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

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February 2021

Preliminary

Abstract

Large-scale analyses to map existing interactions between financial constraints at the sectoral level are still scarce. To fill the gap, this paper identifies short–term predictive relationships between sectors' financial health thanks to the construction of an original micro-based indicator. Using defaults on trade credit as a sign of tighter financial constraint and a high-dimensional VAR model, I test for Granger non-causality and identify predictive relationships across sectors. Past tightening in a sector's financial constraint is shown to be predictive of a narrower budget constraint in other sectors after controlling for macroeconomic determinants. These interactions, both in their existence and magnitude, follow the pattern of input–output network. Such structure of interactions is in line with shock propagation mechanisms described in the literature, both for direct propagation through supplier-buyer input-output relationship but also for indirect one among two suppliers of substituable goods. A few sectors — among which construction, wholesale and retail, and motor vehicles — tend to display a wider set of predictive relationships, making them key to track in monitoring processes.

JEL classification: F14, F36, F44, L14

Keywords: Trade credit; Network; Cross-Sector Interdependencies

Acknowledgement: I thank participants in GSIE Lunch seminar and the College de France Innovation Lab seminar.

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1 Introduction

On 23rd September 2019, the 178-year-old British travel agency Thomas Cook filed for bankruptcy, making headlines in the press. The international ripple effects of the event particularly caught the media attention. 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 have highlighted existing interdependencies in firms' financial health and predictive relationships across firms' and sectors' financial states. While such an event or other types of one-time episodes have provided researchers with the opportunity to study propagation effects through production network, large–scale analyses to map existing interactions across sectors' financial constraints are still scarce. This applies even more when focusing on short-term interactions due to data limitation. Taking advantage of an original dataset from a private credit insurer, this paper maps those financial interactions across sectors in Western Europe through the lenses of trade credit defaults, used as a new indicator of financial health across sectors.
As a credit made by suppliers in the period between the delivery of the good or service and the actual payment of the bill by the buyer, trade credit is a specific term of payment for inter-firm trade, cited as one of the most important sources of short-term financing for firms around the globe (Petersen and Rajan (1997)). Defined as failures from a buyer to repay its supplier as planned, either due to temporary issues or to full insolvency, defaults on trade credits are found to be good indicators of the level of financial constraint in a given sector by Boissay and Gropp (2013). 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. 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 that I actually have an original database from a trade credit insurer, recording defaults on trade credits on a monthly basis. This makes it possible to study defaults and thus firms' financial constraint in a specific sector, without requiring proxies. It becomes unncessary to wait for balance sheet information. On the contrary, using this new indicator allows to test empirically on a larger scale the propagation of financial distress along production network.

Following the seminal work of Acemoglu et al. (2012), the production network literature (see among others Acemoglu et al. (2015), Carvalho (2014)) have shown that if one firm's or sector's output is used by another firm or sector as input, production processes are interdependent. Thus, a production shock affecting a firm's or sector's production process will propagate throughout the supply chain, disrupting production along the chain. Building on this network structure, Bigio and La'O (2016) showed that a financial shock would also propagate across sectors through those production links. In a still nascent empirical literature, Demir et al. (2020) or Barrot and Sauvagnat (2016), among others, exploited one-time policy changes or natural disasters as exogenous shocks and followed their propagation through the production network to explore amplification mechanisms. Firms' financial constraints have been shown to be a key driver of this process. However, while production processes interdependencies can be clearly mapped through input-output data, no large-scale picture have been drawn regarding financial interactions across sectors. This paper therefore tries to answer the following question: Can we find empirical evidence of tighter financial constraint propagation along production network on a longer time–horizon and larger country–sector basis than previously analyzed in the literature? If so, such interactions will prove key in monitoring processes in times when acute assessments of firms' level of financial constraint 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 between levels of financial constraints across sectors and countries. Past data on trade credit defaults in other sectors can help predict future developments for defaults in a sector of interest, taking default on trade credit as an indicator of firms' financial state in a sector. 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. It also sheds light on the correlation between the pattern of those predictive relationships and the input-output structure of the considered economies. The combination of these two facts allows to interpret the existence of short-term predictive relationships across sectors' financial distress as evidence of short-term shock propagation within the production network, in line with the literature. The correlation pattern points towards two key propagation mechanisms: direct vertical propagation but also horizontal one between two sectors supplying substituable inputs. Results also highlight the prevalence of inter-sector interdependencies, rather than intra-sector ones, in five deeply integrated European markets where national borders scarcely matter. 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 novel database from Coface, one of the main trade credit insurers in the world, that records firms' payment defaults on insured trade credits. The dataset used in the analysis gathers information on a total of 131 sectors in Germany, France, Italy, Spain and the United Kingdom between 2007 and 2019. The indicator is available on a monthly basis 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. (2019) for financial stock analysis, I manage to single out predictive relationships across sectors' level of financial constraint, filtering out macroeconomic or third-sector effects. Thanks to the use of a two-step method involving repeated lasso selections, it is possible to balance between over-dimensionality issues and omitted-variable bias. This global VAR model allows to highlight Granger causalities across sectors' default rates on trade credits. A Granger causality from one sector to another defines a directed predictive relationship from one sector to the other. It means that a past increase in defaults in the source sector will help predicting a future increase in the key sector as detailed further in section 2. This holds after accounting for a large set of other potential determinants of defaults in the key sector.

