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

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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.

JEL classification: F14, F36, F44, L14

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

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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 or catering-service firms suffered from this insolvency. These knock-on effects highlighted existing interdependencies in firms' financial health. Researchers have studied propagation effects of one-time episodes through production outcomes. However, 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 to fill the gap. 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 trade credit defaults, and thus firms' financial soundness, in a specific sector, without requiring proxies. Using this monthly indicator allows to test empirically 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. Demir et al. (2020) highlighted the critical role of firms' financial constraints in such propagation processes. However, while production interdependencies can be clearly mapped through input-output data, no large-scale picture exists 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 non-financial corporate debt keeps rising.

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).[1] Results also highlight the predominance of inter-sector interdependencies, rather than intra-sector ones. The prevalence of international cross-sector interactions reflects the indicator's value 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.

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. I take advantage of a new high-dimensional VAR methodology developed by Hecq et al. (2021) for financial stock analysis to balance between over-dimensionality issues and omitted-variable bias

[1] See Acemoglu et al. (2015).

in the mapping process. Thanks to the use of the 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 agreements. I obtain cross-sector 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.

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 specifies the empirical strategy implemented and provides more information on trade credit. Section 3 describes the data. Section 4 provides further details on 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 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.

2.1 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:

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

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):

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

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. It can be estimated using several ordinary least-squares estimations for each individual country-sector. 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:

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

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 indexed by k, 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.

2.1.1 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 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[2]. I include in the information set any variable providing significant prediction power for either the dependent variable or the lags of the Granger-causing variable. This means including any variable selected at least once among the several lasso estimations. The set of selected variables will form my information set I^*_{lasso}.

[2]See Appendix section A.1

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).

$$M1 : FH_{c,s,t} = c + \gamma_1 FH_{c,s,t-3} + \gamma_2 FH_{c,s,t-6} + \alpha I^*_{lasso} + \upsilon_t \quad (4)$$

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

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[3].

Finally, p-values are corrected for multiple testing using the Benjamini-Hochberg procedure [4]. 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 conditional 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. 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 ser-

[3]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.

[4]See Benjamini and Hochberg (1995)

vice 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. This is 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. 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%.[5]

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. 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.

[5]See Coface Universal Registration Document 2020.

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):

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

I divide the number of supplier-buyer agreements registering defaults in a country-sector by the total number of insured partnerships in the country-sector. This allows for comparisons across sectors and see which share of trade credit agreements 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 an unknown grace period between the time of the sale and the due date for payment, it is necessary to take the number of partnerships 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 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 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.

3 Data and Pre-Estimation Treatment

To conduct the empirical strategy described above, I use data from 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. 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 7 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.[6] Finally, the analysis is performed for a total of 131 country-sector variables (see Table 9 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 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

[6] This means the analysis excludes 10% of sectors for which Coface data do not record enough events for the analysis to be representative. As robustness test not reported in the paper, other thresholds were used. Using 0.5 and 0.25 default per month on average as thresholds does not modify the key results of the paper.

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 reason 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 7a and 7b in section 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.

4 Results

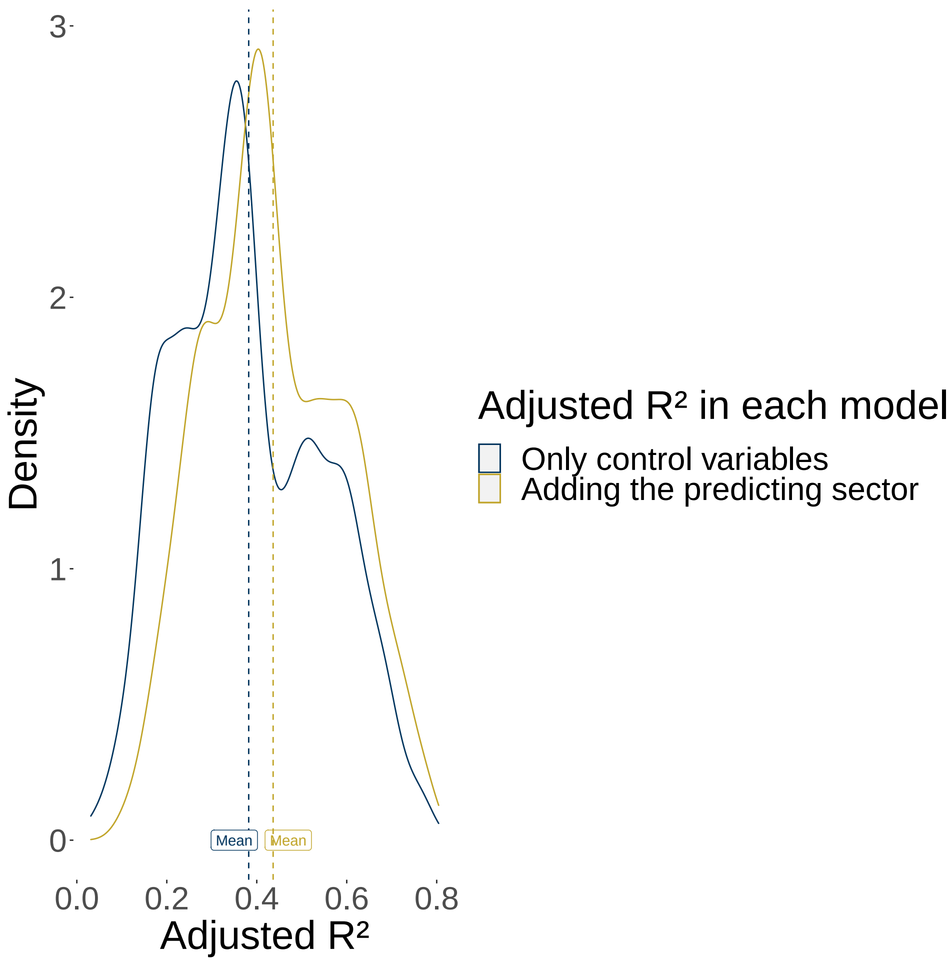
In this section, I detail the two key results of the analysis. First, I describe the network of predictive relationships across sectors' financial health, cleaned from macroeconomic or third-sector omited-variable bias. This result is key to improve monitoring processes at the sector-level. Then, I describe 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.

