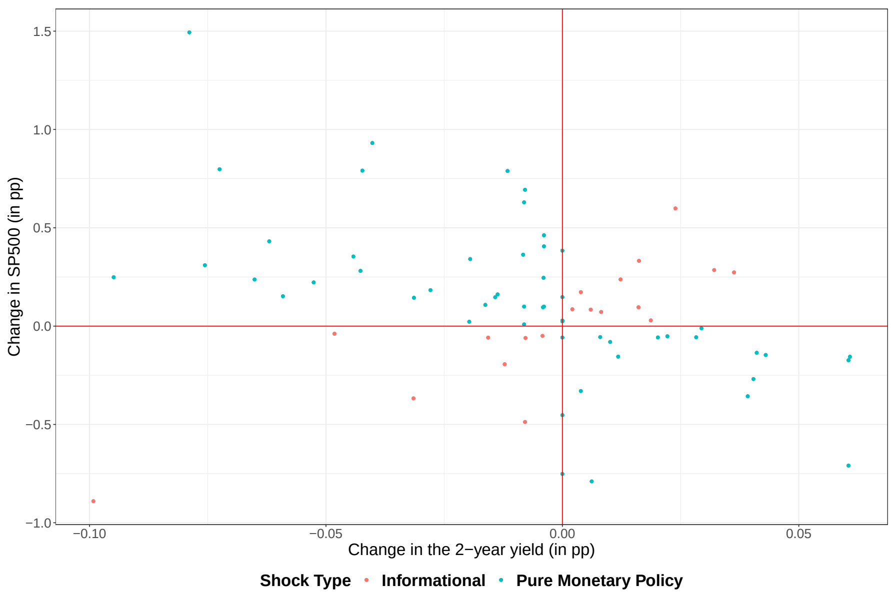


FIGURE 3.B.1 : Change in the 2-year Nominal Treasury Yield and the S&P 500Iindex around FOMC Announcements in pp

3.C Descriptive Statistics for Alternative Policy Indicators

This tables presents the descriptive statistics for alternative indicators to measure the surprise around FOMC announcements. ED4 records percentage point changes in yield for the one-year ahead future on the three-month eurodollar deposits. 5y records percentage point changes on the five-year Nominal Treasury bond yield and 10y the

[19] This simple identification corresponds to what Jarociński and Karadi (2020) call "Poor man's sign restriction". They get similar results with a more complex decomposition, allowing for both kinds of shocks to be present in a certain proportion at each event.

changes on the ten-year Nominal Treasury bond yield.

Jul. 2010 - Jun. 2019	**Nber**	**Min**	**Mean**	**Median**	**Max**	**Nber of 0**
All Ann. ED4	72	-0.1200	-0.0081	-0.0025	0.0800	8
All Ann. 5y	72	-0.1385	-0.0077	-0.0065	0.0927	1
All Ann. 10y	72	-0.1135	-0.0037	-0.0053	0.0772	1

TABLE 3.C.1 : Descriptive stat. for US Monetary Policy shocks with alternative indicators

NOTE : Unity in this table is percentage point changes in yields.

3.D Sample for Goods and Services

Trade credit (000s USD)	Origin of suppliers	Nber of obs.	Median	Mean	Standard Deviation	Share (%)
	Eurozone	534977	61.2	196.5	781.8	48.7
	Other	137068	75.0	280.0	1014.1	12.5
	UK	19980	51.1	160.0	585.8	1.8
	US	406924	60.0	267.9	1110.8	37.0
	all	1098949	61.2	232.6	943.6	

TABLE 3.D.1 : Descriptive Statistics by Suppliers' Origin for Mexico

Trade credit (000s USD)	Origin of suppliers	Nber of obs.	Median	Mean	Standard Deviation	Share (%)
	Eurozone	1119364	61.2	186.0	986.5	73.9
	Other	310147	30.0	127.3	1073.7	20.4
	UK	63282	40.9	134.3	430.2	4.2
	US	22039	50.0	207.0	726.8	1.5
	all	1514832	44.1	172.1	985.5	

TABLE 3.D.2 : Descriptive Statistics by Suppliers' Origin for Turkey

3.E Data Sources

TABLE 3.E.1 : Description of the variables

Short Name	Description	Source	Start	End
US MP shocks				
ED4	1-year ahead futures on the 3-month Eurodollar deposits	Gurkaynak's database	Jan-10	Jun-19
US 2-year	On-the-run US 2-year Treasury yield	Gurkaynak's database	Jan-10	Jun-19
US 5-year	On-the-run US 5-year Treasury yield	Gurkaynak's database	Jan-10	Jun-19
US 10-year	On-the-run US 10-year Treasury yield	Gurkaynak's database	Jan-10	Jun-19
Global-level controls				
EMBI spread	Emerging Markets Bond Index (EMBI) spread	JP Morgan	Jan-10	Jun-19
ECB Surprises	1-year OIS	Altavilla et al. (2019)	Jan-10	Jun-19
USD FX	USD exchange rate for each currency used	Central Banks	Jan-10	Jun-19
Country-level controls				
Mexico				
IP	Industrial Production Index - VOLA	Inegi	Jan-10	Jun-19
CPI	Consumer Price Index - NADJ	Inegi	Jan-10	Jun-19
Rate	Target Overnight Interbank Funding rate NADJ	Banco de Mexico	Jan-10	Jun-19
FX Reserves	Foreign currency reserves	Banco de Mexico	Jan-10	Jun-19
REER	Real Broad Effective Exchange Rate Index - CPI	JP Morgan	Jan-10	Jun-19
Acceptance Rate	Ratio of insurance requested and obtained by suppliers	Coface	Jul-10	Jun-19
Imports	Sectoral Imports	Inegi	Jan-10	Jun-19
Turkey				
IP	Industrial Production Index - VOLN	Turkish Stat. Institute	Jan-10	Jun-19
CPI	Consumer Price Index (%YOY) NADJ	Refinitiv	Jan-10	Jun-19
Rate	1 week repo lending rate NADJ	CBRT	Jan-10	Jun-19
FX Reserves	Foreign currency reserves	CBRT	Jan-10	Jun-19
REER	Real Broad Effective Exchange Rate Index - CPI	JP Morgan	Jan-10	Jun-19
Acceptance Rate	Ratio of insurance requested and obtained by suppliers	Coface	Jul-10	Jun-19
Imports	Sectoral Imports	Turkish Stat. Institute	Jan-13	Jun-19
Supplier-level controls				
IP US	US Industrial Production Index - VOLA	Federal Reserve	Jan-10	Jun-19
IP EZ	EZ Industrial Production Index - VOLN	Eurostat	Jan-10	Jun-19

4 Trade Networks and Natural Disasters : Diversion, not Destruction

Chapter co-authored with Timothée Gigout

Contents

4.1 Introduction 100
4.2 Data and Methodology 103
4.2.1 Data 103
4.2.1.1 Trade Credit Data 103
4.2.1.2 Disaster data 106
4.2.1.3 Estimation Sample 107
4.2.2 Empirical Strategy 110
4.3 Results 112
4.3.1 Main Results 112
4.3.1.1 The decline is entirely explained by the "buyer margin" 112
4.3.1.2 Persistence of the effect after five years 114
4.3.1.3 The effect on the extensive margin is concentrated on top of the distribution of buyer per destination 114
4.3.1.4 Trade in goods and natural disasters 116
4.3.2 Natural disasters decrease the quality of the supplier's networks of buyers 118
4.3.3 The role of supplier heterogeneity 120
4.3.3.1 Larger firms are more sensitive to natural disasters . . . 120
4.3.3.2 Firms with highly specific output loose less buyers than firms with lower specificity. 121
4.3.3.3 For a given level of specificity, larger suppliers exhibit greater reductions in the number of buyers 123
4.3.4 Net Supplier Effect: A Restructuring of the Network 123
4.4 Robustness 127
4.4.1 The effect is not explained by buyers defaulting on their trade credit 127
4.4.2 The effect is not explained by credit insurance rationing 127
4.4.3 Absence of anticipatory effects per ratings category 128
4.5 Mechanisms 128
4.6 Conclusion 131

Abstract :

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

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

Keywords : Firm Dynamics ; Trade Networks ; Natural Disaster.

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4.1 Introduction

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

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

To test these theoretical predictions, we use novel firm-to-firm trade credit data from one of the top three international credit insurers (Coface). We pair data on French exporters between 2010 and 2019 with exhaustive worldwide disaster data from EM-DAT. We then estimate the effect of natural disasters on various firm-level outcomes, describing the size, shape and quality of the French exporters' international trade networks. We use a dynamic difference-in-differences identification strategy. We employ the de Chaisemartin and D'Haultfoeuille (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.

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

Related Literature

We contribute to the literature on the propagation of shocks in international production networks. We are closely related to the literature that leverages natural disasters as exogenous shocks to production networks. Our contribution relative to this literature is three-fold. First, we use data on all large natural disasters between 2008 and 2020 rather than focusing on a specific event. Second, our data is not restricted to foreign affiliates, publicly traded firms or trade in goods. It covers a much more common type of cross-border linkages : goods and services sold under trade credit. Finally, while most of the literature focuses on how the network contributes to the propagation of the shock, we focus instead on how the network itself is affected by the shock. Boehm et al. (2019) show that relationships between US affiliates and Japanese parent companies were mostly resilient to the 2011 Tohoku Earthquake. They show that the earthquake caused a significant drop in sales of Japanese firms to their US affiliates over the short term. This lead to major disruptions of production processes in the US, highlighting shock propagation through production linkages. However, they show this effect is only short-lived. It does not endanger the relationship between the firm and its affiliate over the long-term. In contrast, we find a persistent effect (beyond five years) of natural disasters. Foreign buyers and French suppliers included in our data set are not locked in a relationship the same way US affiliates of Japanese firms are. The sunk cost associated with regular trade relationships is lower than with foreign direct investment (Helpman et al., 2004). The persistent effect we find would be consistent with a model of forced experimentation as in Porter (1996). 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. (2021). 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. (2021) study the effect of the 2011 tsunami on Japanese production networks only. They find upstream and downstream propagation, up to the fourth degree of separation. Barrot and Sauvagnat (2016) focus on the production networks of publicly traded US firms but include data on all natural disasters occurring in the US between 1978 and 2013. They find the intensity of the downward propagation to be highly dependent on input specificity. The more specific the input, the harder it is to switch to another other source of input and the greater the consequences for the firm downward on the chain. We extend this result by showing that suppliers of more specific products tend to preserve their networks in affected countries despite natural disasters.

This paper relates to the literature on the adjustment margins of international trade to exogenous shocks. As in Bernard et al. (2018) and Garcia-Appendini and Montoriol-Garriga (2013), we find that the buyer margin is the primary source of adjustment following a large shock. This result contrasts with the mostly intensive–margin effects of the Great Financial Crisis identified in Bricongne et al. (2012) [2] or in Malgouyres et al. (2021) following a large positive technological shock.

Our study also relates to the firm-to-firm trade literature. Lenoir et al. (2021) 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. (2021) 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).

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

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

Moreover, our work is related to the literature on trade credit 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 4.2 presents the data and details our empirical strategy and section 4.3 shows our baseline results. We conduct further robustness tests in section 4.4. Section 4.5 provides a discussion of our empirical results in the context of existing theories of trade and heterogeneous firms. Section 4.6 concludes.

4.2 Data and Methodology

We first describe our two main source of data in Section 4.2.1.1 and 4.2.1.2. Then, we show some stylized facts from our estimation sample in Section 4.2.1.3. Finally, we present our empirical strategy in Section 4.2.2.

4.2.1 Data

4.2.1.1 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 4.1 : Sample Descriptive Statistics - Trade & Trade Credit Data

	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 (K EUR)	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 4.D for the details on the computations of those variables.

