MASTER PROJECT

Spillover Effects from the Financial Sector: A Network Analysis for the Eurozone

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Contents

Abstract

We identify contemporaneous and Granger-causal linkages between the 86 biggest companies, representing both the financial and real sectors, of the Eurozone economy that serve as paths of shock transmission. Network analysis lends itself very naturally to the study of systemic risk due to its preoccupation with interconnections and notions of centrality. We employ an estimation methodology introduced by Barigozzi and Brownlees (2018) using market data for daily volatilities from the Eurostoxx index. Our results are in line with the existing literature - the banking sector is found to be highly interconnected and responsible for most Granger-network spillovers. Moreover, only a small subset of firms appear to Granger-cause other residual volatilities, providing support for regulators' targeting of Systemically Important Financial Institutions.

Keywords – Networks, Granger-causation, NETS algorithm, Systemic risk, SIFIs

1 Introduction

This paper offers empirical insights into the cross-sectional dimension of Eurozone systemic risk. While largely agnostic regarding the theory of how contagion is generated, we focus on delivering a practical empirical measurement of systemic risk and paths of contagion that can be of use to Eurozone regulators. This is achieved firstly by identifying which Eurozone financial institutions make the greatest contributions to systemic risk and could thus be considered Systemically Important Financial Institutions (SIFIs)[2]. Secondly, we track the channels of contagion both within the financial system and running from the financial system to the real economy. The cross-sectional dimension of systemic risk reflects the distribution of volatility in the financial system which may be a function of institutional size and leverage, as well as the concentration of an institution's activities and their interconnectedness. Emphasized throughout is our belief that network analysis is an appropriate tool for capturing systemic risk and its spread - particularly appealing feature is that a shock to a central node can have potentially vast rippling effects. Furthermore, going beyond banks and other financials to include non-financial firms sheds light on the critical issue of how contagion spreads from the financial system to the real economy.

This modern preoccupation with how contagion spreads to the real economy is inherited from the Global Financial Crisis of 2008-2009 following which there was a widespread acknowledgement that regulators had focused too narrowly on the idiosyncratic risk of individual financial institutions. Micro-prudential regulators imposed minimum capital requirements on firms in the belief that if each institution in the financial system is sound, the financial system itself ought also to be resilient. This "fallacy of composition" overlooked the important concept of systemic risk and that, in a time of crisis, there exist strong financial system externalities which create financial instability and negative

[2]SIFIs are those firms described by the phrases "Too Big To Fail" or "Too Connected To Fail". In the words of global regulators, "SIFIs are financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity", Financial Stability Board (2011).

spillovers to the real sector.[3] Unless the external costs of systemic risk are internalised by each financial institution, the institution will have the incentive to take risks that are borne by all. A post-crisis consensus emerged that greater efforts were needed to contain systemic risk.

Given this recent regulatory pivot, one would think there is a universally-accepted definition of systemic risk, but it remains elusive.[4] Among the numerous proposals, a crucial distinction emerges. Need systemic risk only threaten the smooth operation of the financial system or should a definition of systemic risk explicitly require negative spillovers to the real economy? By the inclusion of firms representing the real economy alongside banking firms, this paper is explicitly in the spirit of the latter. Where previous research has focused exclusively on interconnections within the banking system, this paper investigates not only the transmission of risk between different financial institutions but also the spreading of risk to and from firms in the real economy.

The rest of the paper is structured as follows. Section 2 gives a brief overview of relevant literature and places our contribution in proper context. A description of the data, estimation approach and parameter-selection follows in Section 3. Section 4 presents the results and Section 5 places the findings in context and offers a discussion of their implications.

2 Literature Review

Given the ambiguity surrounding systemic risk the literature has proposed many different approaches to quantifying the concept. To give an illustrative example - Bisias et al. (2012) provide a detailed taxonomy of 31 different measures while Silva et al. (2017) review more than 260 articles in order to analyse this developing field of study.

According to Freixas et al. (2015) systemic risk measures can be divided into two groups

[3] Think here of the fire sales, panics, credit crunches described in detail in Freixas, Laevan and Peydro (2015).

[4] Economists and regulators analyzing systemic risk are fond of invoking the logic of Justice Potter Stewart: they are unsure how exactly to define systemic risk, but they know it when they see it. This is an obviously unsatisfying approach when dealing with such an important concept.

depending on the type of input information. "Fundamental approaches" rely on balance sheet or credit register data and include, among many others, network models of interbank contagion based on inter-institution exposure which are recommended by IMF (2009) as a tool to asses systemic linkages. However, the main shortcoming of the fundamental approach is the ownership and constrained accessibility of the necessary information.

Therefore researchers not affiliated with central banks or other regulatory authorities resort to using a "market data approach", inferring interconnections from the easily observed empirical distribution of returns – this methodology is adopted here. Using market data requires an assumption that prices reflect all the available information, implying that market-based measures could perfectly quantify systemic risk. Thus it is frequently flagged that deviations from market efficiency (e.g. arising from the government bailouts of financial institutions) may lead to mis-measurements. Nevertheless, the market view of systemic risk quantification prevails in the recent literature.