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

Conducting the procedure described in section 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 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 4 and 5, i.e. with only controls or adding 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.

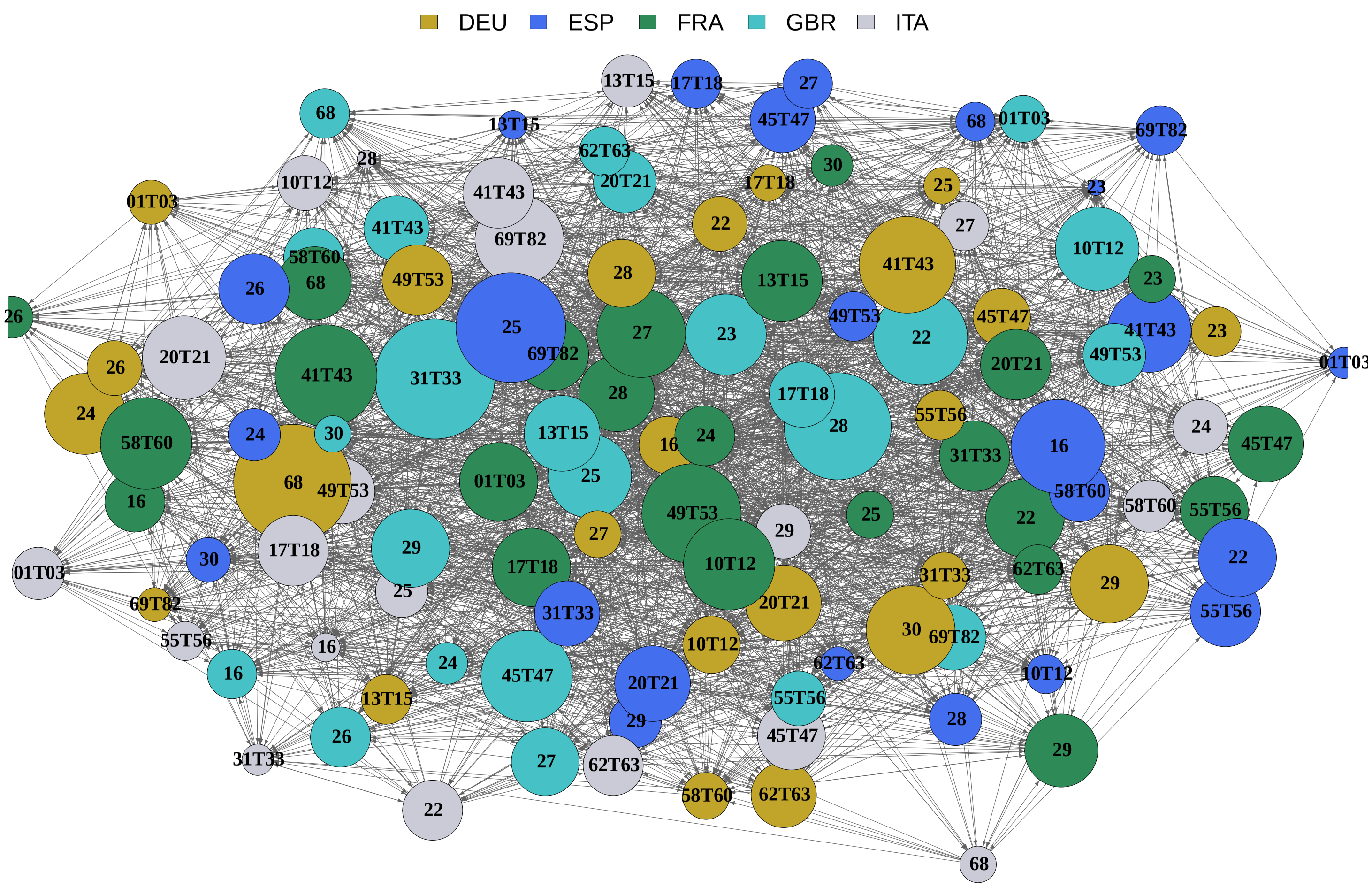
Figure 1: Cross-sector information to add predictive power