Our dataset includes every French suppliers which have subscribed to a trade credit insurance policy at Coface between 2010 and 2019. Supplier are identified by a French fiscal identifier (siren code). In our study, the basic unit of observation is the supplier-destination dyad which we observe every month. We look at the total amount of insured trade credit flows, the number of buyers, the average exposure per buyer and the distribution of the Coface internal rating of foreign buyers. We also have information on the amount of exposure requested by the supplier to Coface and the amount granted by Coface. Finally, we also use the number and amount of payment defaults from buyers notified to Coface in each market. We are able to distinguish between the two main types of defaults : insolvency from the buyer and "protracted defaults" (i.e. partial default/payment incidents). Table 4.1 displays the key summary statistics for the outcome variables, for both supplier-destination dyads (panel A and B) and at the supplier level (panel C). Monthly exposure corresponds to the amount of trade credit insured by Coface for a specific supplier-destination dyad. With a median of €10,000 and a mean of €256,150, the distribution of this variable is highly skewed. The number of buyers per destination is characterised by a large standard deviation (13.5) and a median of 1. It reflects the presence of some suppliers with a very large number of buyers in the sample, compared to some others with few buyers. Payment incidents are rare events, only 23,274 are recorded in our database, although some of those are fairly large (standard deviation of 144,220). Finally, the second part of the table shows that most suppliers included in the sample export to several countries, with a median of five and a mean of eight destination countries. This allows us to control for supplier-time fixed effects in our analysis.

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

In addition, Coface collects the sector of activity for every relationships covered by the trade credit insurance. Because the unit of observation in our final database is the supplier-destination pair, we assign to each pair the dominant sector of the supplier in this destination. In other words, we know whether a firm mostly supply car parts (NACE 2931) or provide management consulting services (7022) to a given destination. In order to account for the relationship specificity of each sector, we assign each NACE 4-digit sector a BEC5 code taken from the UN Statistical Division classification by Broad Economic Activity. This allows us to group sectors together based on the amount of coordination required between the buyer and the seller to establish a relationship. Details on the composition of BEC categories can be found in table 4.E.1 in appendix 4.E.

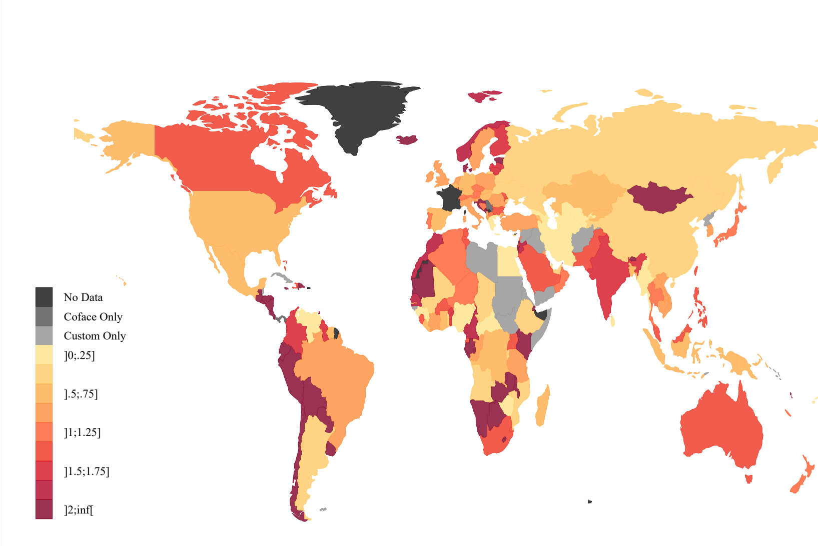
Regarding the representativity of the trade credit data used in the analysis, MuÛls (2015) shows that in Belgium there is a large overlap between exporting firms and firms included in Coface database[4]. In the case of French exporters studied here, for the year 2018, the number of firms in Coface database is equal to 4.1% of those in French custom data and 3.2% of firms in FIBEN. However, Coface firms represented 9.4% of produced value added across FIBEN firms. Figure 4.1 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 for larger coverage than the amount actually needed. At the same time, counteracting this effect, the amount of coverage requested affects the premium paid

[3] Internal Coface documentation.

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

as it affects the risk taken by Coface. Thus, the supplier faces a trade-off and does not request an infinite coverage. Coface also provides incentives to suppliers so that they limit the amount requested to their actual needs as the amount insured defines Coface's capital needs from the regulator's perspectives.

FIGURE 4.1 : 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.

4.2.1.2 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.

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

$$D_{j,t} = \frac{\text{reported damage}_{j,t}}{\text{previous year GDP}_{j,t-1}} \tag{4.1}$$

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

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

$$E_j = \begin{cases} 1 & \underset{j}{\operatorname{argmax}}(D_{j,t}) \cup D_{j,t} > D^{P50} \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

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 4.A.1 in appendix show the selected event per country. The absence of contamination is visible from the different graphs. Appendix 4.A.2 describes the construction of an alternative definition of event, taking the first big event rather than the worst one in a country. We further check that the selected natural disasters do in fact represent a clear break in trend in terms of recorded damage by estimating the impulse response function of damage per GDP ($D_{j,t}$) following an event. We present the results in Figure 4.A.2. The only positive and statistically significant coefficient is the one contemporaneous to the recorded event. It shows that the event variable is not capturing damaged caused by previous or future disasters.

Table 4.2 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 4.B.1.

Figure 4.2 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 4.3 shows the geographical distribution of natural disasters events as defined by Equation 4.2. 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 period to increase the size of the control group. Countries in red enter our treatment group in a staggered fashion. The shades of red indicates the severity (in percentage of GDP) of the damage caused by the event. 50% of natural disasters cause damage lower than 0.77 percent of GDP (Table 4.2).

4.2.1.3 Estimation Sample

We keep observations for which we have both disaster and trade credit data. The final sample (see Table 4.3) consists of 14,692,164 observations (i.e. supplier-destination-month triads) over a hundred and twenty months from January 2010 to December 2019. Our data covers the trade credit activity of 9,615 French suppliers. Those suppliers

TABLE 4.2 : Sample Descriptive Statistics - Natural Disasters

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

This table presents summary statistics for our estimation sample. Panel A is computed at the supplier-destination level using Coface data. Panel B is computed at the supplier-destination level using custom data. Panel C is computed at the supplier level. See Appendix 4.D for the details on the computations of those variables.

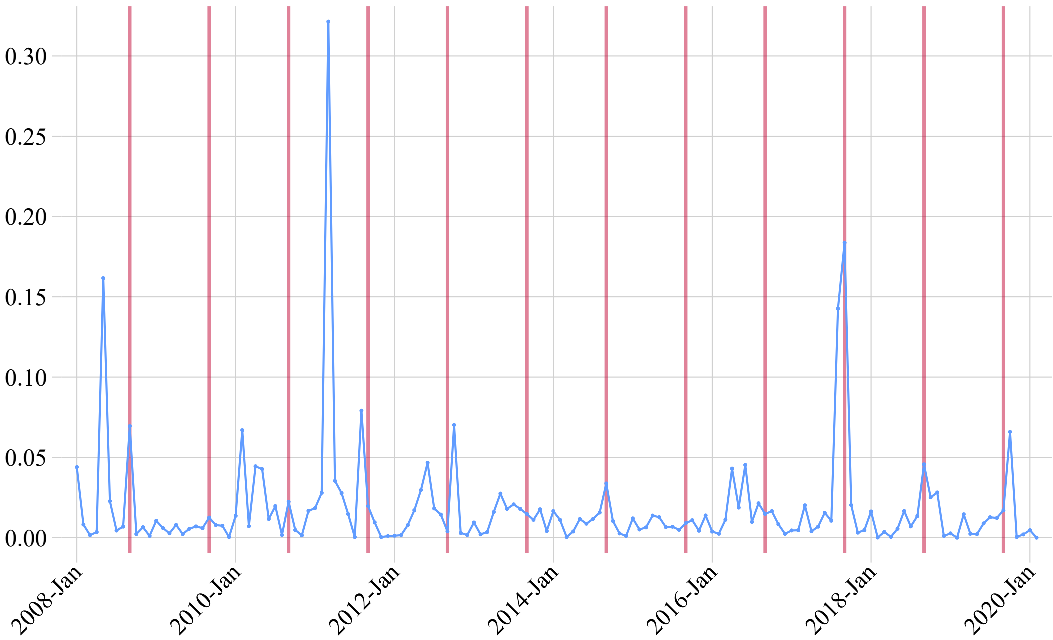
have created 146,833 distinct supplier-destination linkages in 181 different countries. Of those supplier-destination dyads, 29,537 (37%) are never treated. The rest suffers from a natural disaster at some point during the sample period. On average about 2% of those dyads are treated each month. The control group used in the estimation is composed of both never treated and not yet treated observations.

TABLE 4.3 : 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

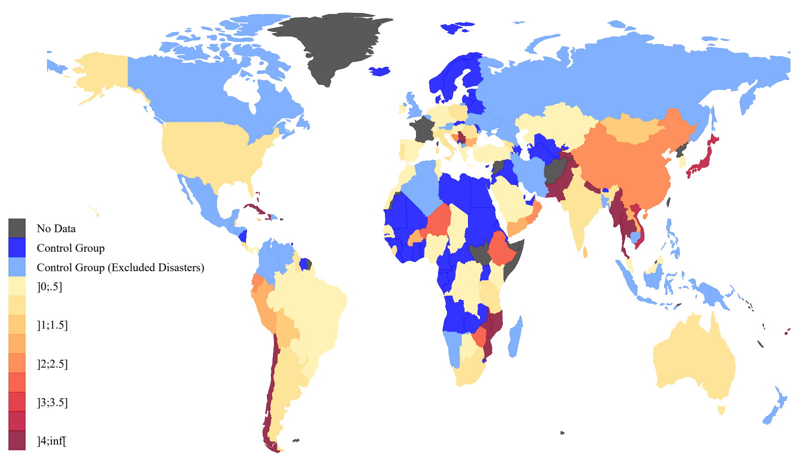
NOTE : The estimation sample ends 12 months early when using customs data.

FIGURE 4.2 : Natural Disasters



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

FIGURE 4.3 : 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

4.2.2 Empirical Strategy

We want to estimate how natural disasters change the structure of the supplier's network of buyers. As shown in Section 4.2.1.2, we define the disaster variable as the worst disaster in the country over the period 2008-2019, conditional on the disaster being above the median of all disasters globally over the period and conditional on the absence of other large events four years before or four years after. This allows us to identify the effect of a larger than usual disaster. This is an important criterion for countries exposed to seasonal storms. Concretely, in some cases, pre and post-event periods may be contaminated by other less damaging events. For this reason, we set as missing any observation during which the country suffered from other disasters with an intensity of at least 50% of the worst one. In appendix 4.A.2, we provide results using an alternative definition of the event variable. We take the first event causing damages relative to GDP greater than the median in the whole sample, and at least 50% of the intensity of the worst event in the country over the period. We also mark as missing any observation polluted with events reaching 50% of the damages caused by this first big disaster. Our results are essentially unaffected. The same can be said taking a third definition of our event, modifying the median threshold for selection. In appendix 4.A.5, we provide our main result using the worst disaster in a country, conditional of having a disaster greater than the *third quartile* of damages. Once again, we mark as missing any observation polluted with events reaching 50% of the damages caused by this worst event.

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

$$Y_{f,j,t} = \sum_{k}^{K} \beta^k \times \texttt{DISASTER}_{j,t-k} + \gamma_{f,t} + \nu_{r(j),s(f),t} + \epsilon_{f,j,t} \tag{4.3}$$

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

To estimate our β^k, we rely on a Difference-in-Differences strategy and exploit the fact that some countries are hit by natural disasters at different times or not at all. We use the de Chaisemartin and D'Haultfoeuille (2021) estimator. It accounts for the weighting issues generated by standard difference-in-differences estimator (see for instance Callaway and Sant'Anna (2020) and Goodman-Bacon (2021)). In particular, they show that the coefficients identified by the canonical two-way fixed effect (TWFE) model are a combination of the actual treatment effect and weights. In the case of a staggered design, the TWFE mechanically computes negative weights for some periods and groups. In some cases it can result in negative estimated coefficients when the treatment effects are in fact positive. This problem is more acute in the presence of treatment effect heterogeneity, either across groups or across periods. The identifying assumption is that suppliers operating in affected and unaffected countries would have had the same outcome in the absence of a natural disaster. This assumption likely holds for two reasons : first large natural disasters are exogenous to local economic activity in the short term, second, we do not detect any significant differences between non treated and not yet treated observations.

