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European stock market volatility connectedness: The role of country and sector membership

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ABSTRACT

The literature suggests that the country in which a company is listed, i.e., its country membership, is the main determinant of its price volatility co-movements in the global stock market but, at the same time, this body of literature also recognizes the relevance of industry sector membership for understanding risk transmission. Drawing on recent advances in time series analysis, we are able to define an extensive network structure for 645 'large-cap' companies from 35 European countries, and to decompose the total market volatility connectedness into its respective country and sector membership contributions. Using the firm level as our unit of analysis, we find that traditional (more aggregate) approaches, which rely on market indices to study international connectedness, present an incomplete (and, biased) picture of risk transmission between international stock markets. We show that, in general, a company's country membership is indeed a more significant determinant than that of its sector membership; however, from a risk management perspective, there are significant heterogeneities at the company level that need to be duly considered and quantified so as to better anticipate crucial dependencies in certain countries or sectors in periods of market distress, such as that resulting from the current conflict in Ukraine and the economic sanctions being imposed. We summarize the connectedness of individual companies in a network that international risk managers and investors can use to assess global financial market dependencies and to inform their risk management practices.

1. Introduction

Unprecedented levels of capital market integration and recurrent financial crises at the global scale have led risk managers to explore just how international financial markets interconnect. The conflict in Ukraine has put this question center stage in the Europe-wide debate that seeks to anticipate which firms, in which countries and in which sectors, are likely to be affected. Risk managers are keen to determine which markets are the main recipients of risk shocks and which individual companies (if any) are critical for the smooth functioning of the global financial network (see, for example, Diebold and Yilmaz, 2009, 2015; Demirer et al., 2018). Here, we focus on sector and country membership to identify firm connectedness. More specifically, on the understanding that energy (oil and gas) and country connections in Europe are certain to be challenged by potential sanctions associated with the war in Ukraine, we locate those firms most likely to be affected. Moreover, the questions we address directly impact the interests

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of central banks and regulators concerned with the preservation of financial stability and largely determine which investors tend to survive episodes of market turmoil and which do not.

The extant literature has employed a rather high level of aggregation in seeking to understand international spillovers and market interconnectedness and, as such, has tended to focus its interest on national and sectoral indices when conducting its empirical analyses (e.g., Baruník and Křehlík, 2018; Chuliá et al., 2018; Lyócsa et al., 2019; BenSaïda, 2019; Baumöhl and Shahzad, 2019). Additionally and alternatively, when working with firm-level data, previous studies have tended to focus on specific sectors – typically financial firms (e.g., Demirer et al., 2018; Lin and Chen, 2021) or the energy sector (e.g., Ewing and Thompson, 2007; Hamilton, 2009; Fukunaga et al., 2011; Du et al., 2011; Elyasiani et al., 2011; Reboredo, 2011, 2012a,b; Balcilar and Ozdemir, 2013; Le and Chang, 2015; Salisu and Oloko, 2015; Reboredo and Ugolini, 2016; Yu et al., 2018; Hamdi et al., 2019) - or on just one country – more often than not, the US (e.g., Barigozzi and Brownlees, 2019; Barigozzi et al., 2021). This reflects, in part, the fact that the econometrics literature has recently developed the tools required to work with large panels of data.[1]

Here, we contribute to this line of research by reducing granularity to the firm level in our efforts to address questions about the cross-sectional determinants of market co-movements. By their very construction, market or sectoral indices remove the idiosyncratic components of asset prices and, as such, they are also likely to eliminate most of the abnormal interdependencies that characterize the market. Indices are appropriate for deriving a factor representation of asset returns but not for understanding the network dynamics of the global financial system. Moreover, the influence of grouping sectors and countries on the price formation of domestic markets likely results in substantial biases in volatility connectedness, because of relevant omitted factors, especially in regions with a low level of economic integration.

We propose novel connectedness indicators, based on the volatility spillover calculations, we follow the seminal works of Diebold and Yilmaz (2009, 2012) and Demirer et al. (2018), among others, in this respect, which are specifically designed to answer our main research question: For any given firm, what is the relative importance of sector and country membership in driving connectedness in an international financial network? To illustrate the utility of the proposed indicators and the network analysis that we carry out, we consider an oil company listed on the London Stock Exchange. From the perspective of risk management, we are interested in determining which has greater relevance: being an energy company (i.e. the sector) or being listed in the UK (i.e. the country). In this context, "greater relevance" can be understood as which type of connectedness is most significant in explaining the volatility of this British energy firm. This question is critical for risk assessment; yet, to date, an answer has remained elusive. On the one hand, risk-diversification is reduced when portfolio assets are highly interconnected; however, on the other, and from the perspective of a chief risk officer, understanding external sources of market volatility is critical for adopting appropriate mitigation strategies or planning adverse scenarios. The answer to this, admittedly, rather simple question requires that the network architecture in which the company's stock is traded be characterized adequately.