In blue, the distribution of R^2 in 4 and in yellow in 5 for the 2,810 significant predictive relationships.

Figure 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: Full network of significant cross-sector interactions

across sectors presented in Figure 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 the literature has highlighted some sectors' centrality in production networks.

A similar heterogeneity is visible at the aggregate sector level as observed in table 2. As for figure 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 4 and 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: 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 4 and 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 4 – which includes only controls as covariates – for each aggregate sector. Column 2 averages the R^2 in 5 which also includes lagged payment defaults for the Granger causing sector.

Figure 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.

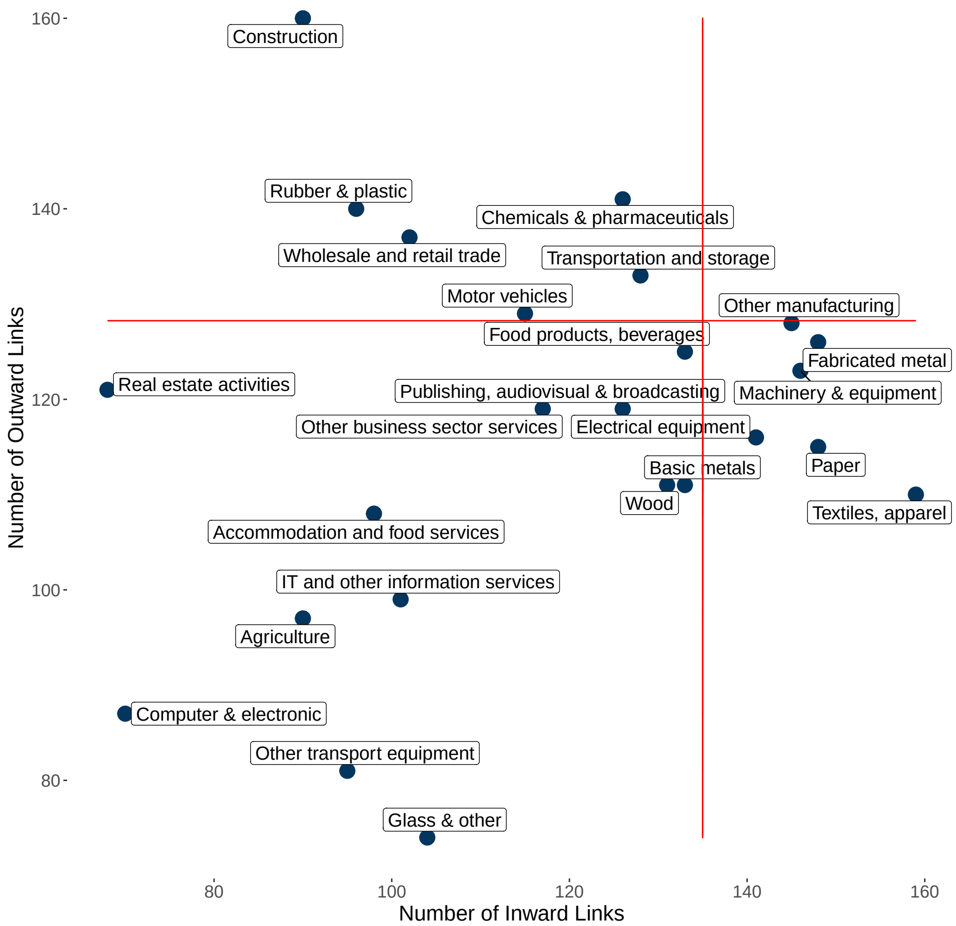
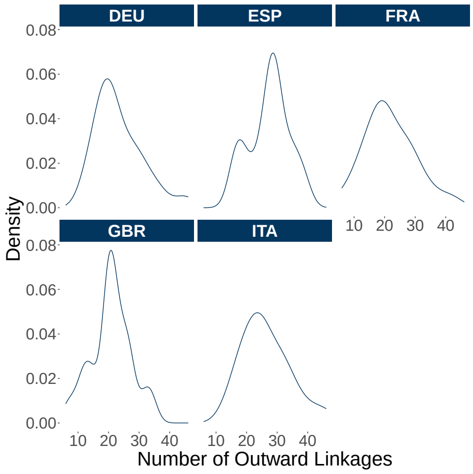
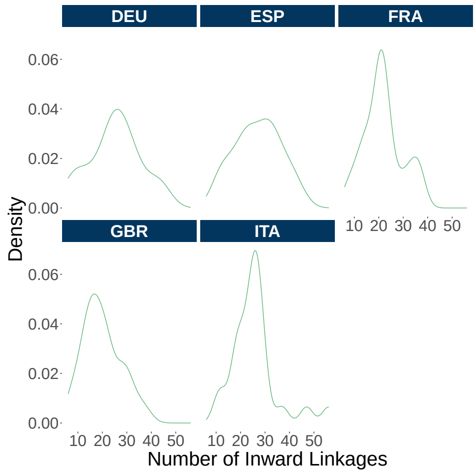