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, in which they show that input–output relationships across sectors act as propagation channels for production shocks. Through those links, a productivity shock in one specific sector will disseminate to other sectors. Sectors' fates are dependent on one another based on quantities exchanged through input–output links. Acemoglu et al. emphasize on the importance of the production network structure. 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, which will impact its own demand for inputs produced by other sectors. 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 this propagation pattern at the firm level. They 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 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. (2017) 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 (2016) 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 the critical role of firms' financial constraints in this propagation. They show that low–liquidity firms amplifies the shock transmission. Altinoglu (2018) and Luo (2019) go further and modelize the interactions of firms' financial constraints through the existence of trade credit relationships 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 the budget constraints for their supplier's future production volumes. 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 the propagation of tighter financial conditions across sectors.
Recent research has shed light on the role of trade credit defaults on firms' financial constraints. Boissay and Gropp (2013) show that trade credit acts as insurance for buyers, which will choose to default on their trade credits when their financial constraints tighten. Rising defaults on trade credits 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 creditor, potentially pushing it into bankruptcy itself for large claims. However, those studies have been limited on a geographical scale, mainly due to the lack of comprehensive data on the subject. This paper addresses this gap by using propietary data from a credit insurer in a wide set of sectors across countries to focus on cross–country and cross-sector interdependencies.

The rest of this paper is organized as follows: section 2 specifies the empirical strategy implemented and provides more information on trade credit. Section 3 outlines the data. Section 4 describes in further detail the results of the analysis, and section 5 introduces some alternative specifications.

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 Granger causality tests. Then, I provide background information on trade credit and the relation between defaults on those trade credits and firms' financial health to construct the indicator.

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' level of constraint, consistent with shock propagation pattern. Such a relationship would exist between two sectors when the prediction for the first sector's financial health is enhanced after including information on past values of financial health 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 its own past level of financial health as well as on the past values in other sectors. Written in matrix form I have the following:

$$FC_t = C + A_1 FC_{t-3} + A_2 FC_{t-6} + \epsilon_t \tag{1}$$

FC_t is a vector of financial constraint indicator in each specific country–sector at time t, while FC_{t-3} & FC_{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 cross-sector 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):

$$FC_t = C + A_1 FC_{t-3} + A_2 FC_{t-6} + BZ_t + \epsilon_t \tag{2}$$

With the matrix Z_t including all the set of macroeconomic indicators and their respective lags as I will detail later on.
In this VAR-X model, I will define a cross-sector interaction as the existence of a Granger causality between two sectors. If German plastics sector is said to Granger-cause the German chemicals sector then information on firms' financial health in German plastics provides additional information to better predict the financial state of firms in German chemicals. In this context, monitoring German plastics will therefore prove useful in keeping track of German chemicals following this directed predictive relationship. Here, I have chosen to focus on Granger causality 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 Granger causality for any considered pair of sectors in the studied economies, controlling for macroeconomic determinants of each sector's level of financial constraint, as well as for third-sector indirect effects affecting

both sectors.

This VAR-X model in equation 2 can be estimated using ordinary least-squares estimations for each individual indicator of financial constraint, and Granger causality tested with a Wald test to identify predictive relationships. In this equation and in the rest of the paper, when mentioning the level of financial constraint in a sector in regressions, 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:

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

Here, the level of financial constraint 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 values of financial constraint 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 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 a test of 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.

2.1.1 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. (2019) in a

VAR framework for financial stock analysis. They developed a methodology to conduct 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 indicator of financial constraint from all country–sectors (excluding pairs $c-s$ and $c'-p$) and lagged macroeconomic variables to estimate the default rate in $c-s$. Next, these selected variables will form an information set, conditional on which 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 6.1 in the Appendix.

Step 1: Building an Information Set Using Lasso Regressions

Following Hecq et al. (2019), 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, $FC_{c,s,t}$. 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, $FC_{c',p,t}$, on $FC_{c,s,t}$. According to Belloni et al. (2014), there is a nonzero 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 Granger Causality

Once I^*_{lasso} is constructed, I perform a Wald test to determine the Granger causality of country–sector c'–p's FC on country–sector c-s's FC 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).

$$M1 : FC_{c,s,t} = c + \gamma_1 FC_{c,s,t-3} + \gamma_2 FC_{c,s,t-6} + \alpha I^*_{lasso} + v_t \tag{4}$$

$$M2 : FC_{c,s,t} = c + \alpha I^*_{lasso} + \gamma_1 FC_{c,s,t-3} + \gamma_2 FC_{c,s,t-6} + \beta_1 FC_{c',p,t-3} + \beta_2 FC_{c',p,t-6} + \eta_t \tag{5}$$

[1]See Appendix section 6.1.1

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 values of financial constraint for $c' - p$ do enhance the estimate of the level of financial constraint 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].
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 5.
I consider as significant any Granger causality with a Benjamini–Hochberg-corrected p–value that falls below the 5% threshold.