We estimate a large network using data for the period October 2, 2015 to March 26, 2021 ($T = 1431$). As input for our network, we use firm-level stock return conditional volatilities, estimated daily for 645 'large-caps' listed in one of the 35 European countries in our database during the sample period.[2] Our network covers almost all the countries on the subcontinent (except for Lithuania, Luxembourg, Moldova and Belarus) and the 16 industry sector categories retrieved from $MarketWatch$. In general lines, we follow the methodological proposal developed by Demirer et al. (2018), which combines elastic networks (Zou and Zhang, 2009) with the spillover statistics proposed by Diebold and Yilmaz (2012).

Other studies of note are Ferreira and Santa-Clara (2011), who evidence the importance of disaggregating the prediction of stock returns into three main parts, the dividend–price ratio, earnings growth, and price–earnings ratio growth. Unlike ours, these authors' contribution points out to the estimation of stock price components and not to volatility prediction for risk management, within a multicountry setting. The closest study to the one reported here is Raddant and Kenett (2021). These authors, however, use a larger number of series ($N = 4000$) and include, in their calculations, firms listed on the North American and Asian markets. These data choices, together with a different methodology, lead to substantively different results. By characterizing the network structure using conditional correlations, their models are unable to estimate the directional predictability across any pair of firms in the system (i.e. they cannot estimate directional connectedness), which is critical for the risk characterization we pursue here. Related to this, in contrast with their study, our approach considers the time series properties of the system in the estimation of each edge (i.e. link) in the network, because it is based on the forecast error variance decomposition of a VAR representation of the system as a whole, instead of resorting to conditional correlations. Finally, they also deal with different time zones, which forces them to transform the original series, reducing their sample size from daily to weekly, with unknown consequences for the network characterization. There exist other methodologies that allow estimating networks in a VAR-sparse context, using correlations or causality tests in the Granger sense or in the frequency domain (see Baruník and Křehlík, 2018; Barigozzi and Brownlees, 2019; Barigozzi et al., 2021. Those papers allow predicting the network but do not providing quantitative spillovers between nodes (the output of the latter two studies is an adjacency matrix only containing zero–one entries). Although they solve important questions about spillovers, they are not entirely suited to answer our research question.

In general, our results point to the relatively greater importance of country over industry categories, in line with findings elsewhere (e.g., Forbes and Chinn, 2004; Raddant and Kenett, 2021). However, our results highlight notable differences across sectors and countries, and between firms within their groups, in terms, that is, of connectedness dynamics, outcomes which have

[1] See Bai and Wang (2016) and Chen et al. (2022) for a review of the literature dedicated to factor models with both large time series and cross-sectional dimensions, and Demirer et al. (2018) and Barigozzi and Brownlees (2019) for time-series network representations based on vector autoregressions with large numbers of cross-sectional units.

[2] Details regarding the sample period are provided in Section 3.

