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

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Motivations

Financial Interdependencies On the News

Figure 1: Thomas Cook in Bankruptcy in September 2019

Fallout from Thomas Cook collapse felt across Europe and Africa

Governments are in crisis-planning mode over efforts to repatriate 500,000 tourists

▲ People line up in front of the Thomas Cook desk at Heraklion airport on Crete. Photograph: Stefanos Rapanis/Reuters

Thomas Cook owed £885 million to trade creditors in addition to bank and customer debts.

⇒ **Financial distress propagates.**

Motivations

Financial Interdependencies On the News

- Thomas Cook's insolvency as one example of **interdependencies on the financial side**. In the literature, most focus on production networks.
- Because of the lack of disaggregated and frequent financial data. No clear picture of financial health interdependencies across sectors.
- This paper asks the following question:
  - In the aggregate, can we detect **cross-sector interdependencies on the financial side**, i.e. abstracting from common macro factors?

What I Do

- Use a **high-dimensional VAR analysis to detect Granger causalities** among sectors' financial health in five Western European countries between 2007 and 2019.
- Mitigate the lack of up-to-date sector-level financial data using **trade credit defaults** as a proxy for financial health across sectors, leveraging an original database from a trade credit insurer.

What I Find

- I identify **significant Granger causalities among trade credit default rates across sectors**, accounting for macro and third-sector effects.
  - ⇒ Monitoring financial health in a specific sector can help predict better **financial health** in other sectors.
- I obtain a map of **cross-sector financial interdependencies, reflecting financial distress propagation.**
- Some sectors as key information providers: **chemicals & pharmaceuticals, wholesale & retail, the automotive sector** among others.

Related Literature

- **Production networks: propagation of shocks** - *Acemoglu et al. (2012) & Acemoglu et al. (2015)*
  ⇒ Contribution: **Focus on a new type of interaction across sectors and firms, on the financial side.**
- **Financial constraint in production networks:** *Bigio and La'O (2016), Luo (2020) & Altinoglu (2021)*
  ⇒ Contribution: **Use a financial-side indicator rather than a production one to reflect propagation of financial shocks.**
- **Trade credit: channel for shock propagation in production networks** - *Bigio and La'O (2016), Luo (2020) & Altinoglu (2021), Boissay and Gropp (2013) & Jacobson and von Schedvin (2015) & Costello (2020)*
  ⇒ Contribution: **Cross-country analysis of financial distress propagation using a new indicator of firms' financial health.**

Aim: **Identifying cross-sector predictive relationships for financial health**, accounting for all other potential determinants.
$\Rightarrow$ Granger causalities across financial health of P country x sectors in a high-dimensional VARX model.

We have FH_1,...,FH_T as a P-dimensional multiple time series process for financial health.
$FH_t = (FH_{1,t}, ..., FH_{P,T})'$ is generated by a VAR-X(6) model on a monthly basis:

$$FH_t = A_1 FH_{t-1} + ... + A_6 FH_{t-6} + CZ_t + u_t \tag{1}$$

With FH_t a Px1 vector of time series, a set of PxP A parameter matrices, Z_t a Hx1 matrix of exogenous macroeconomic time series with their 6 respective lags and a PxH parameter matrix C, and u_t a Px1 vector of error terms.

To test if financial health in German agriculture (r) **Granger causes** financial health in Spanish plastics (m), I test for joint significance in the following:

$$
\begin{aligned}
FH_{m,t} = a + \sum_{k=1}^{6} \theta_k FH_{m,t-k} + \sum_{\substack{n \in P \\ n \neq m \\ n \neq r}} \sum_{k=1}^{6} \gamma_{n,k} FH_{n,t-k} + \\
+ \sum_{h=1}^{H} \sum_{k=1}^{6} c_{h,k} Z_{h,t-k} \\
+ \sum_{k=1}^{6} \beta_k FH_{r,t-k} + u_t,
\end{aligned}
$$

$$\text{with the country-sector pair n} \neq \text{(m, r)} \quad (2)$$

Granger-causality test: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$ **?**

Finding the right balance between omitted-variable bias and over-dimensionality issues: *Belloni et al. (2014) & Hecq et al. (2021)*

A solution based on *Belloni et al. (2014) & Hecq et al. (2021)*.