We follow de Chaisemartin and D'Haultfoeuille (2021) to estimate the effect of disasters and use this estimator :

$$DID_k = \sum_{t=k+2}^{T} \frac{N_t^k}{N_{DID_k}} DID_{t,k} \tag{4.4}$$

Where

$$DID_{t,k} = \underbrace{\sum_{f,j:E_j^d=t-k} \frac{1}{N_t^k} (\overbrace{\tilde{Y}_{f,j,t}}^{\text{Now}} - \overbrace{\tilde{Y}_{f,j,t-k-1}}^{\text{Before}})}_{\text{Treated}} - \underbrace{\sum_{f,j:E_j^d>t} \frac{1}{N_t^{nt}} (\overbrace{\tilde{Y}_{f,j,t}}^{\text{Now}} - \overbrace{\tilde{Y}_{f,j,t-k-1}}^{\text{Before}})}_{\text{Not yet Treated}} \tag{4.5}$$

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 (2021) Difference-in-Differences estimator allows to estimate dynamic effects across k periods following the disaster. It also absorbs permanent differences between destinations. To account for time varying shocks, we residualize the outcome variables over region-sector-time and firm-time fixed effects prior to the estimation.

The former accounts for common shocks across suppliers in a given market (here a NAF 4-digit sector in large geographical region). The latter accounts for common shocks across the various destination countries of a given suppliers. Identification results from comparing a firm outcomes across all of its export destinations after absorbing time-varying destination market factors. This specification limits the sample to supplier present in two or more destinations and to markets that source from a least two suppliers. We cluster the standard errors at the region-sector level. It allows for autocorrelation of the error term within regional sectors. It also allows for correlation across buyers within those regional sectors.

Throughout the paper, we show the results of estimating DID_k to evaluate the time-varying impact of natural disasters on the international network of French suppliers. As a baseline, we estimate DID_k with the outcome variables $\tilde{Y}$ measured in level (amount in euros, number of buyers, etc.). This yields the average change ΔY in affected destinations relative to unaffected destinations. It does not require the omission of observations taking the value zero as opposed to using the log of those outcomes. We expect a higher frequency of zero flow to the affected destination in the aftermath of the disaster. Dropping those observations would bias $DID_{t,k}$ toward zero. We provide results robust to functional forms mis-specification in Section 4.3.1.3.

4.3 Results

We first present our main results in section 4.3.1 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 4.3.2. In 4.3.3, we examine to what extent some suppliers can better adjust to disasters. Finally, in 4.3.4, we provide a measure of the suppliers' aggregate response to a natural disaster in one of their destinations

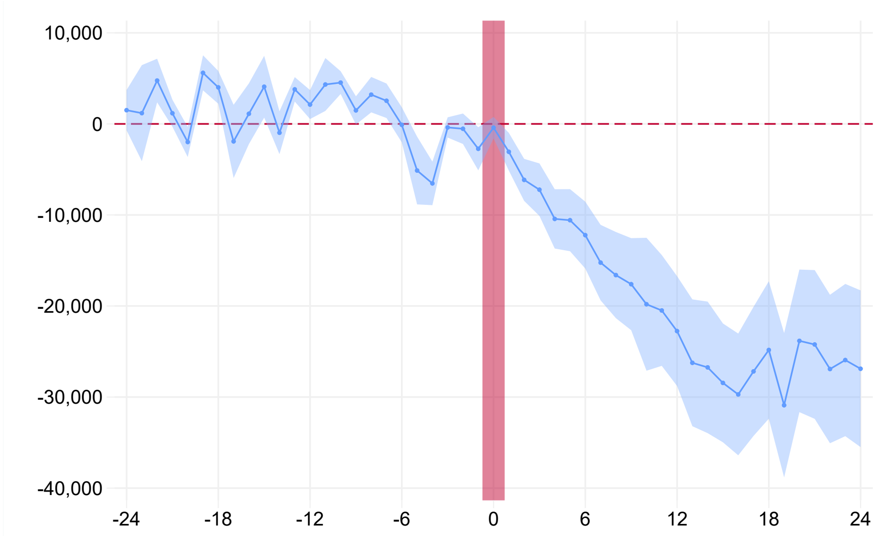
4.3.1 Main Results

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

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

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

FIGURE 4.4 : Effect of Natural Disasters on Exposure



NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the amount in euros of trade credit insurance for a given supplier in the affected country. See Appendix 4.D for the details on the computations of this variable.

start exporting under trade credit terms with insurance in the country and the "buyer extensive margin" i.e. the number of buyers using trade credit terms in the destination country. To measure the effect on the intensive margin, we compute the average trade exposure per trade credit buyer in the destination country. We provide details on the computations of those variables in Appendix 4.D.

In Figure 4.5, 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 4.6a). The average number of buyers in the sample is 2.49 (P50 = 1). This represents a 8.4% decline in the number of buyers using trade credit 24 months after a disaster. Meanwhile, we find no impact on the intensive margin (Figure 4.6c). Looking at the probability to export under insured trade credit terms, we find a slightly positive effect, with a 2% increase in the probability to export under insured trade credit terms (Figure 4.6b). This increased probability is however absent from customs' trade in goods data (Figure 4.B.2). We interpret this as an increase in demand for trade credit from some buyers which translate into a higher probability of having at least 1 insured buyer in the affected destination. We provide a further decomposition of the extensive margin effect in Section 4.3.1.3. It confirms that the negative average effect on the number of buyers originates from a lower probability of having many (more than 10) buyers.

In section 4.B.2 in appendix, we focus on the buyer margin and the heterogeneity in terms of disasters, following EM-DAT classification. We find that geophysical events (e.g. earthquake), while being the most destructive (see table 4.2), are also the events that cause the steepest fall in the number of buyers in the affected country. After 2 years, there is a decrease of -1.4 buyers following a geophysical event. Meteorological (e.g. typhoon) and climatological (e.g. drought) events tend to cause a smaller response even though negative. For hydrological events, the small but positive effect should be interpreted in line with the limited damage typically caused by this type of disaster (see table 4.2). Such results reflect the heterogeneity in the extent of damages caused by each type of disaster.

4.3.1.2 Persistence of the effect after five years

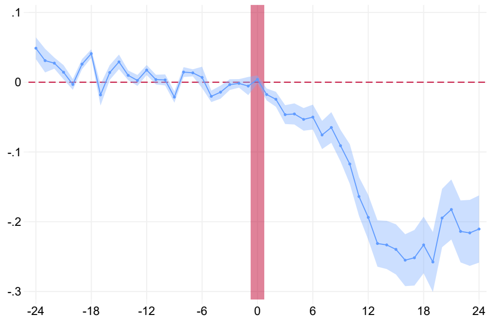
To assess the long run consequences of natural natural, we repeat the same estimation procedure as in Equation 4.4 and Figure 4.6a on a sample aggregated at the yearly level. We average the monthly trade credit stocks over the year. We present those results in Figure 4.7. We find that the number of buyers in the affected country decreases persistently, and doesn't come back to its pre-disaster level within a five-year window. The average loss at this horizon is 0.81 buyers per supplier. Using the alternative definition of a disaster event (Appendix 4.A.3), we see that the orders of magnitude are very similar, with a loss of 1.01 buyers per supplier for the first event. The difference between both estimate is small and each estimate falls within the other's confidence interval. Wee provide additional results with a third definition of our event that selects disasters greater than the third quartile in the whole sample distribution. We see again very similar results (Appendix 4.A.5). We further confirm our result by checking that they do not reflect ex-ante differences between treated and non treated. In Appendix 4.A.4, we repeat the estimation with our alternative definition of event (first big disaster). This time we exclude the never treated observations and use only the not-yet-treated dyads as control group. We find an even greater effect, with the fall in the number of buyers reaching 2 buyers after 5 years.
Our results are robust to various definitions of the event variable and to potential differences across the treated and non-treated.

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

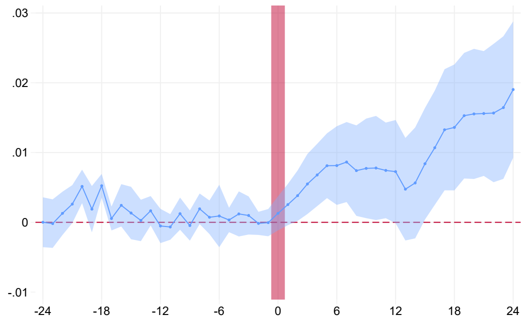
In Section 4.3.1, we showed that the buyer margin was driving the negative effects of disasters while the country margin (i.e. the probability to have 1 or more buyers in the affected destination) exhibited small but positive effects. To further disentangle the margin through which firms adjust to external shocks, we estimate the effect of a natural disaster on the cumulative distribution of buyers per supplier-destination. It allows us to isolate which part of the distribution of the number of buyers per supplier is most affected. We estimate the same equation as in Equation 4.4 but we replace the

FIGURE 4.5 : Extensive and Intensive margin

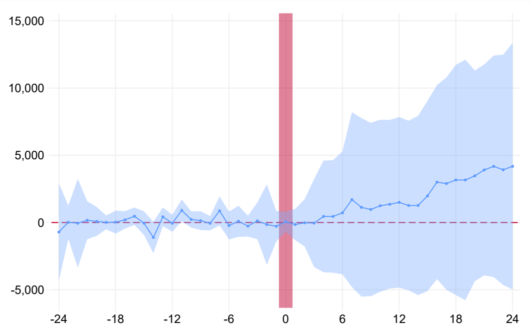
(a) Number of Buyers with Trade Credit



(b) Probability of Export under Insured TC Terms



(c) Trade Credit / Number of buyers



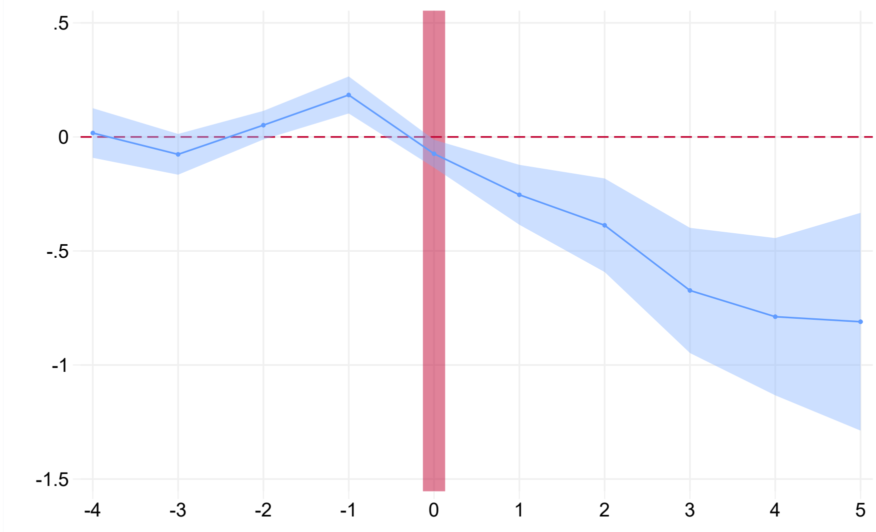
NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. In Panel 4.6a, 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 4.6b, the outcome variable is a dummy indicating whether the supplier has at least one trade credit relationship in the affected destination. In Panel 4.6c, the outcome variable is the average amount of trade credit per buyer in the affected destination. See Appendix 4.D for the details on the computations of those variables.

outcome variable with a dummy equal to one for supplier-destinations with a number of buyers greater than x. We repeat this estimation for every possible value of x (from 0 to 50, the 99^{th} percentile) in increments of 1. This method allows to estimate the entire conditional distribution. Importantly, it does not require the outcome to have a smooth conditional density as in quantile regressions (Chernozhukov et al., 2013). [6]

Figure 4.9a plots the effect on the distribution along the values of the outcome variable, here the number of buyers. We see that the effect measured in our baseline

[6]See Aghion and Melitz (2021), Goodman-Bacon and Schmidt (2020) or Blanc (2020) for recent applications.

FIGURE 4.7 : Long run effect (yearly data)



NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5 at the yearly level. We include here a supplier-time and sector-region-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers of trade credit insurance for a given supplier in a country. See Appendix 4.D for the details on the computations of all LHS variables.