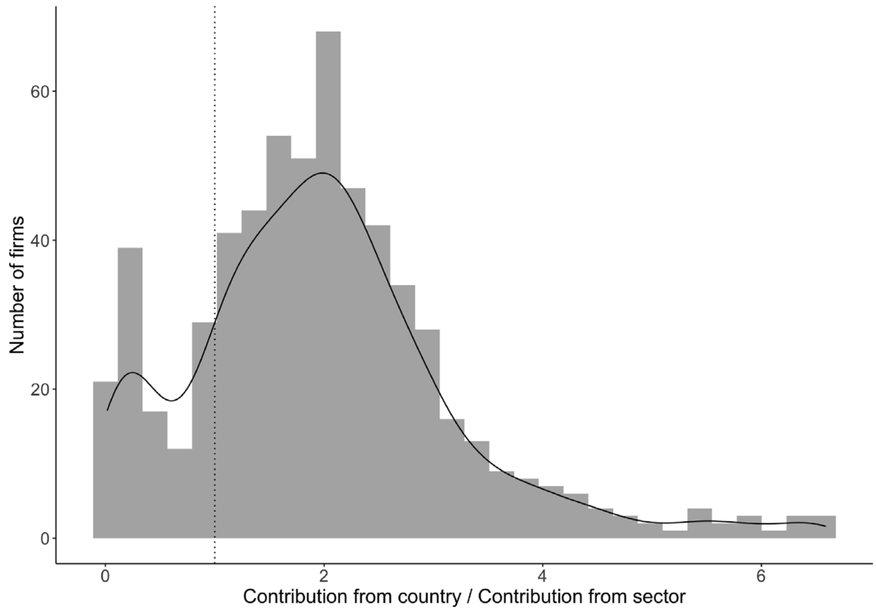

Fig. 1. Histogram and smoothed kernel density estimate of the ratio of average contributions from a firm's country and against average contributions from a firm's sector. Value equal to one means that a firm has exactly the same connectedness from their country than from their sector.

to date gone totally unreported. Fig. 1 presents a rapid overview of our main results and the contribution of our study. For any given firm i in our sample, $i = 1, \ldots, 645$, we estimate the average influence of firms within its country and we estimate the average influence of firms within its industry sector. This figure plots the frequency occurrence and the kernel density plot of the ratio of the average country vs. sector influence for all firms. A number greater than 1 means, in short, that country membership is more relevant than sector membership in explaining connectedness for firm i. This is, in fact, the case for most of the companies in our sample, but not for all of them. Indeed, a second peak occurs in the distribution below one, indicating that heterogeneities exist at the firm level. These patterns – described in detail in Section 4 – are not apparent, however, when we employ a higher level of aggregation or when we focus on one sector or on one country at a time.

Our study has direct implications for the literature that examines interconnectedness and which, moreover, has tended to emphasize the role played by industry and country factors in driving market returns in international stock markets (Forbes and Chinn, 2004; Bekaert et al., 2009, 2011; Lewis, 2011; Dutt and Mihov, 2013; Di Giovanni and Hale, 2021). After all, at least since (Roll, 1992), sector similarity across countries has been considered a likely explanation of co-movements in international financial markets while, at the same time, country specific effects are deemed a salient feature of portfolio holdings among international investors, i.e. home-bias (see Lewis, 2011). These studies, however, suffer from a high level of abstraction either because the stock level information is condensed in indices before connectedness is estimated or because their attention is restricted to just one market or just one country at a time. Here, we empirically illustrate the limitations of these approaches for characterizing the complex network formed by European financial markets. We do so by comparing our baseline network with the network obtained when using the sectoral or country indices as input variables as opposed to individual stock volatilities. We show that the information obtained using an aggregate approach is of limited relevance for an investor interested in individual stocks, or for a regulator monitoring financial stability and the systemic evolution of major companies, and highlight the fact that intra-group connectedness presents heterogeneous behaviors.

Professional opinion has changed (on multiple occasions) with regards to the existence of abnormal interdependence across global financial markets that might emerge during episodes of crisis, swinging from rebuttal (e.g., Bracker et al., 1999; Rigobon, 2002; Forbes and Rigobon, 2002) to outright support (e.g., Corsetti et al., 2005; Diebold and Yilmaz, 2009; Raddant and Kenett, 2021). Here, we provide further evidence of changes in the network structure during periods of turmoil, which can be tracked down by analyzing changes in the interconnectedness within sectors and within countries. Our contribution is, we believe, a natural complement to the aforementioned literature, based on indices and a factor representation of international stock markets. While these previous studies have focused on sector and country as factors for explaining average returns, we directly explore the role played by these grouping variables in terms of interconnectedness, an approach – to the best of our knowledge – undertaken here for the first time. It is our contention that this analysis can be used to assess, for example, the impact of sanctions derived from the conflict in Ukraine, on the understanding that, in this instance, European firms with close ties to Russia or Ukraine or to the energy sector are likely to be the ones most affected.[3]

The rest of this study is organized as follows. Section 2 presents a detailed outline of the methodology, Section 3 describes the dataset used, Section 4 contains our main results and Section 5 concludes.

2. Methodology

Here, we present the models used to estimate the volatility of log-returns, the mathematical definitions of connectedness, the elastic net regularization techniques that have to be applied to address the curse of dimensionality, and a set of novel connectedness indicators across country- and sector-clustering attributes.