Figure 3: Aggregate sector distribution - Inward & outward links
The x axis represents the total inward interactions for each sector, that is, the information provided by other sectors to enhance the estimation in each sector. The y axis represents the total number of outward interactions, that is, the information each sector provides to improve other sectors' estimates. Red lines indicate the third quartile for each measure.

Figures 4a and 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. Distributions of inward and outward links also strongly vary 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 4: Inward and outward link distribution

From this first set of results, appears the value 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.

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 8 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 (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 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 amplitudes 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 3: Post-Crisis Period - Amplitude of Interactions - Significant Linkages

Statistic	Coefficient First Lag	Coefficient Second Lag	Combined Effect – Sum of coefficients
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

Mechanisms in the literature

Based on the network literature described in section 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 disruptions 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, 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 9 and 10 in appendix.

Table 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[7]. 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 the time of writing. The coefficient in table 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 $c'p$ to cs. 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 5. Table 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 corre-

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

Table 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 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.

lated 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.

Table 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 $\beta_2 >= 0$ in 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.

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 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 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 6.

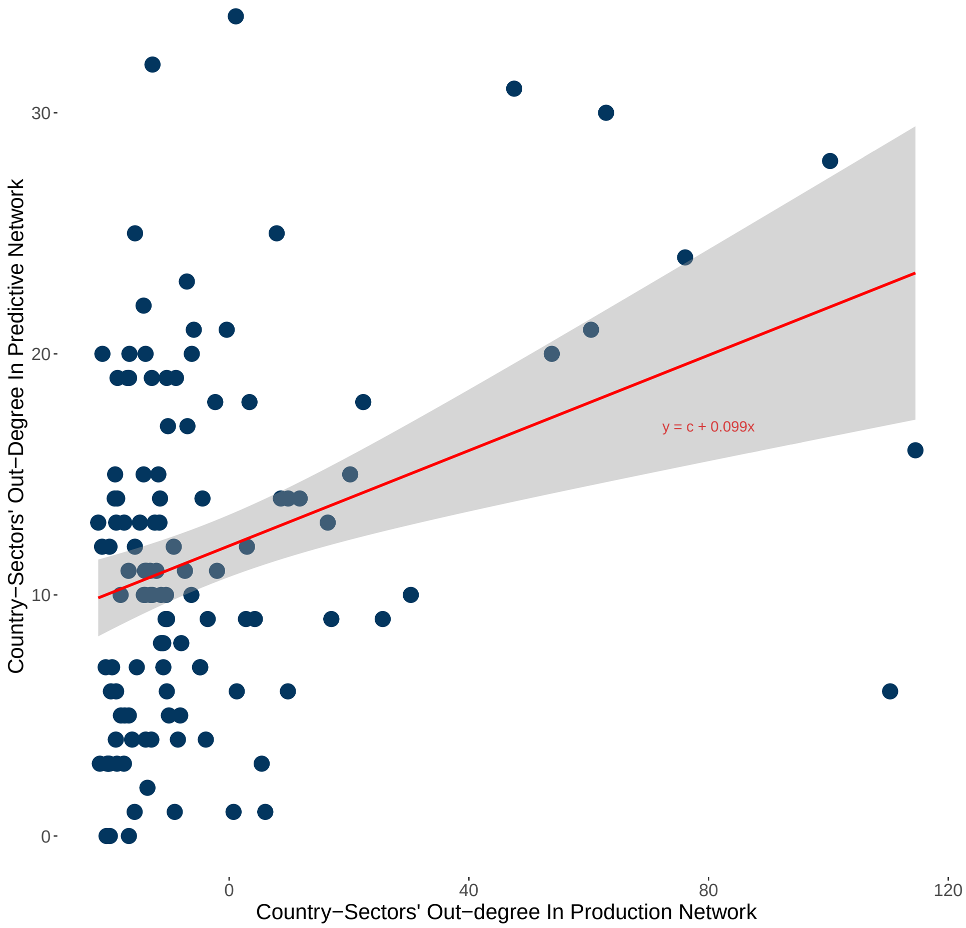


Figure 5: Centrality in production and Granger-causality networks
The x axis represents the out-degree of each country sector in the production network, weighted by the amount of intermediate goods exchanged. The y axis displays the out-degree of each country-sector in the predictive network. In blue, the linear relationship between the two measures.

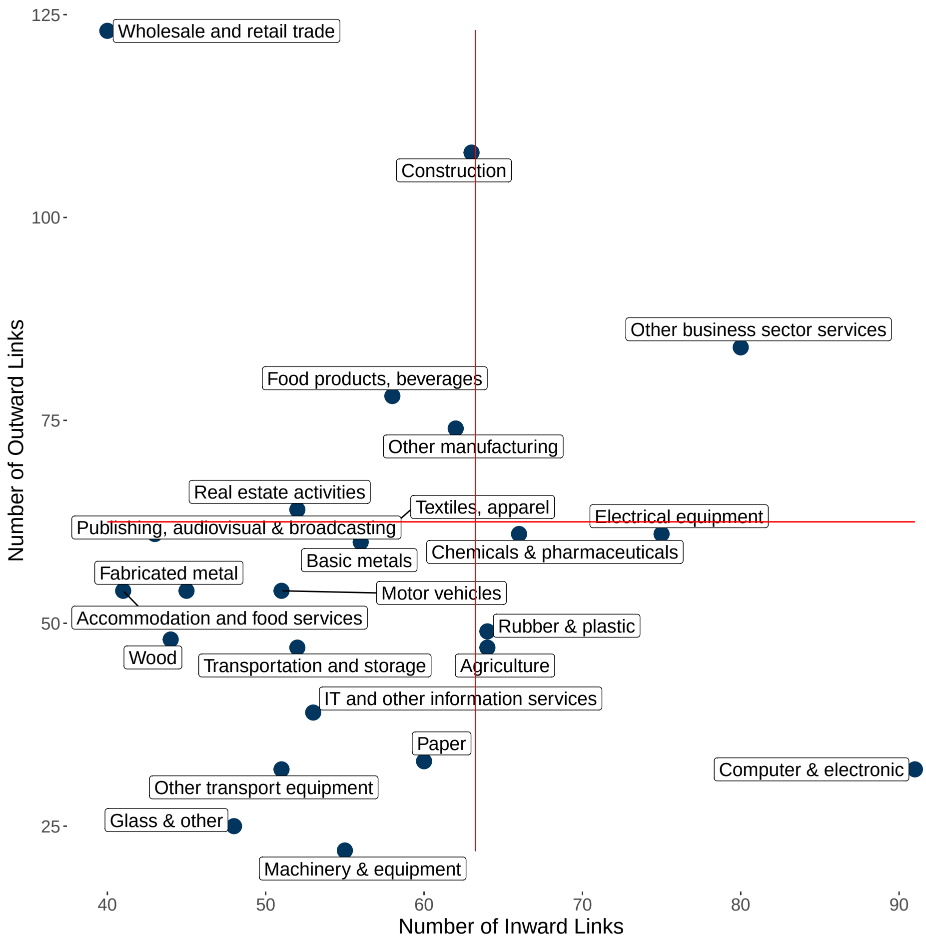


Figure 6: Inward and outward links in positive network
The x axis represents the total number of positive predictive signals received by each sector. The y axis represents the total number of positive predictive signals sent. Red lines indicate the third quartile for each measure.

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 8 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.

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' 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.

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 (1372 with BH correction). However, this new output agrees with the key points of the analysis. Cross-sector interactions are still 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 6 displays coefficients of a logistic regression similar to the one described in Table 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 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 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.	

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 between 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 value of cross-sector interactions in international monitoring processes. Then, I show how the positive predictive signals detected reflects 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.

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APPENDIX

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

A.1 Lasso estimations

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[8]:

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

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 K 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)

[8] see Hecq et al. (2021)

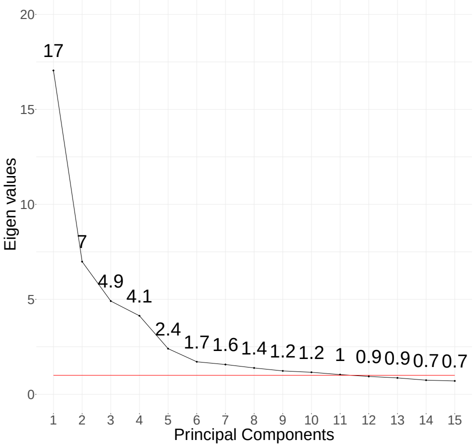
I will include as controlled variables, conditional on which I test for conditional Granger-causality, any variable selected at least once among those regressions.