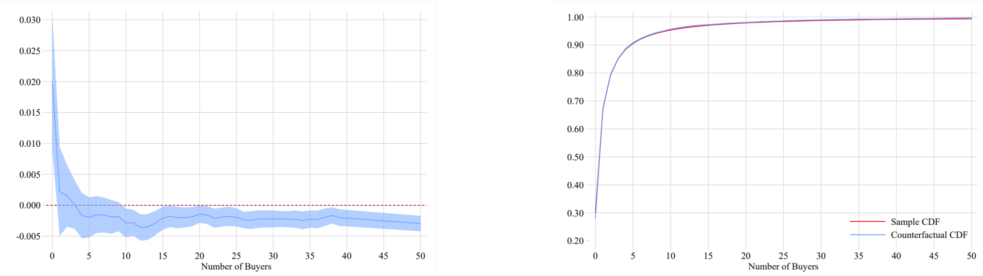
specification is largely explained by a decrease in the probability of having at least 10 buyers or more per destination. The effect on the probability of having at least a single buyer is slightly positive (about two percentage points). A disaster decreases the probability of having more than twelve buyers by 0.3 percentage points and more than fifty buyers by about the same. With a small dip between 10 and 15 buyers, the effect is quite stable until 38 buyers before slightly increasing. We show in Figure 4.9b that it results in a shift of the cumulative distribution towards the left for any number of buyers greater than 3. In other words, the new distribution of buyer-per-supplier includes a lower number of suppliers with a lot of buyers. Suppliers with a single foothold did not loose it and suppliers with a small local buyer base went mostly unaffected.

4.3.1.4 Trade in goods and natural disasters

We've established that natural disasters leads to a lower amount of buyers using trade credit in affected destinations. While the data doesn't allow us to unambiguously determine if the end of a trade credit relationship means the end of the underlying trade relationship, the decrease in the number of buyers using trade credit likely reflects a lower number of domestic firms sourcing from French suppliers. Based on

FIGURE 4.8 : 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 4.4. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2013 and 2020, we consider only the largest one. The outcome variable is the number of buyers per supplier-destination. In Panel 4.9a, we plot the sequence of coefficients from estimating the baseline equation for every value of x. In Panel 4.9b, we plot the observed CDF in red and the estimated counterfactual CDF in blue. For details on distribution regressions see Chernozhukov et al. (2013).

previous work (Garcia-Appendini and Montoriol-Garriga, 2020), we know that firms rarely switch away from trade credit. In this section, we use customs data on trade in goods to investigate whether there are any effects on actual cross-border flow of goods. We unfortunately do not have the corresponding data on trade in services. We keep the same specification as before and average the export variables over a three-month rolling window. This sub-sample contains firms that are present in both French customs and Coface datasets. As a consequence it only extends from 2010 to 2018 for the exports of goods. We first estimate the effect on the total value in euros exported by French suppliers to their affected destinations. We then repeat the exercise with the quantities (in kilograms), number of products (at the HS6 level in the 2007 nomenclature) and the unit values (euros per kilogram). We report the result in Figure 4.10. In panel 4.11a, we show that the values of the transactions toward the affected destinations experience a clear break in trend around the time of the disaster. The estimate is however relatively small (about €10,000) and noisy. It decreases until 15 months after the disaster, without being fully significant at 1%. It likely reflects strong heterogeneity in the response. In panel 4.11b we see a small and short-term decline in the quantity exported before a medium-run increase albeit non-significant. The same non-significant increase is visible for unit values in panel 4.11c. Finally, panel 4.11d indicates that natural disasters do not lead to a lower number of exported products. We also do not find evidence of an effect on the probability of exporting to a country struck by a natural disaster (Figure 4.B.2).

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

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

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

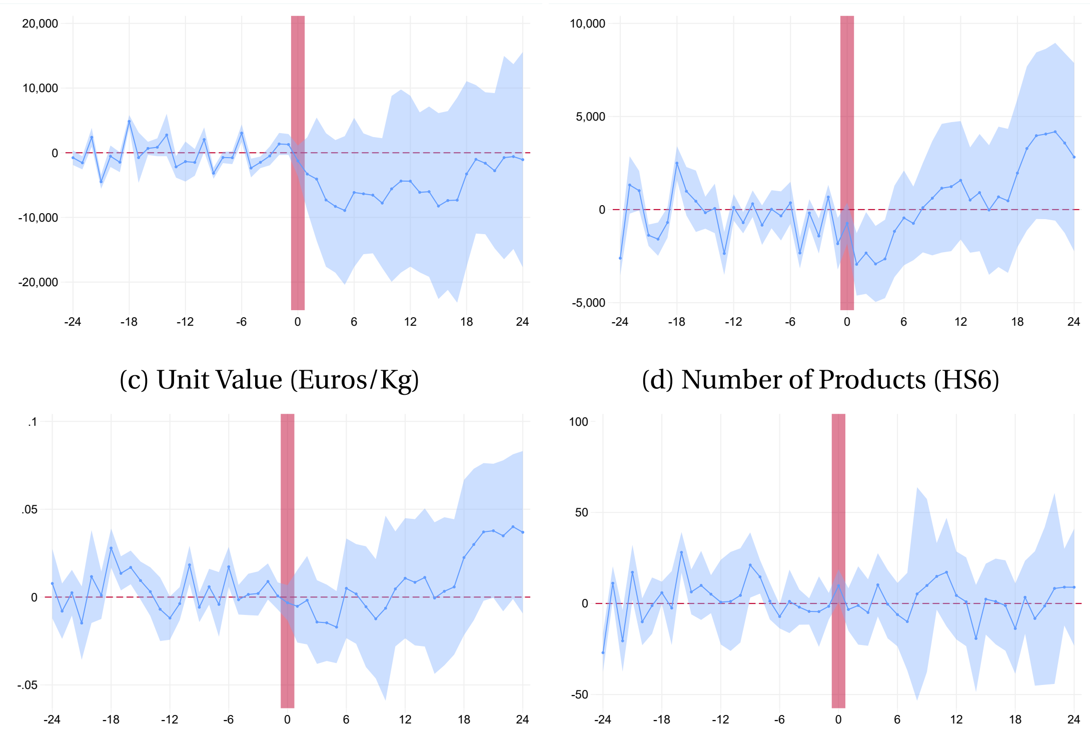
We compute the number of buyers in each rating category : $T^r_{j,f,t} = \sum \mathbf{1}(EXPO_{j,b,f,t} > 0 \cup R_{b,t} = r)$. We estimate the effect of natural disasters on the number of buyers per supplier in each rating category using the same estimator as before, i.e. the de Chaisemartin and D'Haultfoeuille (2021) estimator with region-sector-time fixed effect and supplier-time fixed effect. We find that natural disasters induce a negative shift in the distribution of buyer quality two years after the event. We show the results in Figure 4.12. The bins in red represent the sample average number of buyers in each rating category. The bins in blue represent the counterfactual average number of buyers per category after subtracting the coefficient from the sample average.

We find that in the aftermath of a disaster the distribution of ratings has shifted toward the left, i.e. it has worsened. In particular, there is a much lower number of suppliers in ratings 7 to 9. [7] At the same time, there are slightly more buyers in some of the bottom categories (1 to 4). However, we find that natural disasters are associated with a lower number of unrated firms and firms rated 0. This overall effect on the distribution is a combination of "treatment effect" i.e. buyers are being downgraded or "composition effect" i.e. good buyers disappears from the suppliers network.

In Figure 4.13, we present the same analysis as in Figure 4.12, but this time we freeze

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

FIGURE 4.10 : Effects of Natural Disasters on the Export of Goods



(a) Total Transaction Value (Euros)

(b) Total Transaction Quantity (Kg)

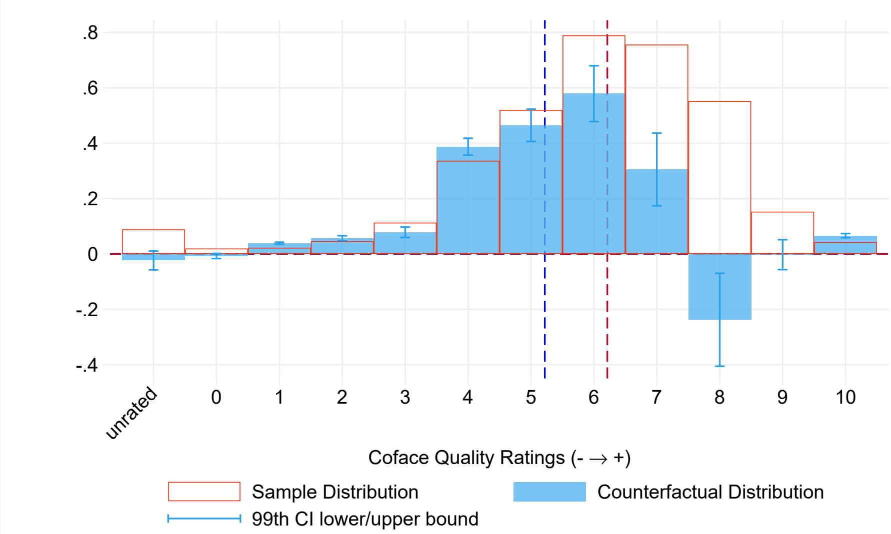
(c) Unit Value (Euros/Kg)

(d) Number of Products (HS6)

NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5. We include here supplier-time and sector-region-time fixed effects. 99% error bands, computed with robust standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2010 and 2019, we consider only the largest one. In Panel 4.11a, the outcome variable is the three-month rolling average total value in euros exported by French suppliers to their destination. In Panel 4.11b, the outcome variable is the three-month rolling average quantity exported in kilograms. In Panel 4.11c, the outcome variable is the three-month rolling average unit values (euros per kilogram) of the exports. In Panel 4.11d, 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 4.D for the details on the computations of those variables.

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

FIGURE 4.12 : 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 4.5. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers each supplier has in each rating category. We plot the sample distribution of ratings in red and its counterfactual distribution in blue.

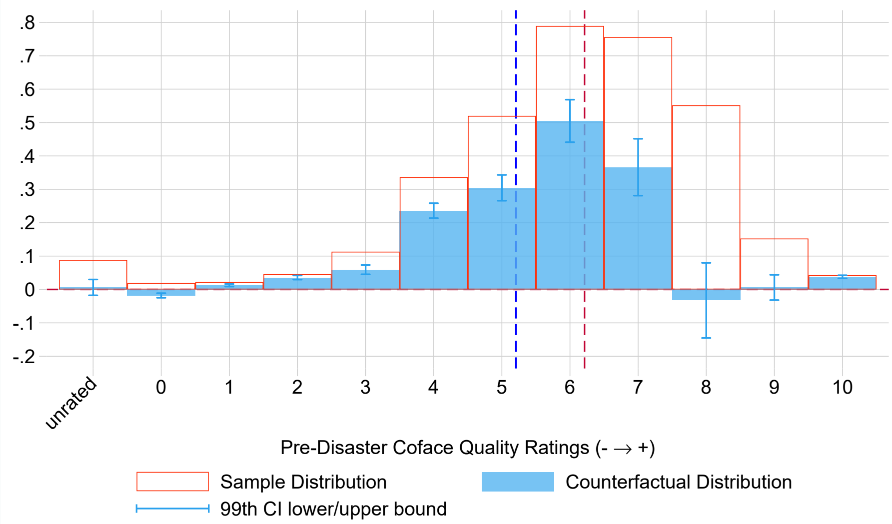
4.3.3 The role of supplier heterogeneity

In this section we investigate the heterogeneity in the ability of suppliers to adjust to natural disasters abroad. Factors such as a geographically diversified client base, financial constraints or the sunk cost associated with the establishment of a relationship are likely to affect the choice to pivot toward unaffected destinations or maintain relationships with buyers in the affected destination.

4.3.3.1 Larger firms are more sensitive to natural disasters

We start by looking at the role played by the overall size of the supplier's customer base in its sensitivity to country-specific shocks. Firms with a large client base are much less reliant on the relationships with their buyers in the affected destination. Compared to small firms, we expect large suppliers to loose more buyers in destinations affected by natural disasters relative to unaffected destinations. We use the same estimator as before but we split the sample along the deciles of the distribution of supplier size and repeat the estimation procedure for each bin of size. We show the results two years after the disaster in Figure 4.14. We measure size with either the initial total number of buyers (panel 4.15a) or the initial total trade credit exposure worldwide (panel 4.15b).

FIGURE 4.13 : Effect of Natural Disasters on the ex-ante Distribution of Buyer Quality after 2 years



NOTE : These figures present estimates of the counter-factual distribution of buyer quality after a natural disaster event from estimating Equation 4.5. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers each supplier has in each rating category taken at the time of the event. We plot the sample distribution of ratings in red and its counterfactual distribution in blue.