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. 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. The payment takes place at the end of a grace period, which varies according to the supplier–buyer relationship. 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.

[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.
[3]See Benjamini and Hochberg (1995)

In this paper, default from a buyer specifically means a failure of the buyer to meet payment obligations. It can be due to either temporary constraints on the buyer's cash flows or 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. It is in the supplier's interest to declare payment default as soon as the grace period expires. Hence, data compiled by 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 constraint 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' level of financial constraint in a given country–sector using trade credit defaults recorded by a trade credit insurer named 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):

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

I divide the number of defaults recorded by the insurer by the initial number of insured partnerships, to allow for comparisons across sectors and see which share is in default. This also controls for changes in Coface's risk policy. Given the existence of a grace period between the time of the sale and the due date for payment on the bill, it is necessary to take the number of partnerships six months before. Taking it with a six-month lag allows for the integration of a majority of cases despite heterogeneity in the length of grace periods.

Using this indicator, the model presented in equation 2 becomes:

$$DR_t = C + A_1 DR_{t-3} + A_2 DR_{t-6} + BZ_t + \epsilon_t \tag{7}$$

where DR_t is a vector of all country–sector-level time series across all countries at month t, while DR_{t-3} and DR_{t-6} record the same country–sector-level time 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 default 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.

3 Data and Pre-Estimation Treatment

To conduct the empirical strategy described above, I use data from one of the leading trade credit insurers globally, Coface, on five main Western European countries: France, Germany, Italy, Spain and the United Kingdom. In these countries, the trade credit insurance market is mature, and trade credit is a widely used trade financing tool.
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 11 in the Appendix for a full description).
I have excluded all public-service sectors, as well as financial and insurance sectors, from the Granger causality analysis. However, I do include them among the R sectors for the lasso selection of controlled variables. In addition, I have restricted the considered sectors to record on average at least one default every month, for the analysis to be representative. Finally, the analysis is performed for a total of 131 country-sector variables (see Table 12 in the Appendix for a full list of included sectors by country). Table 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 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 a 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 taken 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 rate 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.

Regarding default rate time series, macro series 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. These 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 and from July 2013 to December 2019 to avoid including periods of macroeconomic crisis.
Macroeconomic variables are key in all information sets. Only macroeconomic principal components are selected by the different lasso regressions. The prediction power of macroeconomic trends outweighs information provided by individual sectors when taken altogether.

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 constraint, cleaned from macroeconomic or third-sector residuals. This result is key to improve monitoring processes at the sector-level. Moreover, I highlight the link between the existence and the intensity of those predictive relationships and the amount of input-output flows. From there, I show that cross-sector interactions are likely to reflect shock propagation mecanisms across sector, either directly between suppliers and buyers, or indirectly between two suppliers of susbstitutable inputs.