Reduce dimensionality in the model using lasso regressions while accounting for the probability that lasso selections might omit relevant variables and create a bias:

1. Post-double selection procedure to **construct a relevant information set**;
2. Wald test for **Granger causality** of r on m **conditional on the information set**.

Methodology

Step 1 - Post-double estimation procedure

Lasso selections among the set I of control variables:

- the H macroeconomic series with their 6 respective lags, synthesized with PCA. Macro variables
- all country–sector p's financial health, excluding m and r, with their 6 respective lags.

Seven lasso selections:

- Lasso 1: $FH_{m,t}$ on I
- Lasso 2: $FH_{r,t-1}$ on I
- Lasso 3: $FH_{r,t-2}$ on I
- Lasso 4: $FH_{r,t-3}$ on I
- Lasso 5: $FH_{r,t-4}$ on I
- Lasso 6: $FH_{r,t-5}$ on I
- Lasso 7: $FH_{r,t-6}$ on I

$\Rightarrow$ **Are included in the information set I^* all variables that were selected at least once in the seven lasso regressions.**

Wald Test:

$$M1 : FH_{m,t} = c + \sum_{k=1}^{6} \theta_k FH_{m,t-k} + \alpha I^*_{lasso} + v_t \tag{3}$$

$$M2 : FH_{m,t} = c + \sum_{k=1}^{6} \theta_k FH_{m,t-k} + \alpha I^*_{lasso} + \sum_{k=1}^{6} \beta_k FH_{r,t-k} + \eta_t \tag{4}$$

We test the hypothesis H0 of non-Granger-causality:
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0.$

Multiple testing corrections using Benjamini-Hochberg's method. Results

Data: Indicator

Following Boissay and Gropp (2013), Bourgeon and Bricongne (2016), I use **trade credit default rate as an indicator of a sector's financial health.** Trade Credit Description

For country x sector p at month t:

$$DR_{p,t} = \frac{\frac{1}{3}\sum_{j=t-2}^{t} \text{Number of Defaults}_{p,t}}{\text{Number of Trade Credits}_{p,t-6}} * 100 \tag{5}$$

Data: Default rate series

Using data from Coface, one of the top-three credit insurer worldwide.
Default rate series on a monthly basis in Germany, France, Italy, Spain and the UK.
From January 2007 to December 2019.
⇒ **156 observations for 176 sectors in total: High dimensionality**

Table 1: Descriptive statistics - Coface trade Credit Data

Statistic	Number of trade credits	Number of defaults	Default rate indicator
N	27,612	27,612	27,612
Mean	11,879.72	18.74	0.30
St. Dev.	30,268.52	79.22	0.42
Min	6	0	0.00
Pctl(25)	1,097	0	0.06
Median	4,273	2	0.18
Pctl(75)	9,464.5	8	0.38
Max	323,728	2,472	10.00

Default rates are made stationary using Loess decomposition.