B Sector Codes

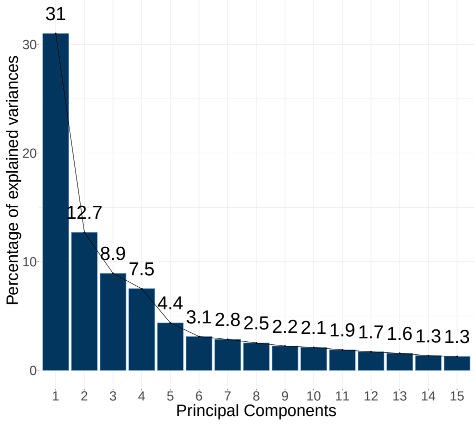
Table 7: Sector codes

	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

C Principal Component Analysis on Macroeconomic Indicators



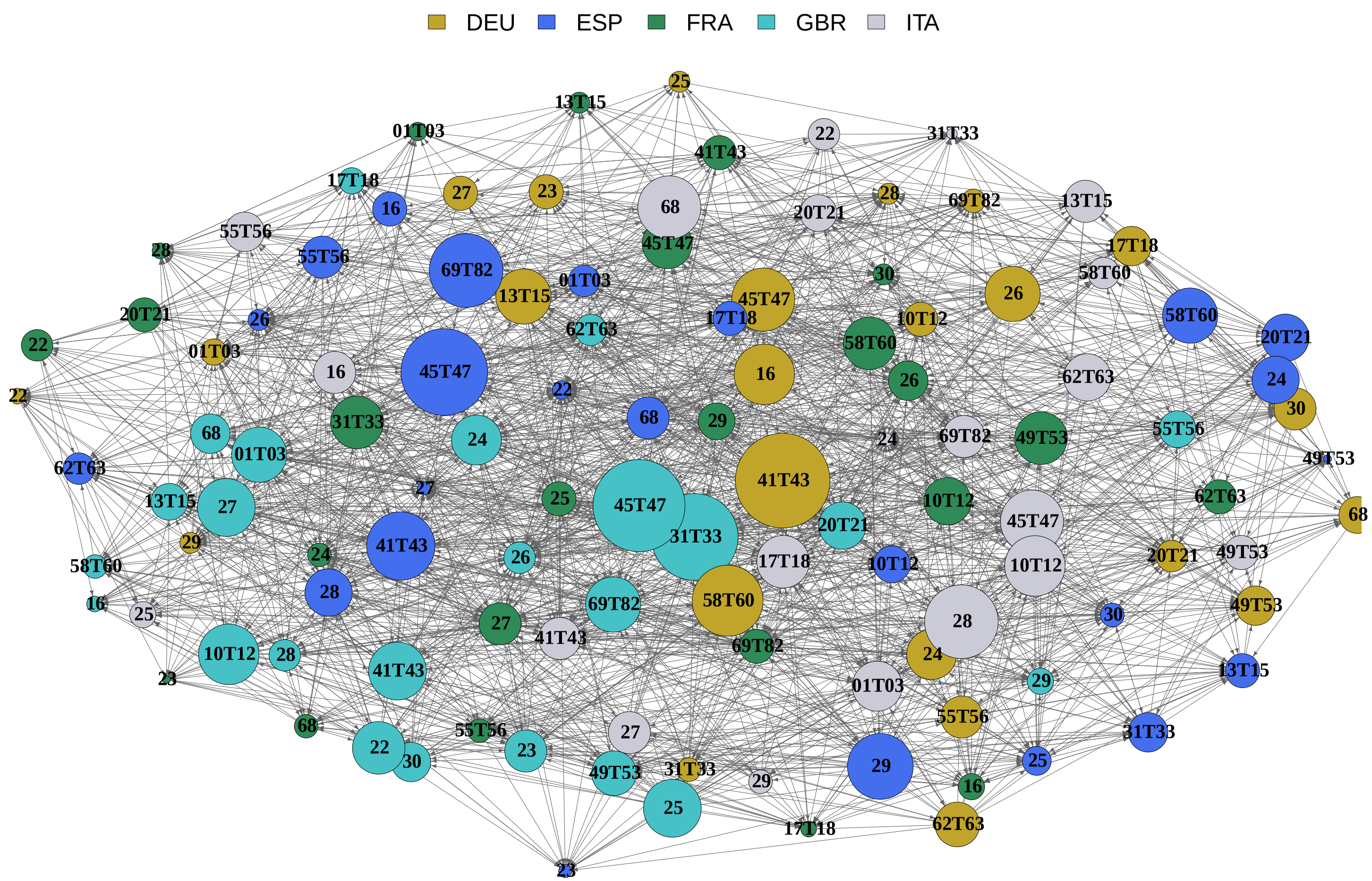
(a) Eigen values for each principal component
Are selected principal components with an eigen value greater than 1, corresponding to the horizontal red line.