4.1 A Network of Cross-Sector Interactions to Enhance Sector-Level Monitoring

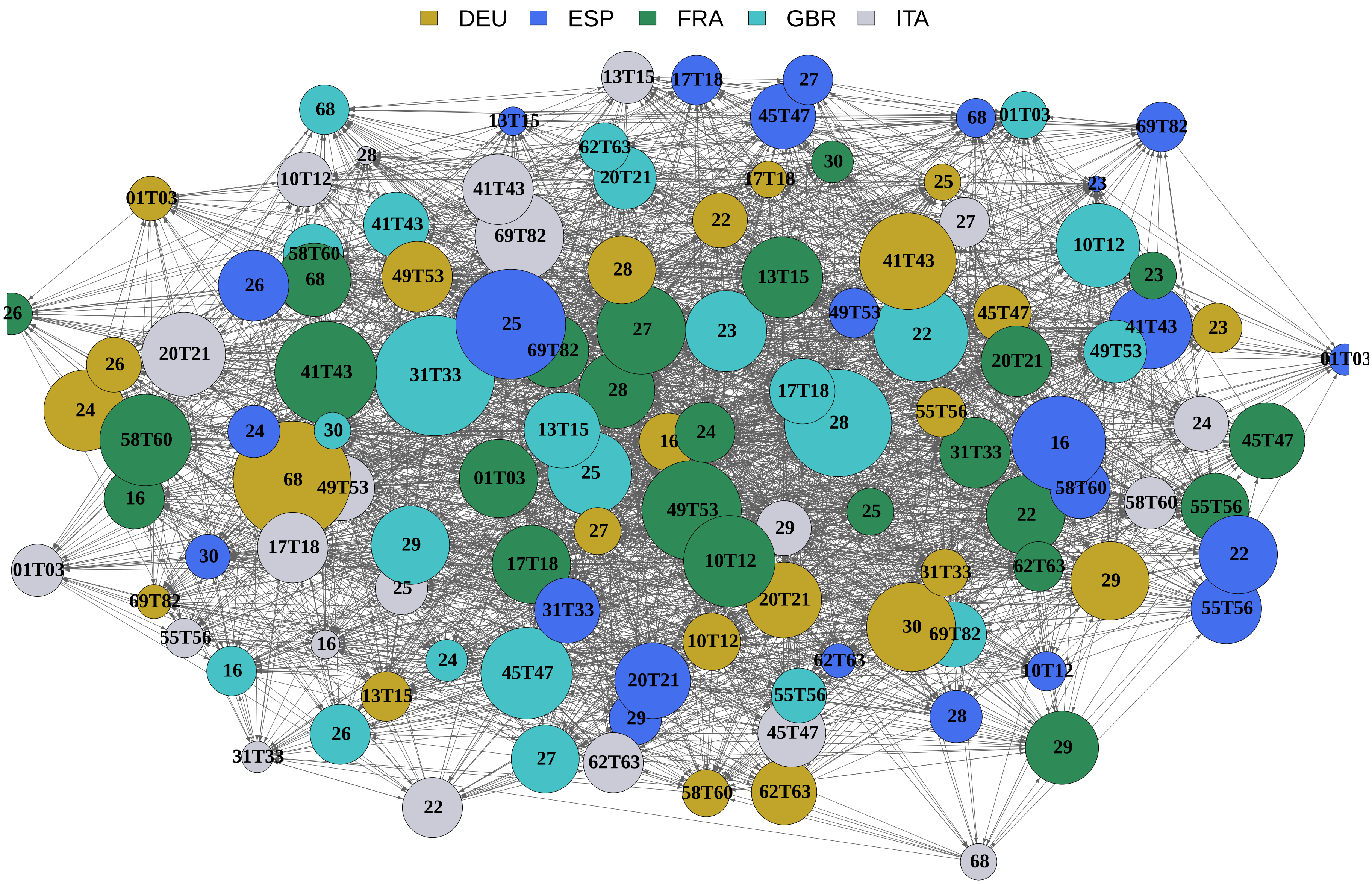
The first key result of the analysis is presented in Figure 1. When conducting the procedure over all sector pairs, I obtain a network of significant predictive relationships. Out of 13,572 potential interactions, 2,810 are deemed significant. Past outcomes in other sectors can help to predict future developments in one sector. This holds even after controlling for trends in the macroeconomic cycle through control variables.

Figure 1 maps those interactions, with arrows representing the directed predictive relationships between two country-sectors symbolized as circles. The size of the circle is proportional to the number of interactions streaming from the sector. The network is characterized by a majority of inter-sector and international links. Most links are between different sectors located in different countries. While cross-sector interactions reflect sectors' interdependence in production chains, international patterns mirror market interdependencies in Western Europe.

Of these links, 616 are bidirectional. This means that if my sector of interest provides useful information for another sector, the reverse also holds.

Table 2 summarizes descriptive statistics for the adjusted R^2 in model M2 over the full sample. It shows that the general model M2 – that includes information set variables and cross-sector-interactions– can explain 38% of total variance for each sector's default rate, on average.

Table 3 focuses on significant links over the period. Included are sectors with significant inward links, meaning that they receive useful information from other sectors. For these sectors, the share of variance explained is even higher, at 44%. The difference between the first and second columns synthesizes the additional explanatory power of brought by the significant cross-sector predictions compared with only the information set. As mentioned in section 3, the information set is composed only of macroeconomic



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. 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 1: Full Network of Significant Cross-Sector Interactions

Table 2: Full Period—All Interactions—Percentage of Explained Variance

Statistic	Adjusted R^2 Model M2
N	13,572
Mean	0.38
St. Dev.	0.16
Min	0.01
Pctl(25)	0.26
Median	0.37
Pctl(75)	0.51
Max	0.80

variables. Thus, the difference in the two adjusted R^2 values underlines the benefit of adding one specific cross-sector interactions compared with only macroeconomic variables.

Table 4 summarizes the same information as table 3 at the sector level with the third column synthesizing the difference in variance explained between the two models. Payment defaults are much better explained by macroeconomic variables in manufacturing sectors such as motor vehicles, fabricated metals or rubber and plastics. For some others as construction, IT services or real estate, the share of variance explained by macroeconomic variables is lower. It is for the latter sectors that cross-sector links bring the most valuable additional information.

Table 3: Full Period - Only Significant Linkages - Percentage of explained variance

Statistic	Ajusted R^2: Model with only control variables	Adjusted R^2: Model including the Granger causing variable)
N	2,810	2,810
Mean	0.38	0.44
St. Dev.	0.16	0.15
Min	0.03	0.09
Pctl(25)	0.25	0.32
Median	0.36	0.42
Pctl(75)	0.51	0.55
Max	0.79	0.80

Moreover, strong heterogeneity prevails in the interactions. Node size varies strongly across sectors presented in Figure 1. 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.

Table 4: Percentage of Explained Variance - By Sectors

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

Columns 1 and 2 display the percentage of explained variance. Column 3 is equal to the difference between the two (in percentage points). Column 1 averages the R^2 in model M1 – which includes only controls as covariates – for each aggregate sector. Column 2 averages the R^2 in model M2 with additional cross-sector information.