RESULTS

Results

Cross-sector Interactions To Better Monitor Sectors' Financial Health

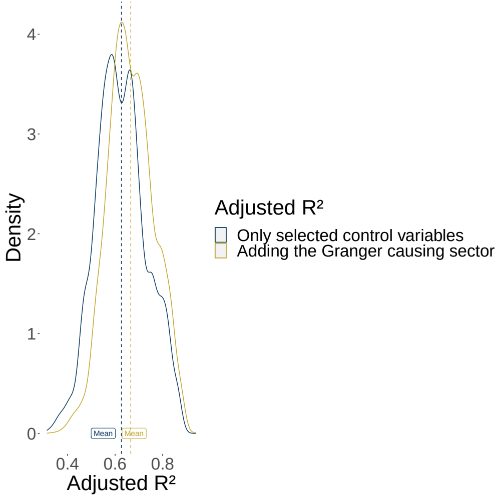
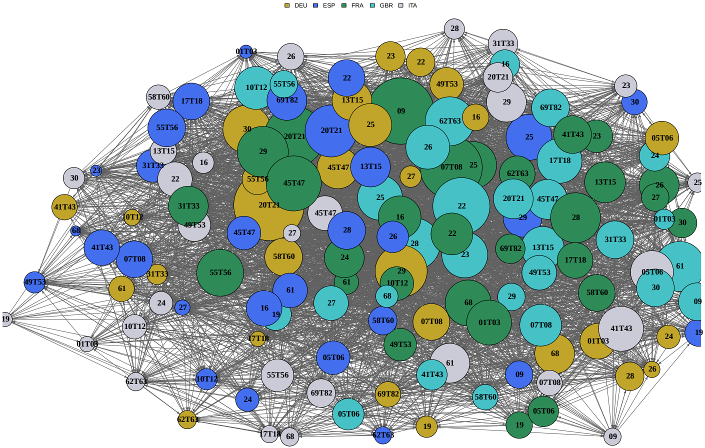


Figure 2: Cross-Sector Information Adds Predictive Power

4,717 significant Granger causalities (GC) out of 20,592 tested. Equation

⇒ Macroeconomic variables cannot explain all dimensions of a sector's financial health, there is a cross-sector component.

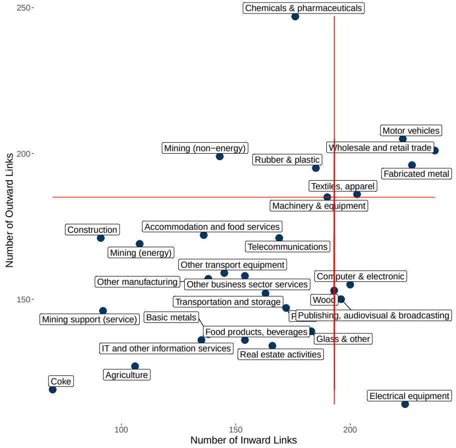
A Map of Financial Distress Interdependencies



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

Figure 3: Full Network of Significant Cross-Sector Interactions

Looking Closer: Some Key Sectors To Monitor



Red lines refer to the third quantile for each measure.

Figure 4: Aggregate Sector Distribution Robustness

Granger causalities network: a cross-sector and cross-country network

- Largely inter-country (78%) and inter-sector (97%), given that we account for macro and third-sector effects.
- **Spain** and **Italy** cumulating most inward (being predicted by others) and outward (predicting others) Granger causalities.
- 30% of Granger causalities (GC) go both ways between two sectors.
- 75% of GC relationships are **positive**: an increase in financial distress in German Agrifood helps predict an increase in financial distress in Spanish plastics.
  - The existence of financial distress propagation positively correlates with the amount of inputs sent from the Granger-causing sector to the other IO Logistic results
- 25% of GC relationships are **negative**.

Conclusions & Future Applications

- Using high-dimensional Granger-causality testing to highlight the existence of **cross-sector financial interdependencies**.
  $\Rightarrow$ This can improve financial distress monitoring.
- Financial health in **Chemicals and pharmaceuticals, wholesale and retail, rubber, the automotive sector** to be monitered in priority.
- Future applications of the method and next steps:
  - Do financial distress interdependencies affect production interdependencies (output co-movement)?
  - Time-varying structure of financial distress propagation: structural versus cyclical?

THANKS!