In both cases we use the size at the time we first observe the supplier in our sample.

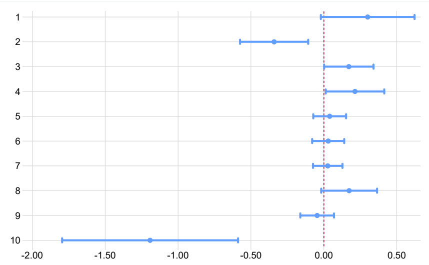
We find that the decline in number of buyers is almost entirely explained by the outcome of suppliers at the very top of the distribution of size. Suppliers above the last decile of the number of relationship worldwide loose 1.2 buyers on average 2 years after the disaster. Meanwhile suppliers below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

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

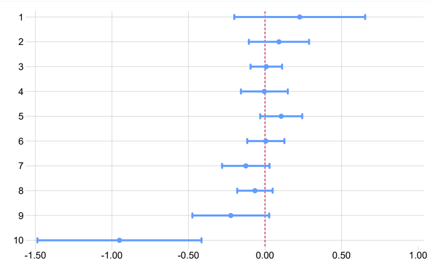
We now focus on the heterogeneity in the response to natural disasters based on the type of goods or services sold by the French exporters. As highlighted by Antras (2020), fixed costs associated with establishing trade linkages are central to explaining the short and medium-term response of Global Value Chains to shocks. They can be of three types : first, the cost associated with information gathering on the targeted

FIGURE 4.14 : Effect of Natural Disasters conditional on the supplier size (k=2)

(a) By number of buyers worldwide



(b) By trade credit exposure worldwide



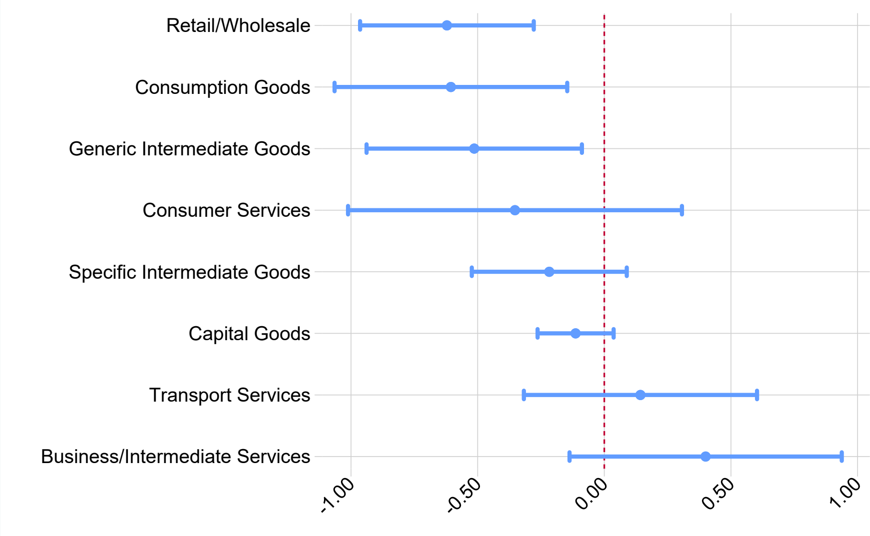
NOTE : Coefficients and 99% confidence interval are reported for two years after the disaster using the de Chaisemartin and D'Haultfoeuille (2021) estimator on sub-populations that includes exporter-buyer pairs where the exporter belongs to the bin of interest. We include here supplier-time and sector-region-time fixed effects.

market, then, the relational capital to ensure contractual security under incomplete contract enforcement, and, finally, the cost associated with the development of physical assets specific to the buyer-supplier relationship. The more specific a good or service traded between the two firms, the higher the sunk cost. Therefore, the higher the losses associated with the death of the partnership for both parties and the lower the benefits to switch towards other partners. Such effect is expected to be even stronger for trade credit relationships that are typically associated with longer-term trade, as described by Garcia-Appendini and Montoriol-Garriga (2020). Therefore, the specificity of the good or service exchanged will weigh in suppliers' and buyers' decision to end the partnership. We would expect the trade response to natural disasters to be muted for highly specific goods and services, while much greater for non-specific products.

To explore this mechanism, we construct a measure of product specificity using as proxy the sub-sector of the French exporters. We use the four-digit NACE classification and match it with the BEC classification to establish eight types of product categories : capital goods, consumption goods, generic intermediate goods, specific intermediate goods, retail and wholesale, consumer services, business services and transport services.[8] We conduct the same analysis as before using the de Chaisemartin and D'Haultfoeuille (2021) estimator on sample restricted to exporters belonging to each of the above category. Figure 4.16 synthesizes the heterogeneity in response by category after two years. As expected, the response observed in aggregate is driven by retail and wholesale, consumption goods, and generic intermediate goods, while it is muted for capital goods, specific intermediate goods and consumer and business services. Partnerships around the latter types involve greater sunk costs. Our interpretation of this result is that suppliers and buyers of such specific products tend to protect their relationship to avoid greater losses and save this initial investment.

[8] See appendix 4.E for full description of each category.

FIGURE 4.16 : Effect of Natural Disasters conditional on supplier output specificity (k=2)



NOTE : Coefficients and 99% confidence interval are reported for two years after the disaster using the de Chaisemartin and D'Haultfoeuille (2021) 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.

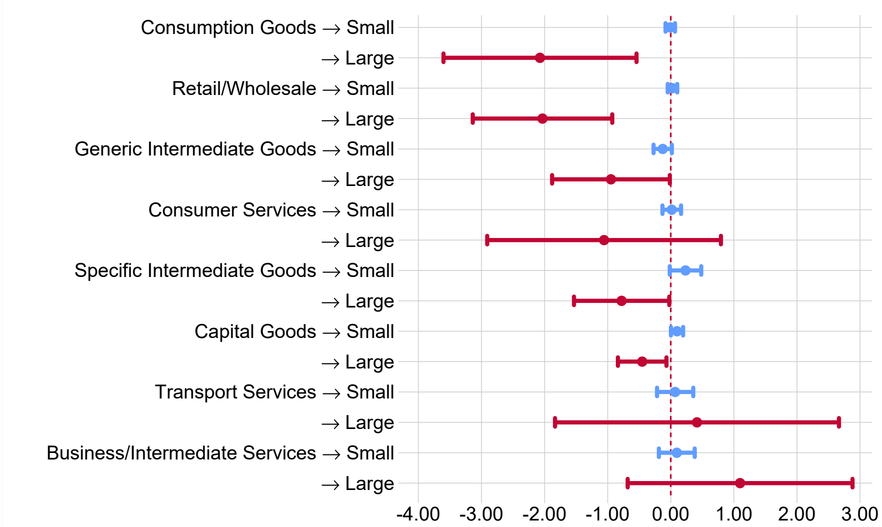
4.3.3.3 For a given level of specificity, larger suppliers exhibit greater reductions in the number of buyers

We now investigate whether the effect of size persists within categories of specificity. We repeat the same estimation procedure as before but we allow the estimated coefficient to vary both by product specificity and size. The specificity categories are unchanged but for simplicity we sort firms within each category into only 2 bins of size. We use the 9^{th} decile of the distribution of the worldwide number of buyers as a cut-off. We report the results in Figure 4.17. We note two facts. First, within each category, the elasticity of response of large firms dwarfs that of small firms. Second, among large suppliers the sorting by sensitivity to natural disasters follows the same pattern identified above. Firms operating in sectors that produce non specific output experience a larger drop in number of buyers in the affected destinations. The largest firms in retail/wholesale loose 2.0 buyers two years after the disaster whereas large firms producing specific intermediate goods loose 0.77 buyers and those selling intermediate services are not significantly affected.

4.3.4 Net Supplier Effect : A Restructuring of the Network

We've established that natural disasters decrease trade credit flows towards affected locations while creating a noisy and limited response in trade flows. We now investigate

FIGURE 4.17 : Effect of Natural Disasters conditional on supplier output specificity and size (k=2)



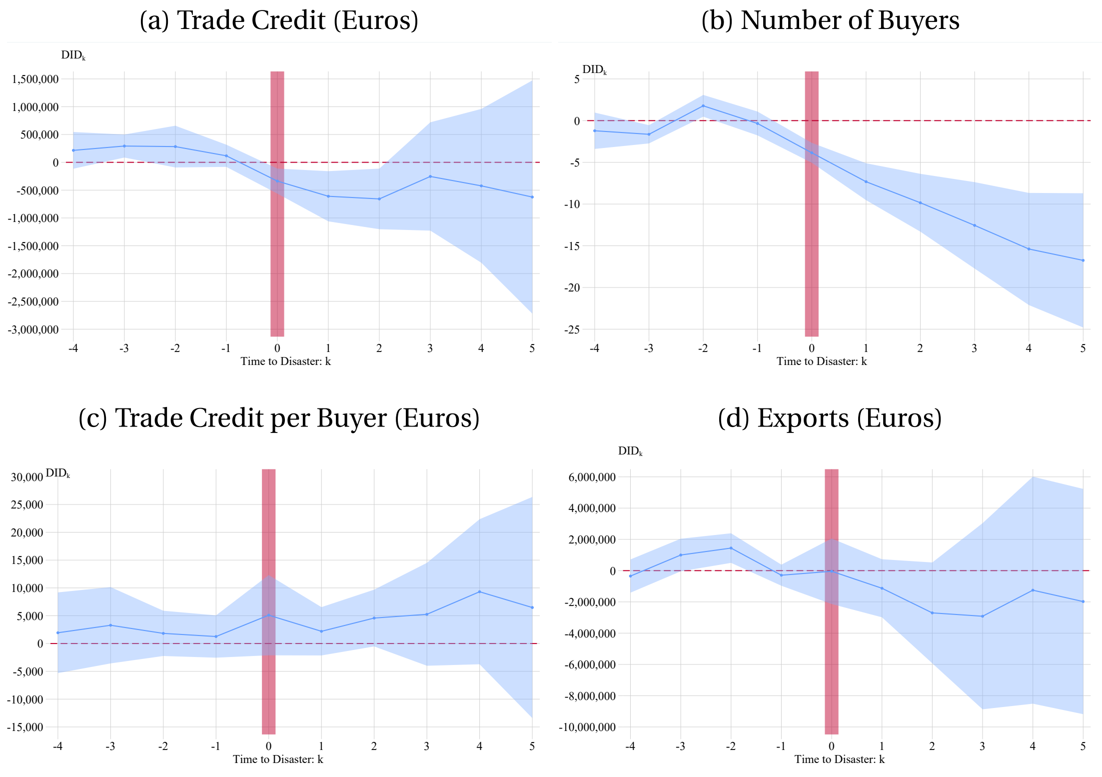
NOTE : Coefficients and 99% confidence interval are reported for two years after the disaster using the de Chaisemartin and D'Haultfoeuille (2021) estimator on sub-populations that includes exporter-buyer pairs where exporters belong to the category of interest. Firms are sorted into categories based 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.

whether this translates into global effects at the firm level. Suppliers might be able to divert partnerships toward unaffected destinations. In this section, we compare the dynamics of trade credit flows and exports for suppliers that suffered from a disaster in one of their export markets with suppliers that did not. We consider that suppliers are affected by a natural disaster if one of their export market is hit by a natural disaster as defined in Section 4.2 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 (2021) estimator. In our baseline specification, we introduce a time fixed-effect. We present the results in Figure 4.18.