Following Diebold and Yilmaz (2014) systemic risk measures can be classified based on the features they intend to capture. The first group focuses on systemic risk exposure, conditioning firm events on market distress. This group includes, for example, the systemic expected shortfall proposed by Acharya et al. (2017) or SRISK implemented by Brownlees and Engle (2017). The second group deals with the systemic risk contribution, conditioning market events on the firm distress. The most widely-applied measures of this kind are CoVaR and ΔCoVaR developed by Adrian and Brunnermeier (2016). The third group is comprised of studies of systemic interlinkages among institutions and this is the part of literature to which we make a direct contribution.

The vast majority of empirical studies on interconnectedness concentrate on the US financial sector. Billio et al. (2012) apply principal components analysis and Granger-causality networks to the monthly returns of hedge funds, banks, broker/dealers, and insurance companies. All four industries became highly interrelated during the first decade of 2000s, which increased the level of systemic risk. Moreover, they find that banks play a much more important role in transmitting shocks than other financial institutions. Similarly, Härdle et al. (2016) - focusing on the tail event driven interconnectedness - show that on average banks dominate the outgoing links while insurers spread less risk than other financial entities. Diebold and Yielmaz (2014) propose several measures built from variance decompositions and apply them to daily volatilities of stock returns of 13 major financial institutions. They find especially tight links between companies that experienced the most severe difficulties during the 2007-2008 financial crisis.

Barigozzi and Brownlees (2018) examine the connectedness not only within the financial sector but across 90 US bluechips from different industries. A LASSO-based algorithm identifying Granger-causality linkages, contemporaneous and long-run partial correlation linkages is applied to daily volatilities of stock returns. They find that financial institutions have the highest degree of interconnectedness and show that entities heavily involved in the 2007-2008 financial crisis are associated with the largest spillover effects.

Hitherto, studies focusing on Europe have been devoted solely to the banking sector and hence do not capture transmission of shocks to the real economy. Hautsch et al. (2014) employ a high-dimensional linear model based on Value-at-Risk (VaR) measure using both market and fundamental data for 20 banks, which reveals the dynamic nature of interconnectedness in the European financial system. Betz et al. (2016) apply a similar methodology to 51 European banks and 17 sovereigns showing that fragmentation of the European financial sector has peaked. Moreover, banks from countries participating in the EU-IMF programme exhibit the greatest systemic risk contributions during the sovereign debt crisis while the same holds for global banks during the 2007-2008 financial crisis. Covi et al. (2018) estimate the network of banks in the Euro area based on large exposure data, revealing a core-periphery structure in the interbank network. Moreover, they show that there is a value for policymakers associated with network-based measures as in general they highly correlate with simple size-based interconnectedness indicators but for some banks these quantifications deviate considerably.

3 Data and Methodology

This paper adopts the methodology introduced by Barigozzi and Brownlees (2018) to analyse interconnectedness in the Eurozone using a panel of volatility measures. Use of this LASSO algorithm (called nets), having factored out market wide as well as sectoral and country specific volatility factors, allows us to estimate contemporaneous correlations and predictive Granger relations.

Daily stock market prices for major Eurozone firms (or bluechips) are retrieved from the Eurostoxx index. More precisely, we take the 100 largest firms ordered by total equity and we remove 14 firms due to missing values[5]. Thus, we consider a panel of 86 Eurozone firms across 10 different industry sectors and 10 different countries. The list of bluechips with corresponding country and industry sector can be found in Table 1. By the very nature of the Eurostoxx index, banks and industrial firms are overrepresented in our sample, as are French and German companies. The sample spans from May 1st, 2008 to April 15th, 2018 which corresponds to 2393 trading days. With a sample of 86 firms we are in line with Barigozzi and Brownlees (2018), who use 90 US companies.

As a first step we measure volatility for each firm i on day t. This is done using the high-low range estimator introduced by Parkinson (1980):

$$\tilde{\sigma}_{it}^2 = 0.361 \cdot (\rho_{it}^h - \rho_{it}^l)^2, \tag{1}$$

where ρ_{it}^h and ρ_{it}^l denote the maximum and minimum log price of stock i on day t, respectively. Brownlees and Gallo (2010) show that while more complex measures of volatility have been proposed in recent years, simpler estimates such as that of Parkinson (1980) can have a similar or better performance. To analyse volatility interconnectedness conditional on market, sector, and country specific factors, a so-called factor structure in volatility is needed. In the literature a wide range of evidence has been found that this structure exists (see Barigozzi et al., 2014; Luciani and Veredas, 2015).

[5]The missing values are mainly due to the fact that firms were listed in the stock market at a later stage during the sample period. In some specific cases, the volatility was 0 due to a firm not trading. In that case, the volatility is set to the previous value.