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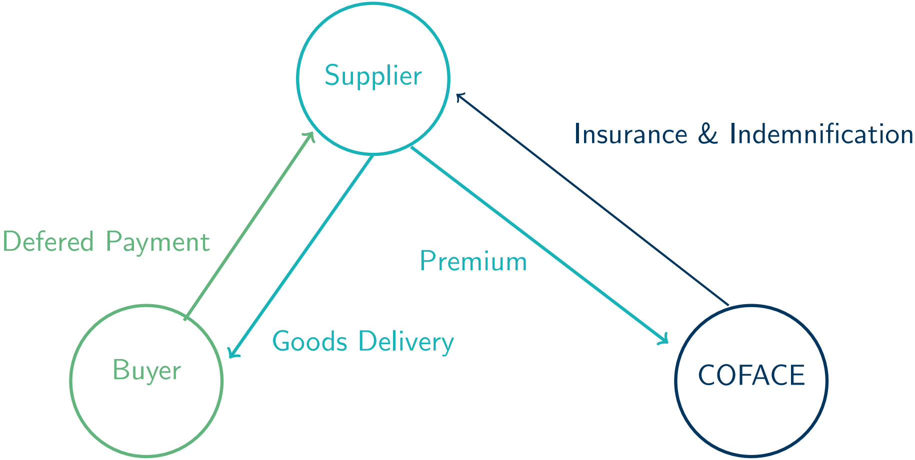
APPENDIX

Trade Credit Back



Data: Macroeconomic control variables Back

Set of macroeconomic monthly indicators, detrended and seasonally-adjusted when needed, synthesized using Principal Component Analysis.
$\Rightarrow$ **10 principal components forms the Z matrix with 0 to 6-month lags.**

- Industrial Production Indices
- Industry Business Confidence and Consumer Confidence surveys
- M2 money supply
- Interest rate on loans to non-financial corporations up to 1 year maturity
- Yield on 10-year government bonds
- Oil prices
- Exports and Imports separately

Data: Principal Component Analysis

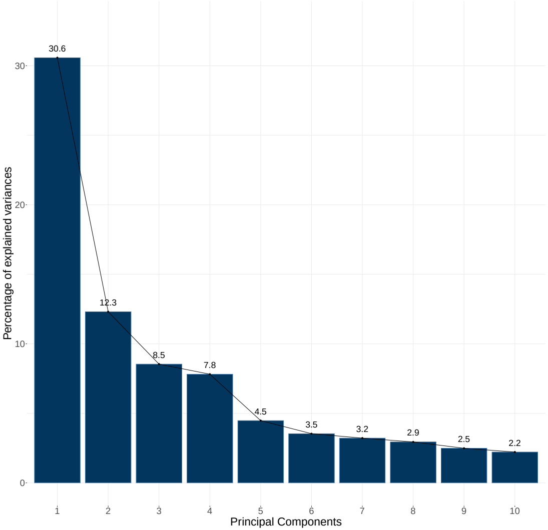


Figure 5: Percentage of explained variance for selected principal components

75% of Positive Granger Causalities

Vertical Propagation in Production Network - Direct and Indirect

Back

Table 2: Logistic regressions - Input-Ouput Flows and Positive Predictive Relationships

	Having a Significant Granger-Causality Link With Positive Net Magnitude	
	(1)	(2)
IO Direct Flow	0.0758***	
	(0.0258)	
Leontief Total Value Added		0.0588***
		(0.0155)
Constant	−1.6449***	−1.6556***
	(0.0189)	(0.0191)
N	20,592	20,592
Log Likelihood	−9,104.7370	−9,102.0210
Akaike Inf. Crit.	18,213.4700	18,208.0400

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: $log(\frac{Pr_{rm}}{1-Pr_{rm}}) = \alpha + \beta IO_{rm} + v$.

Robustness: similar sectors' centrality Back

Using a stricter method for multiple-testing correction (Benjamini & Yekutieli's method), sector ranking is preserved.

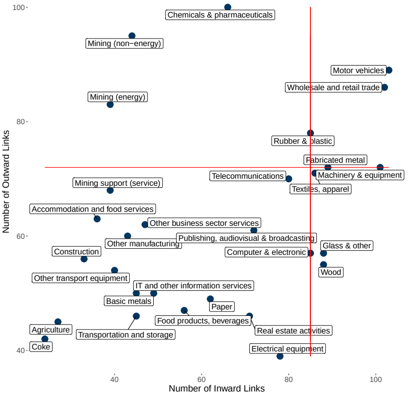


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Figure 6: Aggregate Sector Distribution