We highlight two key results. First, trade credit exposure experience only a temporary drop while the number of buyers under trade credit terms decline persistently, respectively by 646,941 EUR (panel 4.19a, 10.9% of the average exposure per supplier in the sample) and 7.8 buyers (panel 4.19b, 16.7% of the average number of buyers per supplier in the sample) after two years. [9] After 5 year, trade credit exposure is almost back at its pre-disaster level while the number of buyers under trade credit

[9] Because of the differences in the event definition, the estimates are not directly comparable to the destination level results in Section 4.3.1

FIGURE 4.18 : Long Run Effects of Natural Disasters on Supplier-level Trade



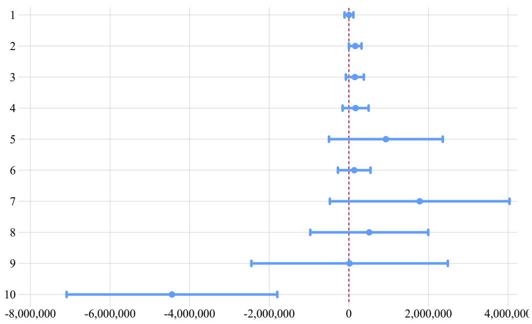
NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5. 99% error bands, computed with robust standard errors clustered at the sector level, are displayed as blue lines. We include time fixed effects. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. For suppliers with multiple affected destinations, we consider only the largest one. In Panel 4.19a, the outcome variable is the total value of trade credit. In Panel 4.19b, the outcome variable is the number of trade credit partners. In Panel 4.19d, the outcome variable is total value of exports. See Appendix 4.D for the details on the computations of those variables.

terms has fallen by 16.7 buyers. This means that suppliers do not compensate globally for the buyers they lost in affected destinations. The difference between amount of trade credit and number of buyers is probably related to a small but noisy increase in the average trade credit per buyer in unaffected destination as visible on panel 4.19c. Second, exports again experience a small and noisy drop (panel 4.19d). It is worth noting that they follow quite closely the pattern of trade credit sales. We interpret this such that, following a disaster, suppliers rearrange their network of buyers globally without creating new trade credit partnerships.

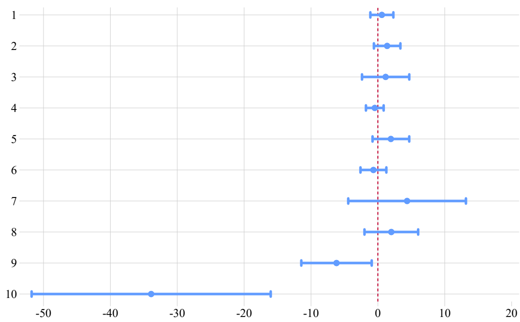
We now investigate whether this effect is stronger for suppliers with a larger partner base globally. Intuitively, firms with many buyers in unaffected destinations should find it easier to compensate for the losses in the affected destinations. Figure 4.21a and Figure 4.21b show that while the largest suppliers are the ones experiencing most of the effect in trade credit exposure, they do not display a significant response in the amount they export (Figure 4.21c). Once again, the response of exports is noisy and displays a strong heterogeneity. The effect of disasters is only significant on the amount of trade credit and number of buyers for suppliers belonging to the top decile. This means that large multinationals are able to restructure their trade network by either deepening or widening their buyer base in other destinations under alternate financing terms (i.e. without using trade credit). This likely reflects their stronger bargaining power that allow them to set the term of the trade and switch buyers at a lower cost.

FIGURE 4.20 : Effects of Natural Disasters after 2 years conditional on Supplier Size

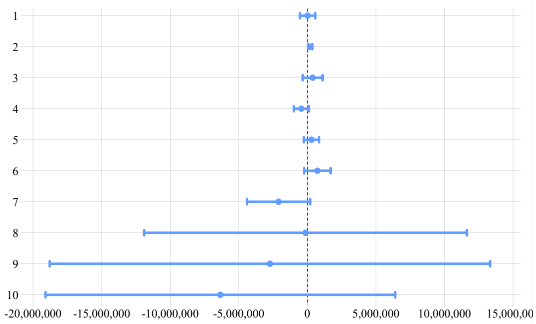
(a) Trade Credit (Euros)



(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 4.5. 99% error bands, computed with robust standard errors clustered at the sector level, are displayed as blue lines. We include time fixed effects. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2018, we consider only the largest one. For suppliers with multiple events, we consider only the largest one. In Panel 4.21a, the outcome variable is the total value of trade credit. In Panel 4.21b, the outcome variable is the number of trade credit partners. In Panel 4.21c, the outcome variable is total value of exports. See Appendix 4.D for the details on the computations of those variables.

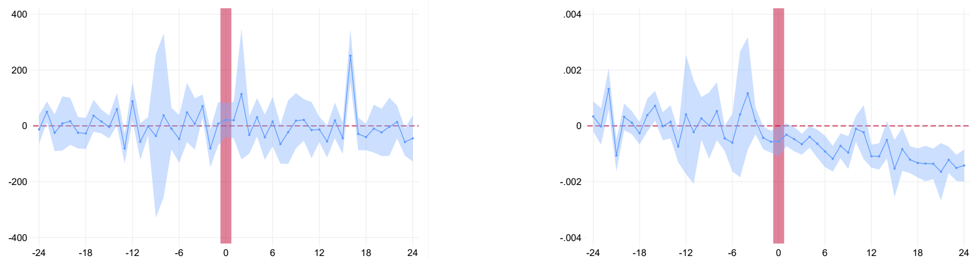
4.4 Robustness

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

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

FIGURE 4.22 : Effect on Default

(a) Amount of Payment Defaults (b) Number of Payment Defaults

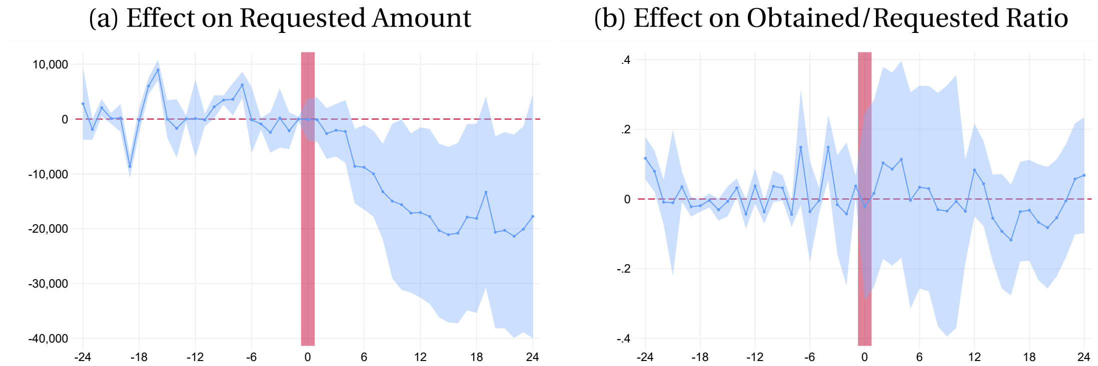


NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.4. We include here a supplier-time and region-sector-time fixed effect. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. In Panel 4.23a, the outcome variable is the amount of trade credit that buyers in the affected destination default on. In Panel 4.23b, the outcome variable is the number of defaults. See Appendix 4.D for the details on the computations of those variables.

4.4.2 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 4.25a, 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 4.25b). We find no significant effect. This indicates that the effect reflects a change in demand by the supplier rather than a change in supply by the insurer.

FIGURE 4.24 : Supplier vs. Insurer Effect



NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5. We include supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variables are : in Panel 4.25a the requested amount of trade credit guarantee requested by the supplier and in Panel 4.25b the ratio of obtained trade credit guarantee over requested. See Appendix 4.D for the details on the computations of all LHS variables.

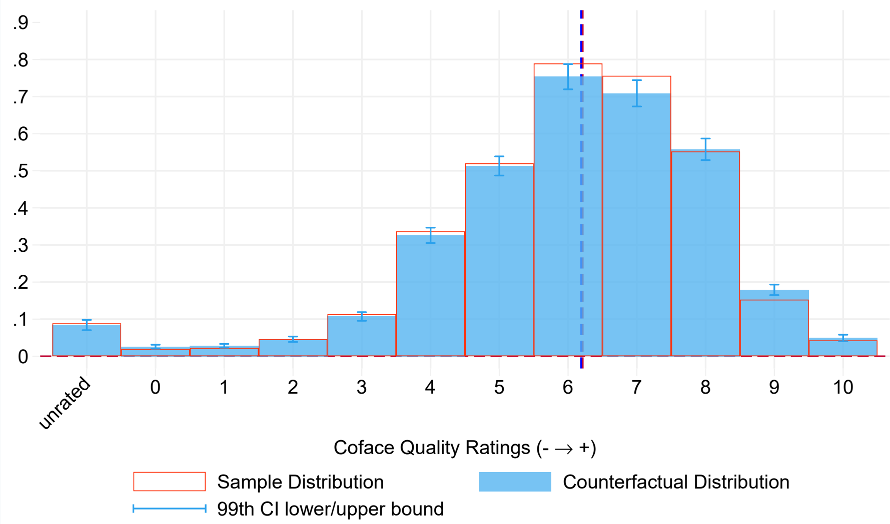
4.4.3 Absence of anticipatory effects per ratings category

A potential threat to our identification strategy is that low quality buyers were already experiencing some form of decline prior to the disaster and would have exited the network regardless of the disaster. To investigate this, we repeat the same exercise as in Section 4.3.1 by estimating the effect on the number of buyers per supplier in each rating category in the two year prior to the disaster. We find no overall meaningful decrease in buyer quality prior to the disaster. We provide the full dynamic response of each rating category in Figure 4.B.3.

4.5 Mechanisms

Our results emphasize the importance of the buyer margin in the adjustment to trade shocks. It matches well with the empirical regularity noted by Bernard et al. (2018). Those results can be easily interpreted within a framework of a model of trade with

FIGURE 4.26 : 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 4.5. We include supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue brackets. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers each supplier has in each rating category. We plot the sample distribution of ratings in red and its counterfactual distribution in blue.

exporter and importer heterogeneity such as Bernard et al. (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 4.6a).

The implications regarding the quality of the surviving buyers are more ambiguous. An increase in trade cost, all else equal, implies a higher selection effect and therefore a higher quality of the remaining buyers. However, a trade cost shock can also provide an incentive for buyers to search for suppliers in destinations with lower trade cost, i.e. a diversion effect. Firms will be affected differently by this mechanism depending on their ability to pay the required search cost. Finally, a fall in productivity among the potential buyers, all else equal, would lead to a lower quality of remaining buyers, i.e. a treatment effect. The fall in quality could also be related to a "flight from quality" phenomena, with households substituting towards lower-quality goods in the aftermath of the disaster, as highlighted in the Argentinean case by Burstein et al. (2005) following a large devaluation. Empirically, we observe a decline in quality after a disaster (Figure 4.12). This decline is driven both by firm ratings being downgraded as well as firms with a good rating leaving the production network of the French supplier (Figure 4.13). "Marginal firms" with a very low rating do not stop importing at a higher rate after a disaster. Similarly, we do not find any evidence that firms default at a higher rate (Figure 4.22). Moreover, we do not find evidence of a "flight from quality" given the noisy and not fully significant response in the volume exported nor in the number of products exported towards the affected destination. Thus, empirically, the trade diversion effect and to a lesser extent the treatment effect of natural disasters appear to dominate the selection effect.

The higher sensitivity of large supplier of non specific outputs (Figure 4.17) in combination with the heterogeneity we observe on the buyer side (Figure 4.13) is indicative of the importance of the adjustment capacity on each side in the aftermath of a large economic shock. The larger the firm, the greater its capacity to respond to the shock and change its sourcing and targeted markets. For both buyers and suppliers, a larger firm will have more opportunities to divert its sourcing/customer base towards more suitable markets. Additionally, firms operating in sectors that do not require a large sunk-cost to establish new relationships have a lower opportunity cost to forgoing existing relationships.

Financial constraints represent another transmission mechanism. Firms that become financially constrained as a consequence of the disaster will choose to reallocate their limited resources towards their more profitable sources. By affecting the value of collateral a firm can pledge to finance trade, it forces them to reorganize their network of partners. While the impact on exporters' financial constraint in the source country is deemed to be only temporary following the disaster, importers will be more durably affected given the decrease in productivity in the country and its long term impact on collateral value. The long-run effect we observe in our analysis tend to favor a prevalence of an impact through the importers' financial constraint. Because of their newly limited resources some buyers are likely to reallocate towards more profitable suppliers. They go through a "forced experimentation" as highlighted by (Porter, 1996) with regards to environmental regulation. Given the amount of information frictions in international trade, many buyers might find a supplier that is good enough and it is not longer optimal for them to re-establish a relationship with the original supplier. This would lead to permanent trade diversion as foreign buyers find new suppliers. This also features in our results : losses after a disaster appear to be permanent (Figure 4.7).