Thus, as a second step we analyse the residuals of the following regression:

$$\log \tilde{\sigma}_{it}^2 = \beta_0 + \beta_1 \log \tilde{\sigma}_{mt} + \beta_2 \log \tilde{\sigma}_{st} + \beta_3 \log \tilde{\sigma}_{ct} + z_{it} \quad (2)$$

where $\tilde{\sigma}_{mt}$ is the volatility of the Eurostoxx market, $\tilde{\sigma}_{st}$ the volatility of the sectoral index s, and $\tilde{\sigma}_{ct}$ corresponds to the volatility of the country index c. The market, sectoral and country factor volatilities are measured with the high-low range estimator introduced earlier. We apply this method to the sectoral indices of the Eurostoxx and for the country factor we use the most relevant benchmark index in each country. Thus, estimating the model by least squares factors out the market, sector and country factor volatilities, leaving the residuals z_{it}.

Finally, having obtained the volatility residuals as a large time series panel, we model them as a VAR and apply the LASSO-based nets algorithm proposed by Barigozzi and Brownlees (2018), which implies regressing each residual z_{it} on other contemporaneous residuals and their p lags:

$$z_{it} = \sum_{\substack{h=1 \\ h \neq i}} \gamma_{ih} z_{ht} + \sum_{k=1}^{p} \sum_{j=1}^{n} \beta_{ijk} z_{jt-k} + \epsilon_{it} \quad (3)$$

The first term of the equation represents the contemporaneous network, which can be visualized as an undirected graph. Thus, if two firms are connected, their residual volatilities are driven by similar shocks. The second term represents the granger causality links, which can be visualized as directed graphs. A significant β means that a shift in the volatility of one firm granger causes a shift in the volatility of another firm. Therefore, it serves as a toolkit for analyzing spillover effects in the economy. Note that our algorithm is based on a LASSO-type estimation in the context of ordinary least squares. Thus, the loss function that we seek to minimize allows for two shrinkage parameters λ_i:

$$\min_{\gamma_{ih}, \beta_{ijk}} \{ |z_{it} - \sum_{\substack{h=1 \\ h \neq i}} \gamma_{ih} z_{ht} - \sum_{k=1}^{p} \sum_{j=1}^{n} \beta_{ijk} z_{jt-k}|^2 + \lambda_1 \sum_{\substack{h=1 \\ h \neq i}} |\gamma_{ih}| + \lambda_2 \sum_{k=1}^{p} \sum_{j=1}^{n} |\beta_{ijk}| \} \quad (4)$$

Therefore, we choose two λ_i, based on in-sample cross-validation to minimize the Mean Squared Error (MSE). Moreover, we choose the number of lags p based on the sample autocorrelation of the residuals z_{it}.

Thus, a brief discussion of parameters is an important preface to the results presented in the following section. Having estimated regression (2) for each firm i, we obtained the residuals z_{it}. An in-sample cross validation minimizing the Mean Squared Error was carried out to find the optimal penalty parameters λ_i. The selection process included mainly Grid search and optimizing the Akaike information criterion (AIC) of the model, eventually arriving at the values **7** and **24**, respectively. This process was complemented with out-of-sample forecasting: after splitting our data 80-20%, we forecast several variables with different parameters to reduce the forecast error and avoid overfitting of the data. Our final parameters are slightly higher than in Barigozzi and Brownlees (2018), but the main patterns are robust to this result; the algorithm simply sets more estimates to be exactly zero. Moreover, by looking at Figure 1 the residuals exhibit few order one autocorrelation which lead us to the conclusion to set the lag parameter p equal to one. With the choice and values of our parameters for the LASSO algorithm we are entirely consistent with Barigozzi and Brownlees (2018).

4 Results

In this section, using the specification presented in Section 3, we first present the descriptive statistics of our panel of residuals z_{it}. Second, we investigate intra- and inter-sectoral correlations as well as sample autocorrelations. Third, we focus on the main findings of the estimated network after applying the nets algorithm, mainly Granger and contemporaneous linkages between sectors and countries.

In Table 2 we display the main statistics of the residuals z_{it} and the R^2 of each factor of the regressions, grouped by sector. All of the volatilities display leptokurtic distributions, i.e. the tails are fatter than in the normal distribution. This implies that, especially in the case of banks, there is an increased likelihood of days with high volatility. In general, the sectoral index accounts for most variation in the volatilities, followed by the country index. Clearly the volatility of each firm is highly dependent on their sector. We can also infer that the country market is still an important source of risk for the top European countries, more than the whole European-wide index. As expected, all of the autocorrelations decay with time, but it is interesting to note higher persistence in the banking and real estate sectors. This becomes even more clear when looking at the right hand side of Figure 1. Moreover, in the residuals we observe higher intra-sectoral correlation than inter-sectoral correlation, and we expect this pattern to be transmitted to the networks. Billio et al. (2012) is one of many papers which finds that the banking sector exhibits very high intra-sectoral correlation. Our results show that intra-sectoral correlation is highest in the banking, industrials and technology sector. These correlations suggest that the banking sector is particularly connected with industrial, real estate and insurance firms.