When looking at the aggregate sector level, some sectors stand out. Figure 2 maps each sector according to inward and outward links with other sectors. By inward link, I mean that another sector's past values help to predict my sector of interest. By outward link, I mean that my sector of interest helps to boost predictions for another sector. Construction, chemicals and pharmaceuticals, rubber and plastics, wholesale and retail, transportation, and motor vehicles help to predict other sectors, whereas few sectors can help to 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 outcomes 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.

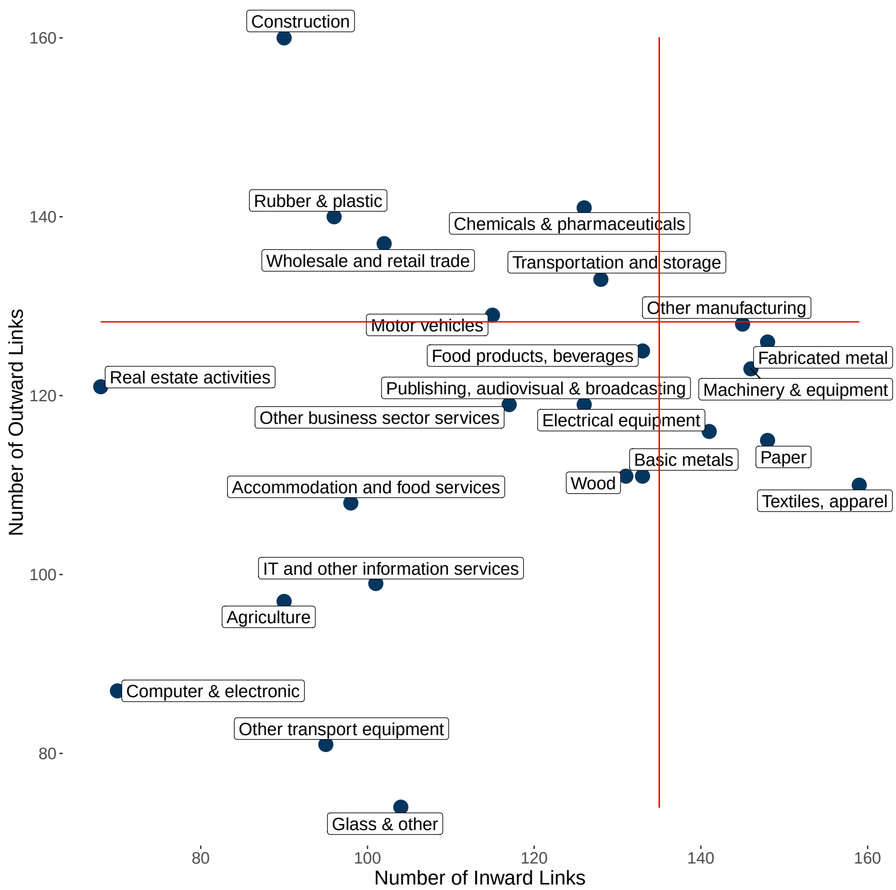
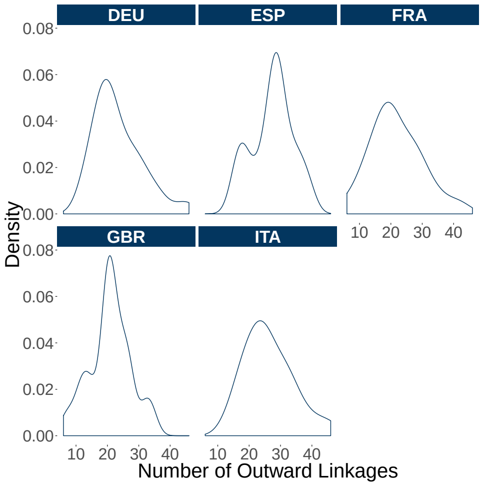
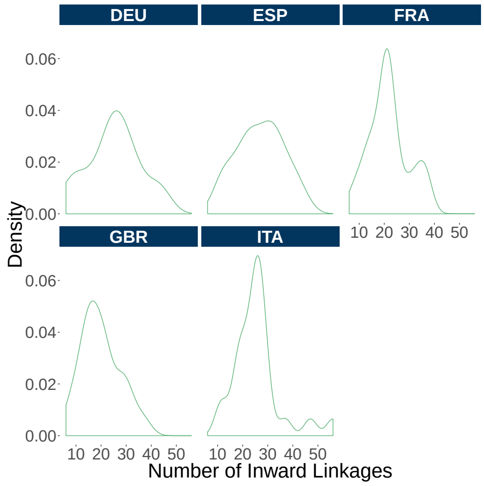


Figure 2: Aggregate Sector Distribution
The x axis represents the total inward interactions for each sector, that is, the information provided by other sectors to enhance the estimation in each sector. The y axis represents the total number of outward interactions, that is, the information each sector provides to improve other sectors' estimates. Red lines indicate the third quartile for each measure.