4.6 Conclusion

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

Appendix

4.A Definition of events

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

FIGURE 4.A.1 : Timing of selected events

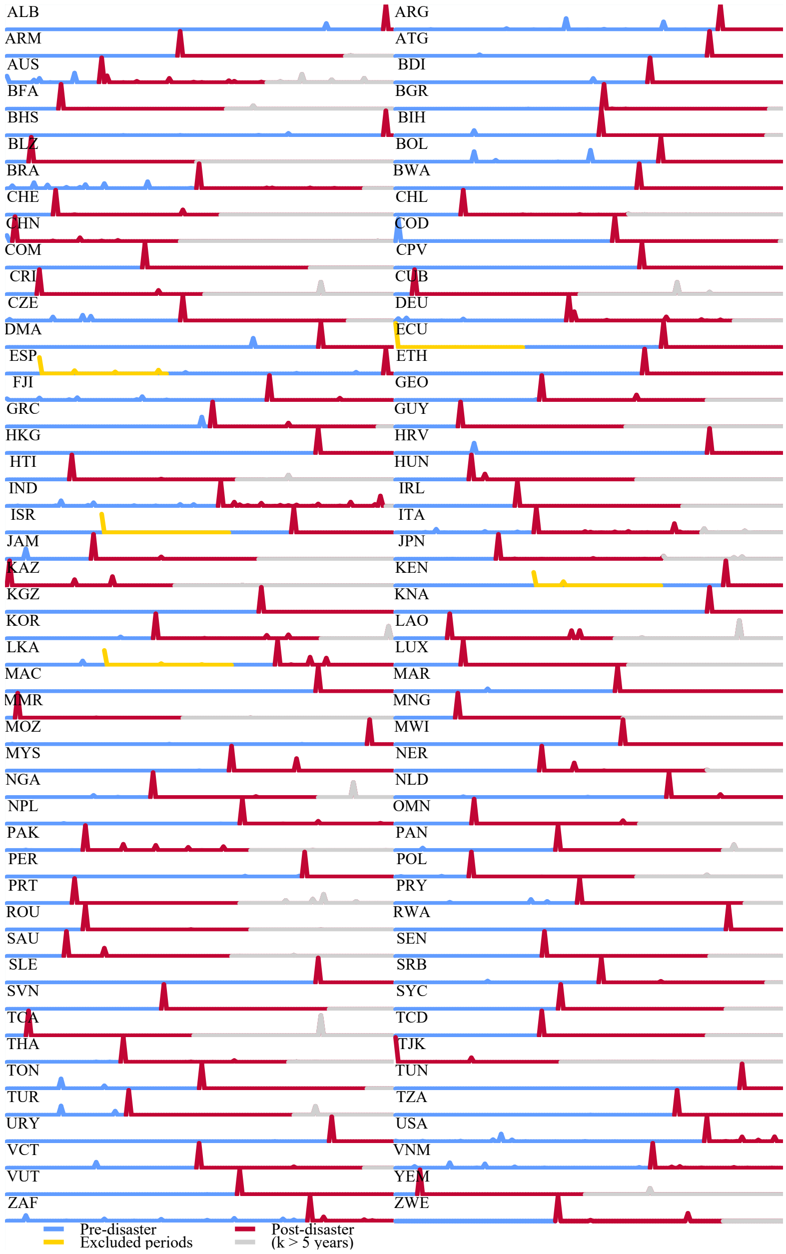
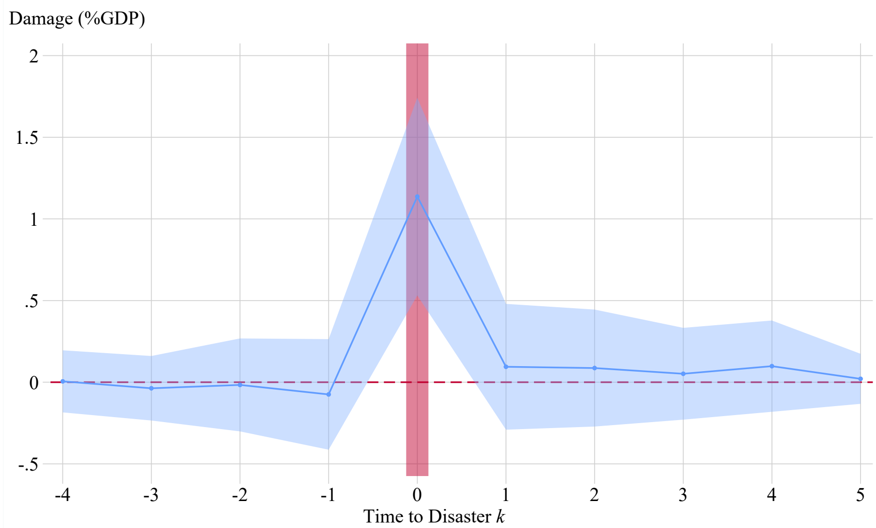


FIGURE 4.A.2 : Natural Disasters

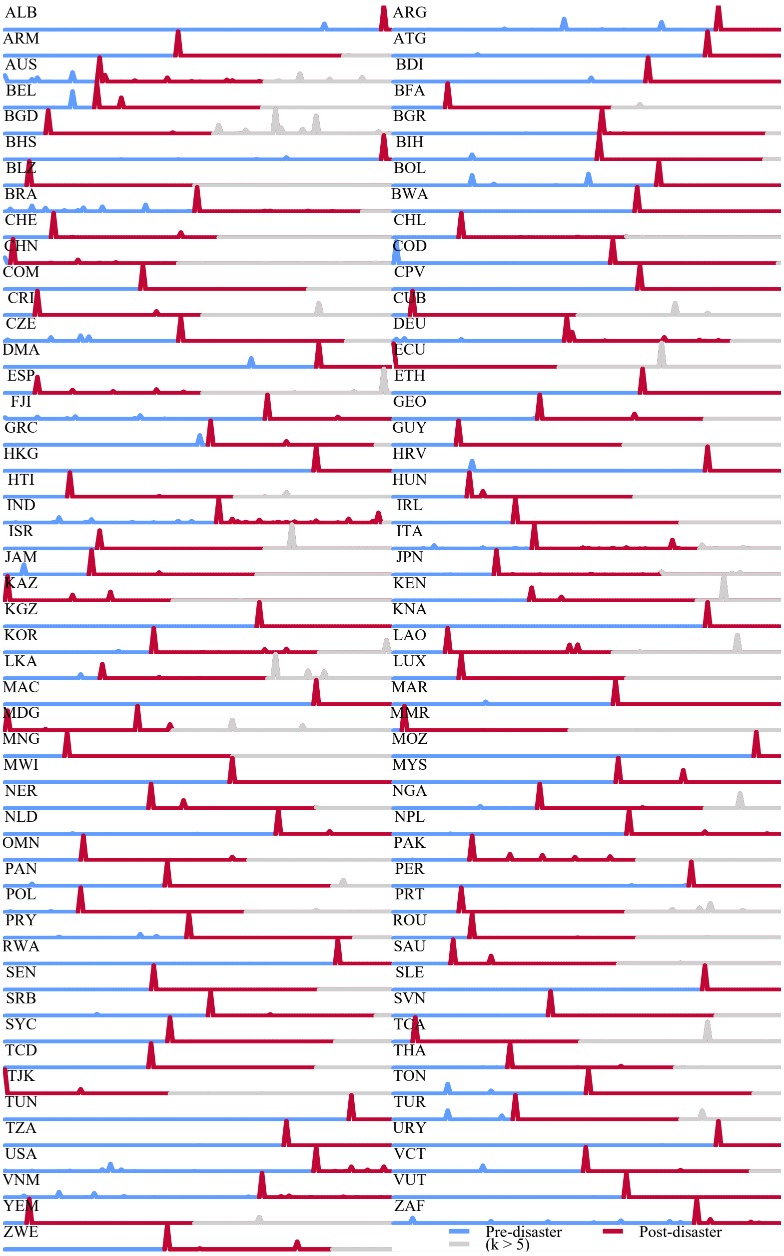


NOTE : These figure presents the response function of estimated damage in percentage of GDP around a natural disaster with our baseline definition. The estimated equation is $D_{j,t} = \sum_k \beta_k + \gamma_j + \gamma_t + \epsilon_{j,t}$

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

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

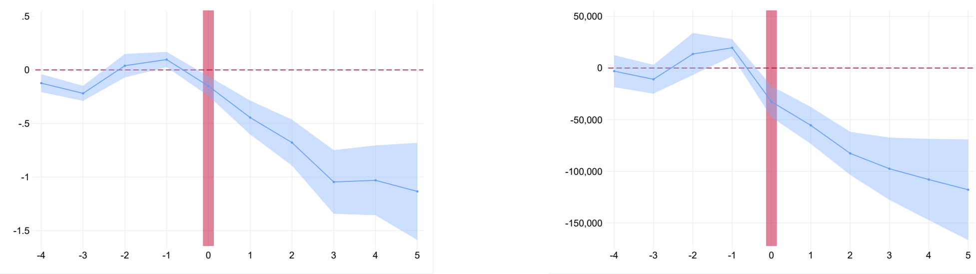
FIGURE 4.A.3 : Timing of alternative events



4.A.3 Main results with first big disasters

FIGURE 4.A.4 : Effect of Natural Disasters on the Number of Buyers - First big disaster

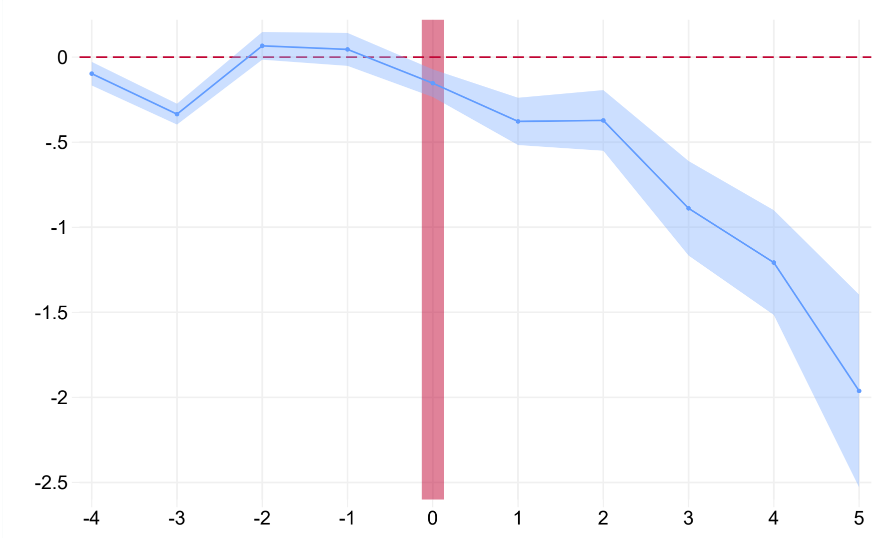
(a) Number of buyers (b) Trade credit amount



NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5 at the yearly level. We include here a supplier-time and a region-sector-time fixed effects. 99% error bands, computed with robust standard errors clustered at the firm-time level, are displayed as light lines. Events are defined as the first big disaster in the country as shown on the timeline in section 4.A.2. The outcome variable is the number of buyers purchasing from the supplier at credit and the amount of insured trade credit.

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

FIGURE 4.A.6 : Effect of Natural Disasters on the Number of Buyers - Excluding never treated

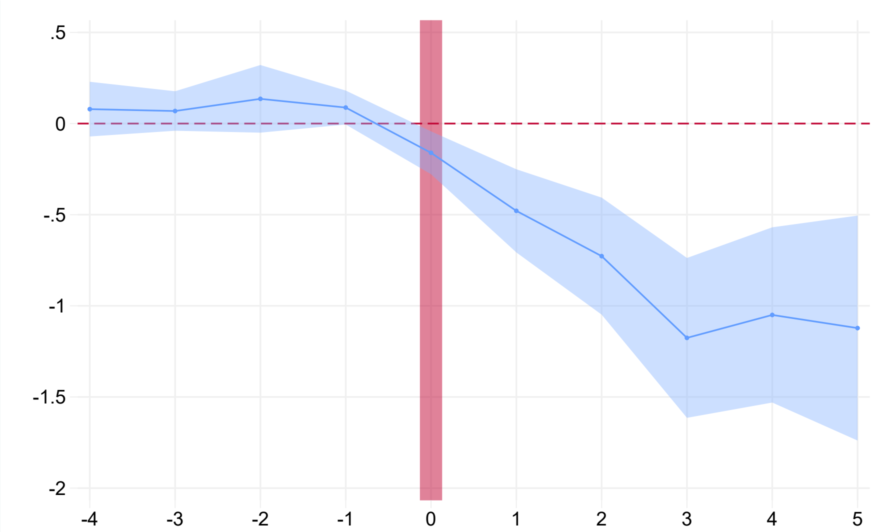


NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5 at the yearly level, excluding the supplier-destinations that are never treated. Events are defined as the first big disaster in the country as shown on the timeline in section 4.A.2. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. The outcome variable is the the number of buyers purchasing from the supplier at credit in each destination country. See Appendix 4.D for the details on the computations of this variable.