The most important firms in both Granger and contemporaneous networks, based on the number of connections (degree), are displayed in Table 3. In both cases, the top three is comprised of financial firms (including banks, insurers and real estate companies). Concomitant with the size of the economies, France and Germany play major roles in the contemporaneous network, although specific firms of the periphery also show up in top positions, especially in the Granger network. Interestingly, at the Granger level we find a prominent role of AIBG, a periphery-country bank that received a bailout. In our network the "troubled" bank AIBG plays an analogous role to the "troubled" insurer AIG in the Barigozzi and Brownlees (2018) network for the US. The other top banks in the Granger network, KBC, CABK and UBI either also received a cash injection from a government or acquired other distressed institutions. In fact, the four most prominent banks in our Granger network could all be called "crisis" banks.

The distributions of the degree (absolute number of connections) and betweenness (measure of centrality) in both networks are shown in Figure 3. We find on average a higher interconnectedness at the contemporaneous level for both measures. Interestingly, there is a high concentration of firms with zero betweenness in the Granger network, while in the contemporaneous one they tend to display at least some connection. While consistent with Barigozzi and Brownlees (2018), this result is also intuitive, as seen in the decreasing autocorrelation of the volatilities: they are more connected at the same t, while at a one-year lag fewer companies remain connected. Firms with high betweenness are firms for which usually the intra-sectoral correlation is high, such as technology and industrials, and of course banks. For instance, a firm with highest betweenness at the contemporaneous level is not the top connected bank (AIBG) but a technology firm (ORAN). However, this is mainly due to the strong intra-sectoral correlation in the technology sector, which stems from the similar structure of the firms. Moreover, in Figure 4 we can see the histograms of the non-zero coefficients for both networks. Especially in the contemporaneous case they tend to be positive, so residual volatilities move in the same direction. More strikingly, the Granger network shows a few positive and large coefficients, implying there is a small subset of firms that Granger-cause other residual volatilities.

Consistent with existing literature (see Billio et al., 2012 or Härdle et al., 2016), the banking sector is most interconnected, followed by industrial firms, as we show in Table 4. Here, we display the absolute level of connections per sector in our sample. In the following tables we standardise these linkages and cross-evaluate them by country. In line with Barigozzi and Brownlees (2018), we find more connections at the contemporaneous than at the Granger level. Simply put, fewer firms are Granger-sources of risk and these source firms do not transmit to all other companies. This result is robust to different calibrations of the model. Our finding that insurers spread less risk than other financial firms is in consistent with Härdle et al. (2016).

We report the relative connections per country, standardised by the number of firms in the sample for each country in Table 4. Given the high interconnectedness of AIBG, Ireland (IE) appears as the biggest relative source of connections. Lane (2014), building on work by Lane and Milesi-Ferreti (2007), shows the extreme level of financial globalisation exhibited by the Irish economy of which AIBG was the largest bank. The rest of the countries, except for Italy, have more connections at the contemporaneous level, from which we can infer that Italian firms are a relatively bigger source of Granger-caused volatility.

The standardised linkages between sectors can be seen in Table 5. Again, banks is the most interconnected sector at the contemporaneous level, followed by industrials, while insurance does not seem to be especially risky based on this measure. Instead, insurers are more connected to banks than among themselves. Overall, the main connections are along the diagonal, which again implies more interconnectedness within than across sectors: even after factoring out the sector index, similar firms are more connected to each other, especially technological companies. At the Granger level, we can observe the systemic relevance of banks: a significant share of connections from each sector lead to the banking sector. Aside from banking, the sectors that receive high shares of connections are utilities and industrials. Barigozzi and Brownlees (2018) also find important linkages in the industrial sector, but less so in the utilities sector which is surpassed by technology firms in their network. The first divergence likely arises from subtle differences in the definition of sectors as we merged utilities with energy companies, while the second divergence suggests that technology firms are simply more interconnected in the US than in the Eurozone.

Table 6 is equivalent to Table 5 but grouping firms by country. It is important to notice a difference with Table 4 where we standardise the linkages by the number of firms per country. Here, we standardise the cross-country connections by the total number of connections of each country. In Table 6 France appears as the main target of connections but in Table 4 French firms have low values. This puzzle is explained by the fact that while France has a high share of firms in our sample, these firms have low degree in the networks. This in turn implies that, at the contemporaneous level, the biggest sources of connections are the biggest economies in the Eurozone. However, in the Granger network this is not as clear, as Germany looks more robust to external volatilities. Mirroring the sectoral results, in both cases we see that there is still clustering, as high share of the connections are still within-country. Countries with less representation in our sample have their connections concentrated instead of spread throughout the Eurozone.