Figures 3a and 3b 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 strong 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 3: Inward and Outward Link Distribution

4.2 Abstracting from Crises: Cross-Sector Propagation Patterns

Given the high degree of volatility that characterizes the first half of the sample with the financial and European sovereign debt crises, focusing on interactions from 2013 to 2019 is likely to give a clearer picture of the mechanisms at work. Results from the analysis point toward cross-sector propagation patterns of financial distress following production links.

Table 5 shows that —when abstracting from crises— macroeconomic variables can explain a much lower share of the variance in default rates in average. This is consistent with the fact that in times of crisis, all sectors tend to be affected by synchronized shocks well synthesized by macroeconomic indicators. This is not as much the case in calmer periods. In those latter times, cross-sector predictive links add even more explanatory power, with an adjusted R^2 14 percentage-point higher.

Table 6 synthesizes the output of a simple logistic test. I test whether for a specific sector pair cs–$c'p$, having a significant predictive relationship from cs to $c'p$ in the model is related to the amount of intermediate good flowing from cs to $c'p$. I test this for both direct intermediate flows from cs to $c'p$ and total value added including flows through third sectors, measured using Leontief decomposition. 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. The coefficient in Table 6 should be interpreted as the influence of a one standard deviation increase in intermediate flows from cs to $c'p$ on the odds of

Table 5: Post-Crisis Period—Descriptive Statistics—Percentage of Explained Variance

Statistic	Adjusted R^2 Model M1 (only control variables)	Adjusted R^2 Model M2 (including the Granger-causing variable)
N	1,774	1,774
Mean	0.21	0.35
St. Dev.	0.20	0.17
Min	−0.15	−0.07
Pctl(25)	0.05	0.21
Median	0.14	0.33
Pctl(75)	0.39	0.49
Max	0.75	0.80

having a significant predictive link from cs to $c'p$. From column 1, we can see that a one standard deviation increase in the intermediate goods flow from cs to $c'p$ raises the odds of having a significant predictive relationship from cs to $c'p$ by $exp(0.067) = 1.069$, i.e. 6.93%. This result is significant at 1%. From column 2, a one standard deviation increase in the total value added flowing from cs to $c'p$ raises the odds of having a significant predictive link from cs to $c'p$ by 1.062, i.e. 6.2%. Coefficients are significant and positive. The effect is slightly stronger when looking at direct intermediate good flows rather than total value added exchanged both directly and indirectly.

Table 6: Logistic regressions - Input-Ouput Flows and Significant Linkages

	Having a Significant Granger-Causality Link	
	(1)	(2)
IO Direct Flow	0.0670^{**}	
	(0.0274)	
Leontief Total Value Added		0.0604^{***}
		(0.0186)
Constant	-1.8961^{***}	-1.9076^{***}
	(0.0255)	(0.0259)
N	13,572	13,572
Log Likelihood	−5,259.6970	−5,257.6850
Akaike Inf. Crit.	10,523.3900	10,519.3700
Notes:	Note: Those regressions are performed under the following logistic model: $log(\frac{Pr_{sp}}{1-Pr_{sp}}) = \alpha + \beta IO_{sp} + v$. Pr_{sp} is the probability of having a significant Granger-causal link from sector cs to c'p using BH correction. IO_{sp} is a measure of input-output, either the direct flow from cs to c'p or the Leontief's measure of total value added from cs to c'p. Both IO measures are standardized and coefficients should be interpreted as the impact of a standard unit deviation on the log odds.	

Table 7 presents the output of correlation tests between the cumulated magnitude of the predictive effect and input–output measures. A Kendall correlation test is performed to allow for nonlinear relations. The cumulated magnitude is equal to the sum of coefficients β_1 and β_2 in equation (5) for coefficients found to be jointly significant. The first two columns in the table present the correlation coefficient and the associated p value for direct input–output flow, while the third and fourth columns refer to Leontief measure of total value added. The results show that the magnitude of the predictive relationship is positively correlated to both the amount of intermediate flow between the two sectors and the total value added sent from one sector to the other. The correlation is stronger and more significant for direct flows which differ from the result on the significance of the link exposed above.

The table also includes the same tests for different samples of interactions based on the country of the predicting sector. Taking this sector as the source of the intermediate good, there is a positive correlation mainly for French and Italian sectors. The relation is stronger for Italy with direct flows and for France with total value added. For the other countries, no significant correlation appears in terms of outward Granger-causing relations.

Table 7: Kendall Correlation Test - Granger-Causing Effect and Input-Ouput Flows

	Direct IO - Correlation	Direct IO - P-value	Leontieff IO - Correlation	Leontieff IO - P-value
All Linkages	0.09	0 ****	0.037	0.018 *
Linkages from German Sectors	0.042	0.229	-0.015	0.667
Linkages from Spanish Sectors	0.011	0.782	-0.059	0.132
Linkages from French Sectors	0.103	0.004 **	0.105	0.003 **
Linkages from British Sectors	-0.009	0.808	0.007	0.851
Linkages from Italian Sectors	0.257	0 ****	0.079	0.015 *