4.A.5 Main results with top quartile disasters

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

FIGURE 4.A.7 : 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 4.5 at the yearly level. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the third quartile in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the the number of buyers purchasing from the supplier at credit in each destination country. See Appendix 4.D for the details on the computations of this variable.

4.B Disaster Types

4.B.1 Definition

TABLE 4.B.1 : Disaster Types

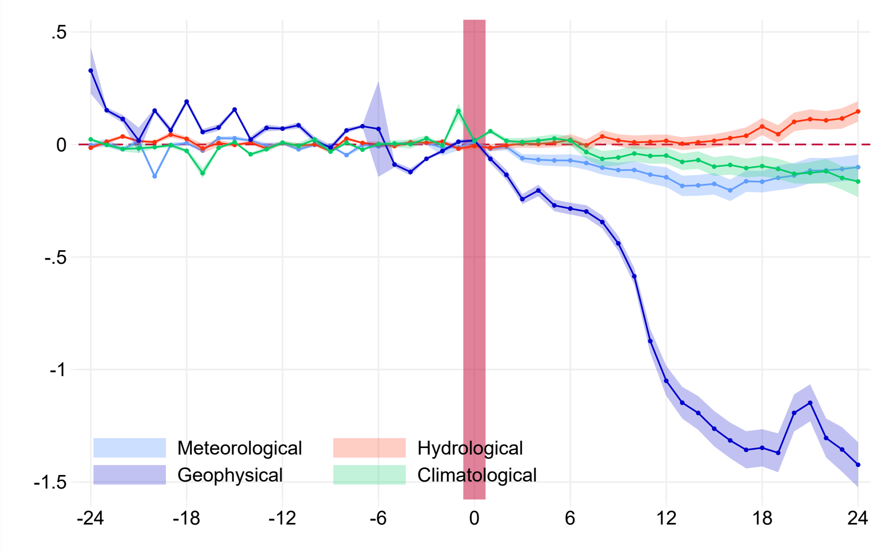
Disaster Group	Disaster Main Type
Geophysical	Earthquake, Mass Movement (dry), Volcanic activity
Meteorological	Extreme Temperature, Fog, Storm
Hydrological	Flood, Landslide, Wave action
Climatological	Drought, Glacial Lake Outburst, Wildfire
Biological	Epidemic, Insect infestation, Animal Accident
Extraterrestrial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

4.B.2 Heterogeneity in Types of Disaster

We conduct the same analysis as in section 4.2 to study the impact of natural disasters on the number of buyers in the affected destination. We use the de Chaisemartin and D'Haultfoeuille (2021) 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 4.B.1. 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.

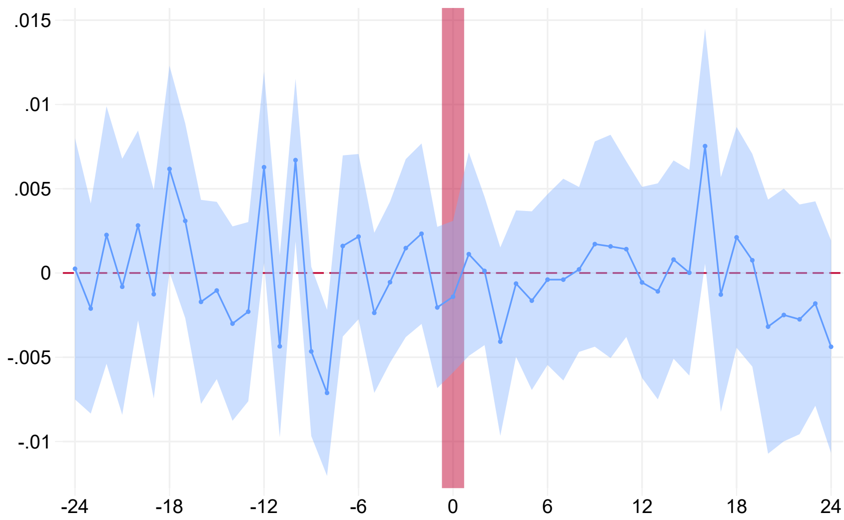
FIGURE 4.B.1 : Heterogeneity in Types of Disasters



NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5. We include here a supplier-time and a region-sector-time fixed effects. 99% error bands, computed with robust standard errors clustered at the firm-time level, are displayed as light lines.Events are defined according to our main definition described in section 4.2.1.2. The outcome variable is the number of buyers purchasing from the supplier at credit.

4.B.3 Trade in Goods - Extensive Margin

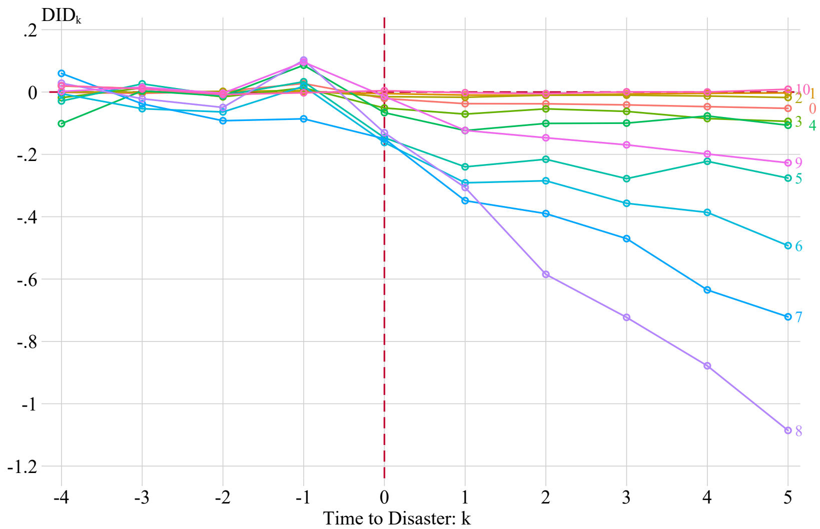
FIGURE 4.B.2 : Trade in goods extensive margin



NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5 at the yearly level. We include here a supplier-time and sector-region-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the number of buyers of trade credit insurance for a given supplier in a country. See Appendix 4.D for the details on the computations of all LHS variables.

4.B.4 Ex-Ante Rating Category

FIGURE 4.B.3 : Effect of Natural Disasters per ex-ante rating category



NOTE : These figures present estimates of the coefficient DID_k associated with natural disaster events from estimating Equation 4.5. Each line represent a different rating category. We include here supplier-time and region-sector-time fixed effects. 99% error bands, computed with standard errors clustered at the region-sector level, are displayed as blue lines. Events are defined as natural disasters above the median in terms of damage. For countries with multiple disasters in between 2008 and 2019, we consider only the largest one. The outcome variable is the amount in euros of trade credit insurance for a given supplier in the affected country. See Appendix 4.D for the details on the computations of this variable.

4.C Notation

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

4.D Variable Description

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

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

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

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

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

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

- Total Number of buyers in each destination country for each supplier for a given rating $R = r$. (Source : Coface)

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

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

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

1

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

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

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

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

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

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

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

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

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

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

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

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

$$q_{j,f,t} = \sum_H q_{j,h,f,t}$$

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

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

4.E End-Use

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

TABLE 4.E.1 : 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.

5 General Conclusion

Contents

This dissertation focuses on trade credit taken as the basis of a network at the crossroad of financial, trade and production flows. In this work, I describe the consequences of the existence of such networks for firms. I take advantage of the granularity of a new database to clearly identify the different mechanisms involved in the propagation of a shock that could not be distinguished in the aggregate.
In the first chapter, I show how inter-firm financial connections allow shocks to propagate. I describe how acknowledging such propagation channels can help better monitor firms' and sectors' vulnerabilities. I map a network of predictive relationships across the financial health of several sectors. I also provide a new advanced indicator to track propagation of financial distress across industries and countries on a monthly basis. I highlight the correlation between these predictive relationships and the production structure in the studied economies. I show that monitoring some key sectors – among which construction, wholesale and retail, or the automotive sector – can improve the detection of financial distress in other sectors. In the second chapter, I further explore the propagation of shocks within the network and study the effect of changes in US monetary policy on trade credit flows towards emerging markets economies (EMEs). I find trade credit to be an additional pass-through channel of US monetary policy to emerging markets and a substitute to other types of financing for EME importers. Specifically, US monetary tightening exerts three distinct effects. First, it increases EME importers' demand for trade credit, used as a substitute to other financing tools themselves restrained. Second, it restricts US suppliers' ability to extend trade credit to their EME customers, thus acting as a liquidity squeeze. Finally, it also affects trade credit flows through an exchange rate channel, impacting differently USD and non-USD flows. In the third chapter, I focus on the network transformation following a shock. I study how natural disasters in destination countries induce large and persistent disruptions to international buyer-supplier relationships. This leads to a restructuring of the trade network of largest French exporters and a change in trade finance sources for affected countries. Larger firms, both on the buyer and supplier side, are more sensitive to the effect of natural disasters. This mechanism is even stronger for large multinationals operating in sectors with low relationship specificity.
In a nutshell, the first chapter of this dissertation highlights the interlocation of firms' balance-sheet and hence, sectors' financial conditions, because of inter-firm trade credit flows. Then, the second chapter describes how such inter-firm links can convert into channels for the propagation of shocks. Finally, the last chapter describes the endogenous behavior of such inter-firm links, and how they transform following the occurence of a shock.

From those results, several lessons can be drawn, both useful for public policy pur-

poses but also within the framework of a private firm's strategy. First, an adequate review of firms' external vulnerabilities needs to encompass a network component covering all types of links that relate a firm with the outside world. This means first looking at inter-firm links, both production and financial ones, as shown in this work. This also means exploring links with financial institutions or any other type of partner. Most importantly, the position of each partner needs to be understood within its own networks and its own exposure to shocks. Then, we saw, in the first chapter, the importance of international interactions across sectors. Therefore, this work should be done both domestically and internationally. Third, networks are not static, they change over time, respond to shocks and restructure. This should enter into any dynamic analysis. Only from this complete overview will it be possible to build proper buffers for firms to protect against shocks.
As the global environment grows more unstable and unpredictable, the need for understanding the economy as a network will grow. Following the global financial crisis, macroeconomists upgraded standard general equilibrium models with financial frictions to analyze the financially-driven demand shocks that characterized the 2010's. However, recent crises have pictured increasingly frequent supply shocks such as the ones triggered by the pandemic and the Russo-Ukrainian war, or those we can expect from climate change. New models should continue to move away from highly stylized real supply side to study such supply shocks and their consequences. They should mirror increasingly complex production apparatus within a multiform globalization framework. The empirical research necessary to go from a highly stylized to a granular, heterogeneous and interdependent understanding of the real sector remains in its infancy; the contributions in this dissertation aim to further that goal.

This dissertation is only the start of a broader research agenda. I would like to continue working on firms' networks, both internationally and domestically. Indeed, the literature on firms' domestic network is still sparse and many questions are still to be explored. For instance, as a follow-up to the second chapter, it would be very interesting to see whether emerging market suppliers modify the trade credit amount they provide to their buyers, both in the domestic and export market. I would be able to compare the results of this analysis with findings from Morais et al. (2019) and Bruno and Shin (2019). Moreover, studying domestic networks could also bring additional information on learning processes between partners and the impact on firms' performance. In an ongoing project with Clément Malgouyres and Timothée Gigout, we start looking at this issue taking the perspective of exporters' domestic suppliers. Finally, using data that are more and more granular, I hope to explore further firms' heterogeneity in response to shocks. On the theme of firms' resilience to climate change, accounting for heterogeneity will be key to frame adequate policy, especially for the transition towards a greener model.

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