5 Conclusions

Following the work of Barigozzi and Brownlees (2018), this paper applies the nets algorithm to study the interconnectedness of the 86 biggest firms in the Eurozone for a sample period spanning from May 2008 to April 2018. We have estimated two sparse networks of return volatilities that allow us to measure systemic risk and detect patterns of its transmission. Compared to the original study of the US economy, we have utilised a more detailed set of industries. What is more, country-specific volatilities were added as an extra factor in order to obtain more precise firm-specific residual volatilities, while still uncovering a large number of connections.

At the contemporaneous level almost all industries exhibit high connectedness, a pattern which became immediately apparent on the initial heatmaps of residual correlations. Even when controlling for sectoral and country volatilities we find clusters of firms reacting strongly with other firms within the same business area. These co-movements are especially remarkable within the banking, industrial, and technological sectors.

However, it is a small subset of companies, mostly financial firms, that displays high interconnectedness at the Granger-causal level. Consequently, we conclude that banks are particularly important risk transmitters in the Eurozone network. The subset of banks is especially susceptible to volatilities stemming from other sectors. This makes intuitive sense as we can think of banks being highly leveraged when compared with other entities (Freixas et al., 2015). Moreover, banks amplify and transmit shocks to all the other sectors, which reflects their unique economic role as financial intermediaries. Altogether, this provides empirical support for the regulatory targeting of certain Systemically Important Financial Institutions.

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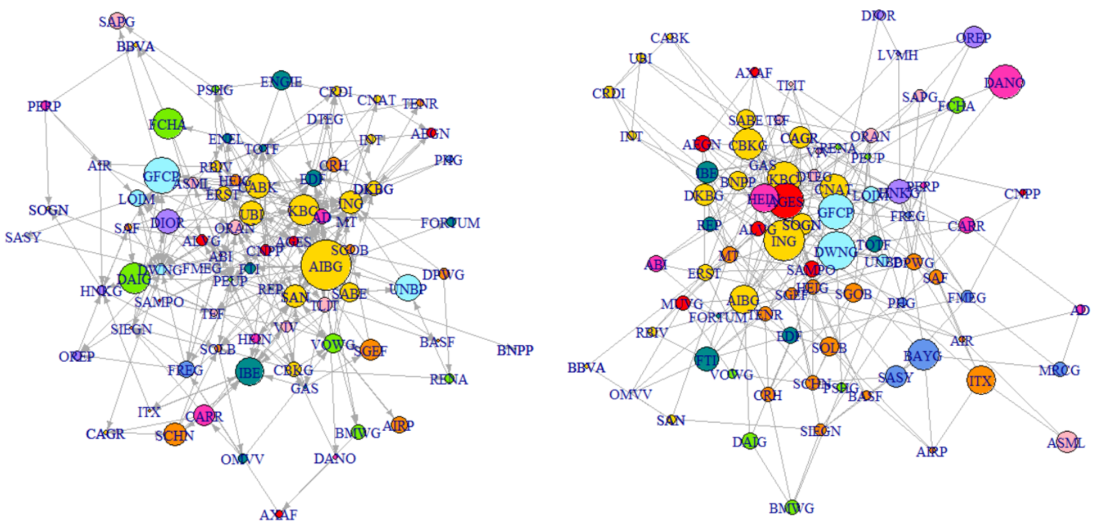
Appendix

Figure 1: Heatmaps: Sample Correlation and Autocorrelation

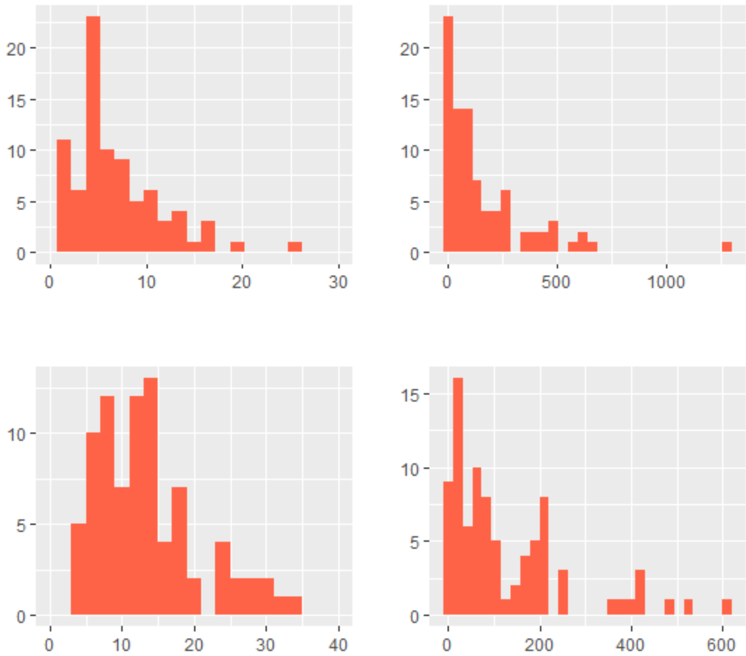
The left-hand side figure shows the correlation of the residuals, while the right-hand side displays the sample autocorrelation of the residuals.