This positive link between predictive relationship and input–output flows should be interpreted within the production network literature discussed in introduction. Predictive Granger causality patterns are likely to reveal cross-sector propagation schemes within the production network from 2013 to 2019. This would explain the importance of cross-sector interactions in explaining the variance of default rates across sectors besides the macroeconomic variables. The positive relation with direct flows is likely to support the vertical propagation hypothesis, from buyers to suppliers or the other way around. The positive relation with the Leontief value–added indicator, however, could reveal more complex patterns, working through global value chains. The strong heterogeneity across sectors is likely to imply composition effects within each sector, in terms of both input substitutability and firms' characteristics. To confirm these hypotheses, further research on more detailed data is needed. However, results are also likely to reveal competition mechanisms across sectors supplying substituable goods. Table 8 displays summary statistics of the amplitude of the predictive power 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, with more than 50% of links having a positive magnitude. However, 23% of the 1,774 significant links from 2013 to 2019 display a negative cumulated effect. Figure 4 in appendix maps the structure of those negative predictive relationships. IT services, machinery, and publishing and audiovisual are the key information senders in this network. Table 9 displays the result of a logistic regression similar to the one previously described but this time targeting the existence of a significant negative predictive relationship. The existence of such relationship is negatively related to the amount of intermediate flows and total value added between the two sectors. In absolute value, the effect of a one standard deviation in the amount of intermediate good flows sent from one sector to the other is stronger than in table 6. Based on the mechanism of horizontal propagation described in Carvalho (2014), this negative predictive relationship – which is inversely related to the amount of intermediate goods sent from one sector to the other – likely reflects competition between two suppliers of highly substitutable inputs. With highly substitutable inputs provided to a third sector, the health of both sectors would be negatively related, one winning while the other loses. Being both suppliers of a third sector, the intermediate flow between the two would be quite low, in agreement with results of table 9.

Overall, predictive relationships across sectors regarding tightening in financial constraints follow a pattern that is consistent with propagation mechanisms described in the literature.

Table 8: 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.

Table 9: Logistic regressions - Input-Ouput Flows and Negative Net Granger Causalities

	Having a Negative Significant Granger-Causality Link	
	(1)	(2)
IO Direct Flow	-0.0910^{***}	
	(0.0296)	
Leontief Total Value Added		-0.0838^{***}
		(0.0228)
Constant	-0.6064^{***}	-0.5920^{***}
	(0.0180)	(0.0183)
N	13,572	13,572
Log Likelihood	−8,805.9620	−8,803.0070
Akaike Inf. Crit.	17,615.9200	17,610.0100
Notes:	Note: Those regressions are performed under the following logistic model: $log(\frac{Pr_{sp}}{1-Pr_{sp}}) = \alpha + \beta IO_{sp} + v$. Pr_{sp} is the probability of having a significant Granger-causal link from sector cs to c'p using BH correction. IO_{sp} is a measure of input-output, either the direct flow from cs to c'p or the Leontief's measure of total value added from cs to c'p. Both IO measures are standardized and coefficients should be interpreted as the impact of a standard unit deviation on the log odds.	

5 Robustness Tests

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' demand 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.

5.2 Multiple Testing Procedures

A second question lies in the choice of multiple testing correction. 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 is formed of 548 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 10 displays coefficients of a logistic regression similar to the one described in Table 6 but applied to the BY network. Coefficients are greater. A one standard deviation increase in direct intermediate flows leads to a 15.7% increase in the odds of having a significant predictive link. A one standard deviation increase in total value added increases the odds by 11.5%. 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 10: Logistic regressions - Input-Ouput Flows and Significant Linkages - Benjamini-Yekutili Correction for Multiple Testing

	Having a Significant Granger-Causality Link	
	(1)	(2)
IO Direct Flow	0.1459***	
	(0.0316)	
Leontief FVAX Measure		0.1092***
		(0.0216)
Constant	−3.1772***	−3.1979***
	(0.0438)	(0.0444)
N	13,572	13,572
Log Likelihood	−2,287.7440	−2,286.1180
Akaike Inf. Crit.	4,579.4880	4,576.2360
Notes:	Note: Those regressions are performed under the following logistic model: $log(\frac{Pr_{sp}}{1-Pr_{sp}}) = \alpha + \beta IO_{sp} + v$. Pr_{sp} is the probability of having a significant Granger-causal link from sector cs to c'p using BY correction. IO_{sp} is a measure of input-output, either the direct intermediate good flow from cs to c'p or the Leontief's measure of total value added from cs to c'p. Both IO measures are standardized and coefficients should be interpreted as the impact of a standard unit deviation on the log odds.	

6 Conclusion

This study has explored a different aspect of the balance sheet, 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 study the lessons trade credit can teach us on 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. I use Belloni et al.'s (2014) post-double-selection procedure, adapted by Hecq et al. (2019) to a high-dimensional VAR framework. This methods allow me to detect cross-sector predictive relationships through short-term Granger causalities. The 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. There is evidence of a relation between the probability of detecting a predictive relationship for a sector pair and the amount of intermediate goods they trade with one another. A correlation also exists between the cumulated magnitude of the predictive power and the input–output indicators. When positive, such overlap of Granger causality patterns and input–output flows is consistent with vertical shock propagation patterns highlighted in the network literature. On the other hand, the existence of negative predictive relationships, which are negatively related to the amount of intermediate goods traded, likely reflects competition mechanisms between suppliers of substitutable inputs.