2.1. Estimation of volatility

Taylor (1982) initially proposed latent autoregressive processes to model the logarithm of the squared volatilities as an alternative to ARCH specifications (Engle, 1982). Thereafter, numerous studies have improved their estimations by means of reparameterization, using simple central hierarchical reparametizations (see Gelfand et al., 1995) or a centered parameterization of a state space model, the preferred method, it is claimed, for the performance of the Gibbs sampler (see Pitt and Shephard, 1999). In each of these cases, the model used to approximate volatility is given by (we omit subindex i for each firm):

$$y_t = e^{\xi_t/2}\varepsilon_t \tag{1}$$

$$\xi_t = \mu + \phi(\xi_{t-1} - \mu) + \sigma\eta_t \tag{2}$$

where y_t are the log-returns for each time t, $t \in \{1, \dots, T\}$, ε_t and η_t are the iid normal innovations with mean 0, and each ξ_t corresponds to the latent time-varying volatility process with initial state distributed according to the stationary distribution. We estimate μ, ϕ and σ following the stochastic volatility models proposed by Kastner and Frühwirth-Schnatter (2014). These authors use Markov chain Monte Carlo sampling, fully implemented in the statistical software R, via the R-package '*stochvol*' (Kastner, 2019), which enhances previous proposals for estimating stochastic volatility of returns by Kim et al. (1998) and Jacquier et al. (2002). The preference for a stochastic volatility model comes mainly because we do not want to assume the volatility deterministically, but as a random variable that can be modeled in the network, which cannot be achieved with an ARCH-based model.

2.2. Elastic net regularization for the variance–covariance matrix

The main input for conducting our connectedness analysis is the variance–covariance matrix of return volatilities. This is calculated in a generalized linear regression framework and solved using elastic net regularization. We apply regularization to all the system equations in our vector autoregressive (VAR) system. Here, for ease of representation, we present a simplified version of elastic nets for the one-series case.

Let us consider an extension of an ordinary least squares (OLS) regression model with a penalization term:

$$\hat{\beta}_{OLS} = argmin_{\beta}\left[\sum_{t=1}^{T}\left(\xi_t - \sum_{i=1}^{N}\beta_i x_{it}\right)^2 + \lambda\sum_{i=1}^{N}|\beta_i|^q\right] \tag{3}$$

where ξ_t is the volatility in period t that we estimate from observed log returns using the autoregressive processes stated in Eq. (2), and x_{it} are the lagged volatilities in a horizon H of stock i at time t. T is the number of observations and N the number of firms, $\lambda, q > 0$. The most common powers used in the penalization term are $q = 1$, which corresponds to the least absolute shrinkage and selection operator or Lasso, proposed by Tibshirani (1996), and $q = 2$, which corresponds to ridge regression (Hoerl and Kennard, 1970). If we expand this model by combining both the Lasso and the ridge regression, we obtain the adaptive elastic net, with the following solution:

$$\hat{\beta}_{AEnet} = argmin_{\beta}\left[\sum_{t=1}^{T}\left(\xi_t - \sum_{i=1}^{N}\beta_i x_{it}\right)^2 + \lambda\sum_{i=1}^{N}w_i\left(\frac{1}{2}|\beta_i| + \frac{1}{2}\beta_i^2\right)\right] \tag{4}$$

Elastic net regularization was first proposed by Zou and Zhang (2009) and it has several benefits that combine with the advantages afforded by Lasso and ridge. These benefits include the same sparsity representation as provided by Lasso, but with a better performance, as it is capable of using a larger number of parameters than of data observations. A weighted parameter is included – obtained with penalized OLS regression from Eq. (3) and with value $w_i = 1/\hat{\beta}_{OLS}$ – which is constant for all firms. After estimating a $\hat{\beta}_{AEnet}$ for each firm, we can then calculate the variance–covariance matrix from the decomposition of the deviation scores of the disturbances as follows:

$$\Sigma = (\Xi - X\hat{\beta})'(\Xi - X\hat{\beta})(1/T) \tag{5}$$

where Ξ is the $T \times N$ matrix with vectors ξ_t for each firm as columns, X is the $T \times N$ matrix where the columns are the lagged volatilities in a horizon H, ξ_{t-H}, $\hat{\beta}$ is the $N \times N$ matrix where the columns are the estimated $\hat{\beta}_{AEnet}$ for each firm.

[3] We have created an interactive app - Individual Risk Spillovers App - in which researchers can build connectedness networks at the firm level for the 645 firms in our sample based on the values of the connectedness indices.