(b) Share of variance explained by each principal component

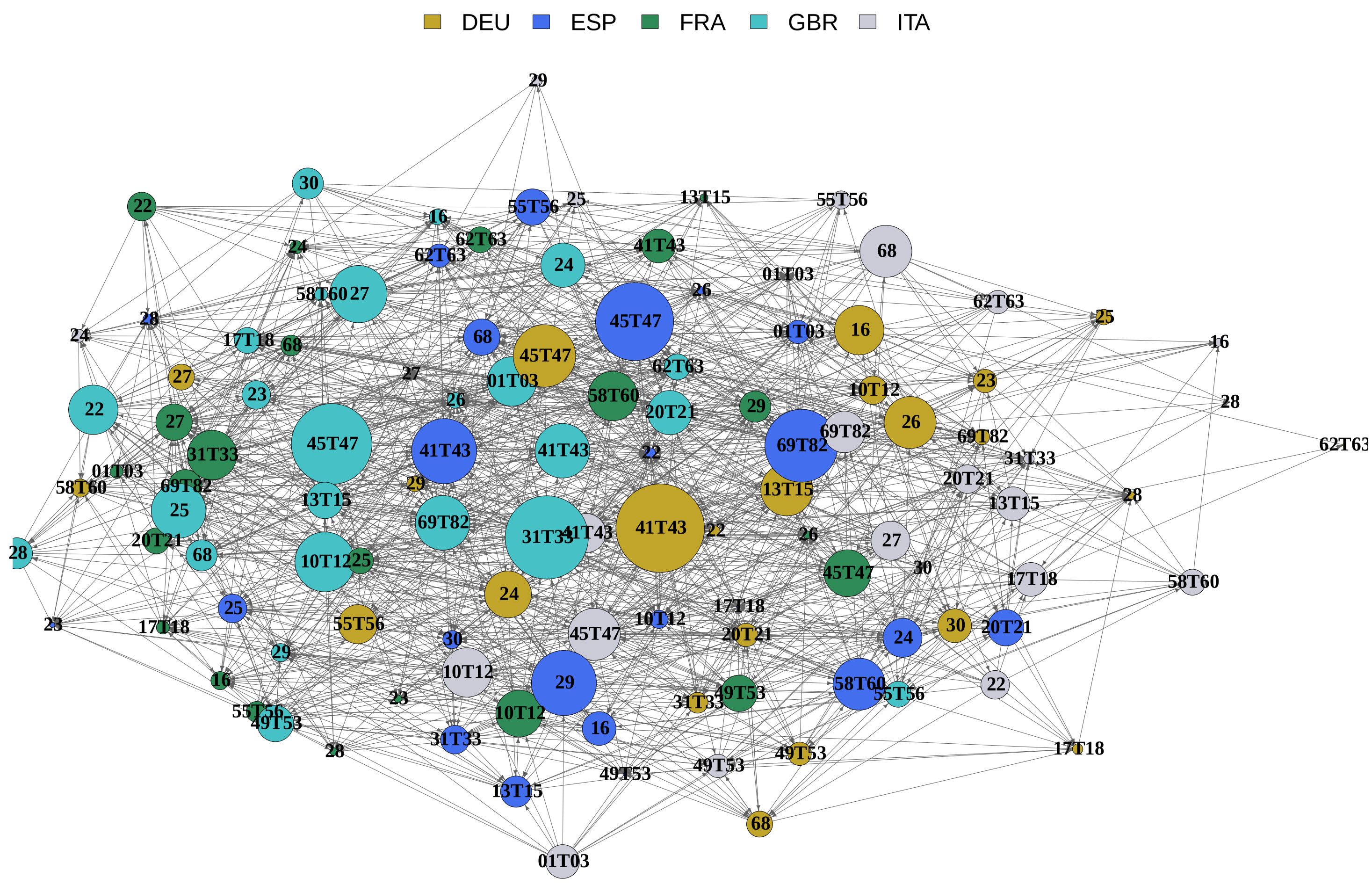
Figure 7: Principal components analysis from 2007 to 2019