Figure 2: Granger and Contemporaneous Network



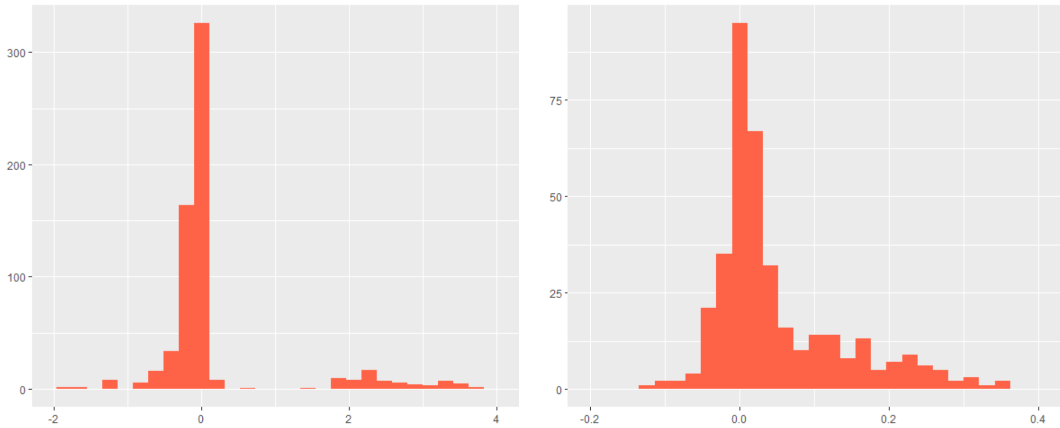
This figure displays both networks, with the size of the vertex varying with the degree of the firm, and the color corresponding to the sector.

Figure 3: Histograms of Degrees and Betweenness



The left-hand side figures show the histograms of the degrees in the Granger and Contemporaneous networks, respectively, while the right-hand side displays the betweenness.

Figure 4: Histograms of Coefficients



Histograms of the non-zero estimated coefficients for the Granger and Contemporaneous network, respectively.

Table 1: Panel of firms

Ticker	Firm	Sector	C'try	Ticker	Firm	Sector	C'try
BMWG	Bayerische Motoren Werke	Automobile	DE	DPWGn	Deutsche Post	Industrials	DE
DAIGn	Daimler	Automobile	DE	SAF	Safran	Industrials	FR
FCHA	Fiat Chrysler Automobiles	Automobile	IT	SCHN	Schneider Electric	Industrials	FR
PEUP	Peugeot	Automobile	FR	SIEGn	Siemens	Industrials	DE
PSHG	Porsche Automobil Holding	Automobile	DE	SOLB	Solvay	Industrials	BE
RENA	Renault	Automobile	FR	TENR	Tenaris	Industrials	LU
VOWG	Volkswagen	Automobile	DE	CRH	CRH	Industrials	IE
AIBG	AIB Group	Banks	IE	SGOB	Saint Gobain	Industrials	FR
BNPP	BNP Paribas	Banks	FR	HEIG	HeidelbergCement	Industrials	DE
BBVA	BBVA	Banks	ES	SGEF	Vinci	Industrials	FR
SAN	Banco Santander	Banks	ES	AXAF	AXA	Insurance	FR
SABE	Banco de Sabadell	Banks	ES	AEGN	Aegon	Insurance	NL
CABK	Caixabank	Banks	ES	AGES	Ageas	Insurance	BE
CBKG	Commerzbank	Banks	DE	ALVG	Allianz	Insurance	DE
CAGR	Credit Agricole	Banks	FR	CNPP	CNP Assurances	Insurance	FR
DBKG	Deutsche Bank	Banks	DE	MUVGn	Münchener Rück	Insurance	DE
ERST	Erste Group Bank	Banks	AT	SAMPO	Sampo	Insurance	FI
ING	ING Groep	Banks	NL	DIOR	Christian Dior	Pers. Cons.	FR
INT	Intesa Sanpaolo	Banks	IT	HNKG	Henkel & Co	Pers. Cons.	DE
KBC	KBC Groep	Banks	BE	OREP	L'Oreal	Pers. Cons.	FR
CNAT	Natixis	Banks	FR	LVMH	M. H. Louis Vuitton	Pers. Cons.	FR
RBIV	Raiffeisen Bank	Banks	AT	DWNG	Deutsche Wohnen	Real Estate	DE
SOGN	Societe Generale	Banks	FR	GFCP	Gecina	Real Estate	FR
CRDI	Unicredit	Banks	IT	LOIM	Klepierre	Real Estate	FR
UBI	Unione di Banche Italiane	Banks	IT	UNBP	Unibail Rodamco	Real Estate	FR
ABI	Anheuser Busch Inbev	Food & Bev.	BE	ASML	ASML Holding	Technology	NL
CARR	Carrefour	Food & Bev.	FR	DTEG	Deutsche Telekom	Technology	DE
DANO	Danone	Food & Bev.	FR	ORAN	Orange	Technology	FR
HEIN	Heineken	Food & Bev.	NL	SAPG	SAP	Technology	DE
AD	Koninklijke Ahold Delhaize	Food & Bev.	NL	TLIT	Telecom Italia	Technology	IT
PERP	Pernod Ricard	Food & Bev.	FR	TEF	Telefonica	Technology	ES
UNC	Unilever	Food & Bev.	NL	VIV	Vivendi	Technology	FR
BAYGn	Bayer	Healthcare	DE	EDF	Electricite de France	Utilities	FR
FMEG	Fresenius Medical Care	Healthcare	DE	ENEL	Enel	Utilities	IT
FREG	Fresenius	Healthcare	DE	ENGIE	Engie	Utilities	FR
PHG	Koninklijke Philips	Industrials	NL	FORTUM	Fortum	Utilities	FI
MRCG	Merck	Industrials	DE	IBE	Iberdrola	Utilities	ES
SASY	Sanofi	Industrials	FR	ENI	Eni	Utilities	IT
AIRP	Air Liquide	Industrials	FR	GAS	Gas Natural SDG	Utilities	ES
AIR	Airbus	Industrials	NL	OMVV	OMV	Utilities	AT
MT	ArcelorMittal	Industrials	LU	REP	Repsol	Utilities	ES
BASFn	BASF	Industrials	DE	FTI	TechnipFMC	Utilities	FR
ITX	Industria de Diseno Textil	Industrials	ES	TOTF	Total	Utilities	FR