2.3. Connectedness indicators

We estimate the system's connectedness following Demirer et al. (2018), who extend previous proposals by Diebold and Yilmaz (2009, 2012) to the case of many series, when the traditional estimation of VAR becomes unfeasible. Let us start from an N-variable VAR of order p, $x_t = \sum_{l=1}^{p} \Phi_l x_{t-l} + \varepsilon_t$, where $\varepsilon_t \sim N(0,\epsilon)$ $\forall t,\ \epsilon > 0$. The moving-average representation of the system is given by $x_t = \sum_{l=1}^{t} A_l \varepsilon_l$, where A_l is an $N \times N$ matrix that follows the recursion $A_l = \sum_{m=1}^{p} \Phi_m A_{l-m}$, where A_0 is the identity matrix. We denote the elements of the variance–covariance matrix Σ calculated in Eq. (5) as σ_{ij}. A selector vector e_i is included, which consists of ones in the ith coordinates and zeros otherwise. According to Demirer et al. (2018), the connectedness from firm j to firm i in the system, H steps ahead, is a function of the generalized forecast error variance decomposition, given by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_j)}, \quad H = 1,2,3,\ldots \tag{6}$$

By construction, the sum of all contributions does not add up to 1, so it is common to normalize each term dividing by the sum of the contributions from the system to the same firm i, which allows us to define the directional connectedness from firm j to firm i as follows:

$$\tilde{\theta}_{ij}^{g}(H) := C_{i\leftarrow j}^{H} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

2.4. Group connectedness generalization

Suppose a division of the N firms in K subgroups. In particular, for a subgroup $k \in \{1,\ldots,K\}$, we have a list of indices $I_k \subseteq \{1,\ldots,N\}$ that define which firms belong to that subgroup. Therefore, calculating the connectedness from a subgroup k to a firm i in a horizon H is straightforward:

$$C_{i\leftarrow k}^{H} = \frac{\sum_{j\in I_k} \tilde{\theta}_{ij}^{g}(H)}{|I_k|} \tag{8}$$

where $|I_k|$ represents the cardinal of the subgroup. In the same way, we can calculate the influence of one subgroup on another. Let it be $k_1, k_2 \in \{1,\ldots,K\}$ two subgroups. The influence of subgroup k_2 on subgroup k_1 is denoted by:

$$C_{k_1\Leftarrow k_2}^{H} = \frac{\sum_{\substack{i\in I_{k_1}\\ j\in I_{k_2}}} \tilde{\theta}_{ij}^{g}(H)}{|I_{k_2}|} \tag{9}$$

Instead of comparing two elements from the same division of firms (e.g., comparing two countries or two sectors), with this methodology we can compare the same element within two group organizations (e.g., compare the connectedness of a firm in terms of its country membership and its sector membership).

3. Data

Stock price data were retrieved from Bloomberg and consist of the daily stock prices in USD for 645 firms listed on one of the 35 national stock markets in Europe between October 2, 2015 and March 26, 2021 (i.e. $N = 645$, $T = 1,431$). The countries considered are Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Malta, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, and the United Kingdom. In addition to the country classification, each firm was classified in one of the following 16 industry sectors: Agriculture, Automotive, Basic Materials/Resources, Business/Consumer Services, Energy Services, Consumer Goods, Financial Services, Health Care/Life Sciences, Industrial Goods, Leisure/Arts/Hospitality, Media/Entertainment, Real Estate/Construction, Retail/Wholesale, Technology, Telecommunication Services and Transportation/Logistics.

We estimate the log differences of the original series of prices and the stochastic volatility of the returns for each firm in our sample as stated in Eq. (2). We present summary statistics of these volatilities in Table 1. The statistics were calculated for each firm in our sample, but in the table, we only show country averages for ease of representation. The first column shows the number of companies in each country. Montenegro, Slovenia, Slovakia and Ukraine present the lowest number of firms, while the United Kingdom and Turkey present the highest number. Spikes in the volatility means, standard deviations, medians, and maximums can be observed in countries such as Bulgaria, Cyprus, Ireland and Latvia, which points to a higher average distribution of volatilities in these countries, and a higher dispersion of their values. Likewise, kurtosis is greater in Bosnia and Herzegovina, Latvia, Malta, Slovakia and Ukraine, which attests to the fat-tails in the volatility distributions across time of these markets. These spikes are mainly a consequence of the relatively smaller number of companies included in the sub-sample of these countries.

We would like to emphasize that we need to balance our time series dimension with our cross-sectional dimension. That is, to be able to estimate our network we need to guarantee a balanced panel of data. The earlier we start the more we are forced to reduce the number of firms in our network (due to the presence of many missing observations at the beginning of the sample). Given that our main contribution is directly related with the number of individual firms, we opted for keeping as many firms as possible and

Table 1
Summary statistics for stochastic volatilities of returns grouped by country.