D Network of Significant Predictive Relationships Over the Period 2013-2019



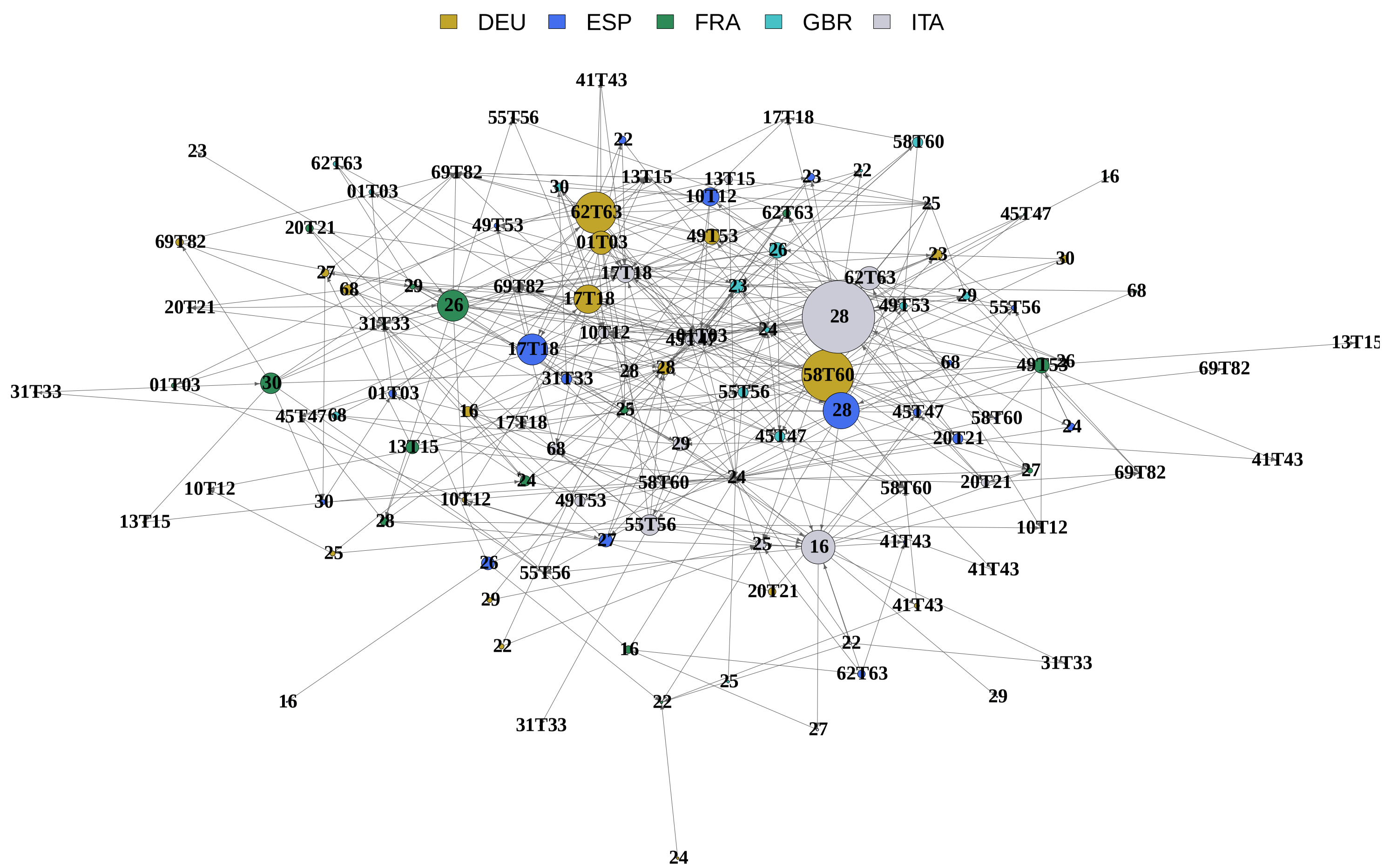
Each circle represents a sector in one country and each arrow the link from one sector toward another. The direction indicates whose past values help explain whose value at time t. Circle size is proportional to the number of links directed toward other sectors. Represented are links only for which the cumulated effect is negative. See appendix section 7 for sector codes.

Figure 8: 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 7 in appendix for sector codes.

Figure 9: 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 10: Network of Significant Cross-Sector Links with Negative Cumulated Amplitude – Period 2013-2019

E Logistic Regression: Negative Predictive Relationships Over the Period 2013-2019

Table 8: 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: $log(\frac{Pr_{ps}}{1-Pr_{ps}}) = \alpha + \beta IO_{ps} + v$. 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 negative net magnitude, i.e. with the sum of β_1 et $\beta_2 < 0$ in 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.

F Distribution of Selected Sectors by Country

Table 9: 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