Table 1 shows a list of all tickers and their respective firm names and sectoral affiliation.

Table 2: Statistical Inference

	Auto	Banks	Food	Heal	Ind	Ins	Pers	Real	Tech	Util	All
variance	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.08	0.05	0.05	0.05
kurtosis	3.88	4.60	3.84	3.81	4.02	3.98	4.05	3.19	3.95	3.69	4.02
ρ_1	0.29	0.32	0.23	0.19	0.26	0.25	0.18	0.36	0.26	0.29	0.27
ρ_5	0.19	0.24	0.15	0.09	0.17	0.17	0.11	0.28	0.17	0.21	0.18
ρ_{22}	0.15	0.18	0.12	0.06	0.13	0.13	0.06	0.23	0.12	0.16	0.14
$\rho_{0,\text{others}}$	0.08	0.06	0.07	0.07	0.08	0.08	0.07	0.11	0.04	0.06	0.07
$\rho_{1,\text{others}}$	0.05	0.04	0.05	0.04	0.04	0.05	0.04	0.07	0.02	0.04	0.04
factor R^2_{isc}	45.2	39.6	36.9	39.3	48.5	49.9	44.5	37.0	35.3	38.8	41.5
sector R^2_{isc}	57.9	53.9	43.7	42.6	52.2	63.8	56.9	25.5	35.2	42.5	47.4
country R^2_{isc}	47.7	50.7	42.3	45.0	50.3	54.9	47.4	38.0	41.1	45.3	46.3

Table 2 reports average descriptive statistics by industry sectors and the overall panel. The set of descriptive statistics considered contains the sample variance, kurtosis, autocorrelation of a trading day, week and month, the average contemporaneous correlation with all other tickers, the average order 1 autocorrelation with all other tickers, as well as the average and overall (in-sample) factor R^2_{isc}, (in-sample) sector R^2_{isc} and (in-sample) country R^2_{isc} of the regressions.

Table 3: Rankings

	Granger			Contemporaneous		
Rank	Firm	Sector	Country	Firm	Sector	Country
1	AIBG	Banks	IE	ING	Banks	NL
2	DWNG	Real	DE	DWNG	Real	DE
3	KBC	Banks	BE	AGES	Ins	BE
4	TOTF	Util	FR	GFCP	Real	FR
5	PEUP	Auto	FR	KBC	Banks	BE
6	EDF	Util	FR	HEIG	Ind	DE
7	AGES	Ins	BE	CBKG	Banks	DE
8	CABK	Banks	ES	HNKG	Pers	DE
9	UBI	Banks	IT	AIBG	Banks	IE
10	ORAN	Tech	FR	CNAT	Banks	FR

Table 3 reports the top firms of each network, their respective sector and country.

Table 4: Network Estimation: Countries & Sectors

	Auto	Banks	Food	Health	Ind	Ins	Pers	Real	Tech	Util	All
Granger	17	55	25	13	41	18	8	17	22	34	250
Contemp.	21	66	20	25	58	38	14	31	23	42	338
	DE	IT	FR	IE	ES	AT	NL	BE	LU	FI	All
Granger	2.25	3.14	2.38	10.5	2.11	3.33	2.50	5.25	3.50	3.00	3.37
Contemp.	3.95	2.14	3.62	8.50	4.33	4.33	4.75	9.75	8.00	5.50	6.58

Table 4 reports the degree of connections on each network per sector in the sample. Moreover, it displays the degree of connections on each network per country standardised by the number of firms from each country in the sample.