Country	Abbreviation	Num.Firms	Mean	St.dev	Min	Median	Max	Skewness	Kurtosis
Austria	AUT	15	0.49	0.19	0.21	0.44	1.78	2.46	10.35
Belgium	BEL	13	0.35	0.15	0.16	0.32	1.31	2.68	11.39
Bosnia and Herz.	BIH	13	0.94	1.15	0.09	0.67	15.62	5.65	57.78
Bulgaria	BGR	10	1.77	1.62	0.16	1.28	17.72	2.57	13.74
Croatia	HRV	12	0.76	0.34	0.25	0.69	3.25	2.54	13.69
Cyprus	CYP	26	2.07	2.47	0.18	1.25	23.50	3.03	15.60
Czech Rep.	CZE	8	0.45	0.17	0.22	0.41	1.69	2.64	11.95
Denmark	DNK	13	0.63	0.25	0.23	0.58	2.07	1.76	5.76
Estonia	EST	11	1.10	1.12	0.17	0.72	11.53	2.74	13.91
Finland	FIN	16	0.50	0.18	0.22	0.47	1.62	2.01	7.21
France	FRA	32	0.33	0.14	0.16	0.30	1.10	2.22	7.42
Germany	DEU	20	0.35	0.14	0.17	0.32	1.08	2.06	6.08
Greece	GRC	37	0.94	0.45	0.30	0.84	3.63	1.98	6.62
Hungary	HUN	10	0.83	0.52	0.22	0.67	4.57	2.41	9.03
Iceland	ISL	12	1.00	0.63	0.21	0.85	5.53	1.72	5.48
Ireland	IRL	22	2.50	3.67	0.20	1.11	38.78	2.77	15.10
Italy	ITA	18	0.40	0.15	0.18	0.37	1.28	2.18	8.17
Latvia	LVA	12	2.12	3.69	0.12	0.96	43.90	5.08	41.33
Malta	MLT	16	0.97	1.53	0.07	0.41	18.85	4.81	46.95
Montenegro	MNE	7	1.28	1.22	0.10	0.89	14.70	3.51	26.75
Netherlands	NLD	17	0.37	0.15	0.17	0.34	1.21	2.11	7.30
Norway	NOR	16	0.56	0.20	0.26	0.51	1.64	2.20	7.55
Poland	POL	19	0.60	0.17	0.32	0.56	1.67	1.85	6.19
Portugal	PRT	11	0.62	0.27	0.23	0.57	2.85	2.01	9.14
Romania	ROU	11	0.63	0.26	0.24	0.57	2.49	2.15	8.47
Russia	RUS	27	0.49	0.20	0.20	0.45	1.82	2.23	8.83
Serbia	SRB	8	0.99	0.72	0.17	0.78	7.37	2.73	12.68
Slovakia	SVK	4	0.88	1.53	0.08	0.58	28.29	9.52	167.52
Slovenia	SVN	7	1.20	0.91	0.22	0.94	10.68	2.29	11.42
Spain	ESP	22	0.43	0.18	0.19	0.38	1.48	2.26	8.17
Sweden	SWE	26	0.40	0.15	0.19	0.36	1.19	2.06	6.32
Switzerland	CHE	17	0.31	0.12	0.14	0.28	1.02	2.38	8.98
Turkey	TUR	61	0.80	0.29	0.33	0.74	2.29	1.53	3.67
Ukraine	UKR	5	1.00	1.91	0.04	0.33	22.19	6.03	60.74
United Kingdom	GBR	71	0.43	0.20	0.19	0.38	1.66	2.44	9.39

reduce accordingly the time-series dimension of our dataset. This means that, while our study is solid for answering our research question, more crises periods would be necessary for providing definite answers in terms of time varying interconnectedness. A future line of research regarding the treatment of missing data would enhance the scope of this study. For example it could be explored the methodology advanced by Freyberger et al. (2021). These authors propose a novel model for data imputation on asset pricing datasets using conditional means and weighted least squares. Nevertheless, such approaches are not designed to input missing values when they are concentrated at certain time periods, e.g., at the beginning or the end of the sample, as in our case.

Our selection of listed companies, in order to include a large set of countries, necessarily consists of big cap companies and our results must be understood in such context. Therefore, risk managers should pay special attention when extrapolating this study results to the risk evaluation of a small or medium firm, which can be substantially different. See Allen et al. (2012) for a way to predict the volatility connectedness of small and medium firms in relation to that of large cap companies.