Building on this first map of international financial interactions across sectors, further research with more disaggregated data will help to clearly identify the mechanisms involved depending on the localization of the sector in the supply chain, either upstream or downstream.

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Appendix

6.1 Post-Double Estimation Procedure: Add-Ons To The New Framework

6.1.1 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[4]:

$$\hat{\beta}_i = arg \min_{\beta i}(\frac{1}{T}\|y_i - X\beta_i\|_2^2 + \lambda\|w_i\beta_i\|_1) \tag{8}$$

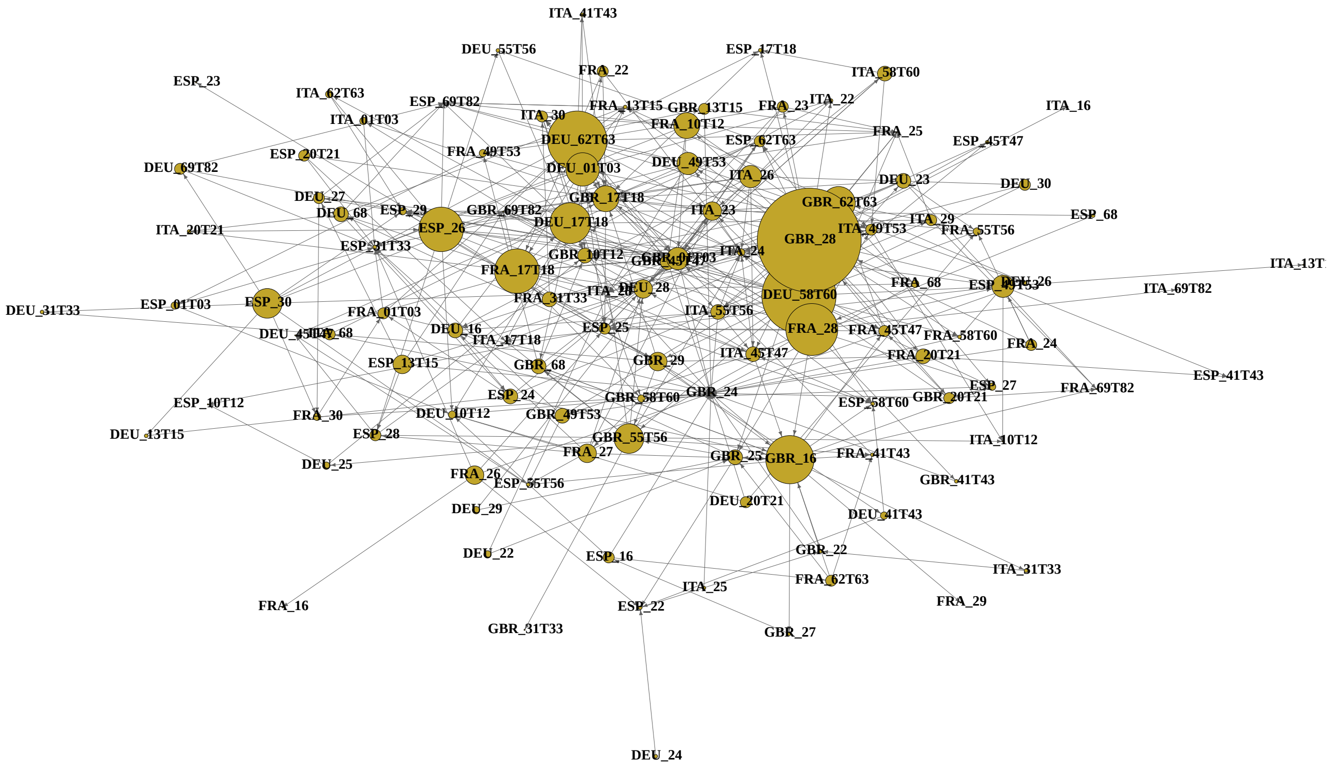
with for any n-dimensional vector x, $\|x\|_q = (\sum_{j=1}^{n} |x_j|_q)^{\frac{1}{q}}$.
Here, the matrix X includes all indicators of financial constraint at t-3 and t-6 for sectors of the set R (all sectors excluding sectors $c - s$ and $c' - p$) , as well as all J macroeconomic principal components 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. (2019), 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 constraint (FC) at time t (dependent variable)
- Sector $c' - p$ FC at time t-3 (first lag of the independent variable)
- Sector $c' - p$ FC at time t-6 (second lag of the independent variable)

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

[4]see Hecq et al. (2019)

6.2 Negative Predictive Relationships



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 to 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 4: Network of Significant Cross-Sector Links with Negative Cumulated Amplitude

6.3 Sector Codes and Distribution Across Countries

Table 11: 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

Table 12: Selected Sectors By Country

	Country	Number of sectors	Included sector
1	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
2	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
3	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
4	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
5	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