Table 5: Cross-Sectoral Linkages

	Granger Components									
	Auto	Banks	Food	Health	Ind	Ins	Pers	Real	Tech	Util
Auto	11.5	4.9	5.6	0	11.1	9.1	0	4.3	11.1	5
Banks	26.9	23.2	22.2	14.3	30.6	18.2	0	26.1	25.9	37.5
Food	3.8	13.4	5.6	14.3	8.3	9.1	0	4.3	7.4	10
Health	0	4.9	5.6	14.3	2.8	4.5	11.1	13	3.7	2.5
Ind	15.4	13.4	11.1	0	11.1	31.8	44.4	21.7	11.1	12.5
Ins	3.8	2.4	5.6	0	5.6	0	11.1	4.3	0	2.5
Pers	3.8	4.9	11.1	14.3	5.6	9.1	11.1	4.3	11.1	7.5
Real	0	8.5	5.6	14.3	5.6	4.5	22.2	13	7.4	2.5
Tech	15.4	8.5	5.6	0	8.3	9.1	0	4.3	7.4	10
Util	19.2	15.9	22.2	28.6	11.1	4.5	0	4.3	14.8	10
	Contemporaneous Components									
	Auto	Banks	Food	Health	Ind	Ins	Pers	Real	Tech	Util
Auto	36.4	2.1	0	6.1	6.2	10.4	0	4.7	2.4	1.7
Banks	9.1	54.2	6.2	12.1	12.5	29.2	13.6	18.6	7.3	25.9
Food	0	1.4	37.5	12.1	3.6	4.2	0	4.7	4.9	6.9
Health	6.1	2.8	12.5	24.2	5.4	2.1	13.6	4.7	2.4	3.4
Ind	21.2	9.7	12.5	18.2	48.2	8.3	9.1	14	17.1	13.8
Ins	0	2.1	0	9.1	1.8	4.2	36.4	4.7	4.9	0
Pers	15.2	9.7	6.2	3	3.6	20.8	9.1	4.7	4.9	10.3
Real	6.1	5.6	6.2	6.1	5.4	4.2	9.1	27.9	7.3	6.9
Tech	3	2.1	6.2	3	6.2	4.2	9.1	7	43.9	3.4
Util	3	10.4	12.5	6.1	7.1	12.5	0	9.3	4.9	27.6

Table 5 reports the amount of linkages from the column sector to the row sector, standardized by the total number of linkages of the column sector. Thus, cell (i, j) reports the share of connections from sector j to sector i, out of all sector j linkages.

Table 6: Cross-Country Linkages

	Granger Components									
	DE	IT	FR	IE	ES	AT	NL	BE	LU	FI
DE	19.7	11.8	25.8	12.5	4.5	25	12.5	29	42.9	0
IT	9.8	5.9	7.9	0	11.4	0	4.2	9.7	0	0
FR	36.1	47.1	29.2	50	36.4	50	25	25.8	14.3	0
IE	4.9	5.9	5.6	0	9.1	0	12.5	9.7	14.3	100
ES	6.6	5.9	11.2	0	18.2	0	4.2	6.5	14.3	0
AT	6.6	17.6	4.5	25	4.5	12.5	12.5	12.9	0	0
NL	4.9	0	5.6	0	0	0	8.3	0	0	0
BE	8.2	5.9	5.6	12.5	9.1	12.5	12.5	0	14.3	0
LU	3.3	0	1.1	0	4.5	0	4.2	3.2	0	0
FI	0	0	3.4	0	2.3	0	4.2	3.2	0	0
	Contemporaneous Components									
	DE	IT	FR	IE	ES	AT	NL	BE	LU	FI
DE	46.3	19	20.9	23.5	17	13.3	20	17.1	5.6	15.4
IT	2.7	28.6	2.1	0	9.4	0	2	0	5.6	0
FR	27.2	19	45	35.3	18.9	26.7	30	41.5	33.3	23.1
IE	2.7	0	3.1	0	1.9	13.3	2	4.9	5.6	0
ES	6.1	23.8	5.2	5.9	26.4	6.7	8	12.2	16.7	7.7
AT	6.8	4.8	7.9	5.9	7.5	6.7	24	9.8	5.6	7.7
NL	1.4	0	2.1	11.8	1.9	13.3	2	2.4	5.6	7.7
BE	4.8	0	8.9	11.8	9.4	6.7	8	4.9	5.6	15.4
LU	0.7	4.8	3.1	5.9	5.7	6.7	2	2.4	11.1	7.7
FI	1.4	0	1.6	0	1.9	6.7	2	4.9	5.6	15.4

Table 6 reports the amount of linkages from the column country to the row country, standardized by the total number of linkages of the column country. Thus, cell (i, j) reports the share of connections from country j to country i, out of all country j linkages.