4. Results

4.1. European stock market network: A preliminary description

Fig. 2 shows the European stock market network with granularity at the individual company level and with the emphasis on the country membership attribute. Each node corresponds to a firm while the links between the nodes represent the volatility connectedness between any pair of firms. The color of each node corresponds to the listing country of each firm, while the color of the edges shows the level of connectedness, ranging from least (brown) to most connected (green). The forecast horizon was established at 10 days in the variance decomposition exercise used for constructing the network. The position of the nodes was determined using the ForceAtlas2 algorithm (Jacomy et al., 2014) implemented in Gephi, with the aim of providing a readable spatialization of the network, with good time performance.

A hub appears in the top right of the figure (colored orange), which corresponds to Turkey. The presence of this hub means we can expect a high degree of interconnectedness between the Turkish firms in our sample, but weaker links between these firms and their international counterparts. A number of other countries can be differentiated from those that make up the main network: for instance, in the bottom left, Russia (brown), and, in the bottom center, Cyprus (light blue). The center is occupied by Iceland (purple), while in the bottom right a small hub of five firms is present representing Bosnia and Herzegovina (pink). As such, relatively

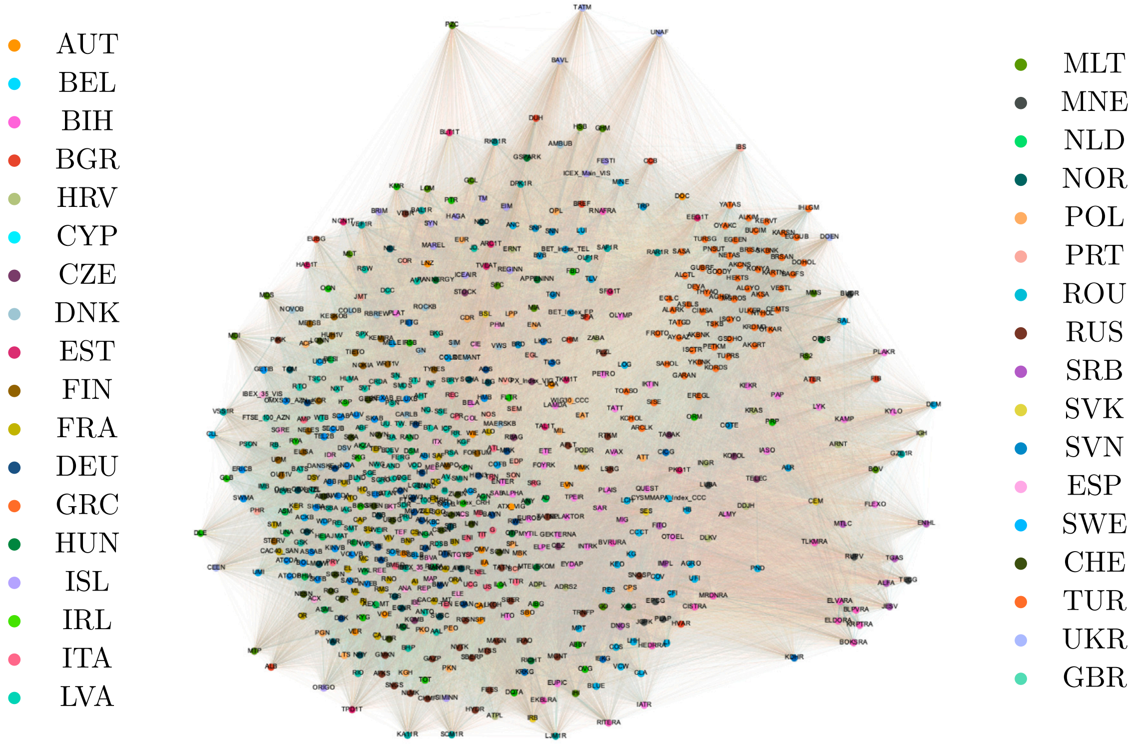

Fig. 2. Individual firm network graph. Node color corresponds to each firm's country. Edge color corresponds to each firm's connectedness, ranging from brown (lower) to green (higher). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

isolated countries are easily distinguishable from the European network as a whole; yet, in contrast, countries such as the United Kingdom, occupying a position roughly to the left of the figure (light turquoise), are barely distinguishable as a separate color unit within the network, because of the interconnections that the firms in these countries present with each other and with the rest of the system.

Likewise, Fig. 3 shows the network based on sector attributes, with the color of each node corresponding to the sector in which the firm operates. To facilitate visualization, we have opted to remove those countries – namely, Serbia, Rumania, Bosnia and Herzegovina, Iceland, Montenegro, Ukraine and Turkey – with a low degree of connectedness. Notice that some sectors, including Financial Services (colored gray) are located in the middle of the network. The Energy Services sector (orange) is also readily identifiable grouped largely to the right of the network. In contrast, for some sectors, including Basic Materials/Resources and Consumer Goods, it is not possible to identify any kind of interconnectedness by simple visual inspection. Both Figs. 2 and 3 plot the values described in Eq. (7).

Fig. 4 shows the results of a further preliminary analysis which focuses on the connectedness estimators grouped by country and by sector, as explained in Eq. (9). A number of general patterns emerge: for instance, in the case of grouping by country (left network), we estimate a low degree of connectedness with the rest of the system for Eastern and Southern European countries (green and pink nodes, respectively), with the ForceAtlas2 algorithm locating them at some distance from the network's main hub. In contrast, Western European countries tend to be concentrated relatively close to each other in the central region of the network, indicating a higher degree of connectedness than that of their Eastern and Southern European counterparts. In the case of grouping by sector (right network), the pivotal role played by Financial Services in the European stock market network is evident, as not only does it occupy the center of the network, but also its incoming and outgoing links tend to be thicker than those of the rest of the network. A ring of sectors of secondary importance surrounds the Financial Services made up of companies operating in Energy Services, Basic Materials/Resources, Real Estate/Construction, Consumer Goods and Industrial Goods, all of which we would expect to be more directly affected by risk shocks originating from the Financial sector. Other sectors, such as Agriculture, remain somewhat isolated from the network's main hub.

Albeit a step in the right direction, a traditional network analysis of financial connectedness – as the one outlined above – even when conducted at the level of the individual company, cannot fully address our main research question: that is, is country (sector) membership driving a firm's volatility more strongly than sector (country) membership?

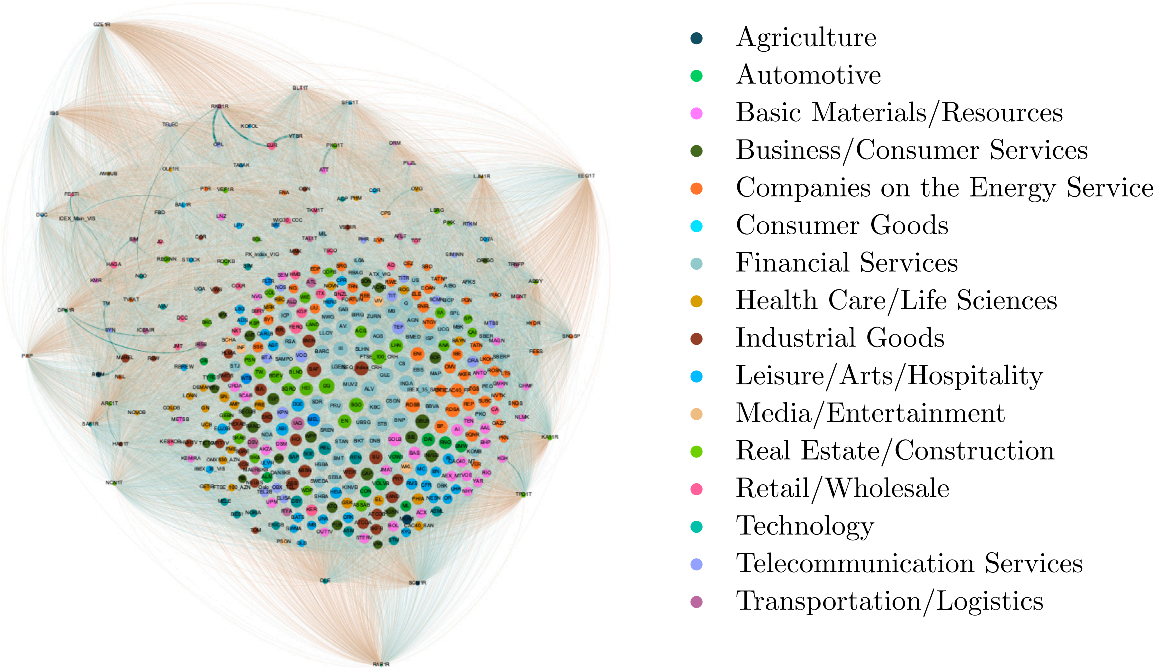

Fig. 3. Individual firm network graph after some disconnected countries were removed. Node color corresponds to the firm's sector. Edge color corresponds to firm's connectedness. Both directions are plotted ranging from brown (lower) to green (higher). Node size represents connectedness degree calculated by Gephi. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

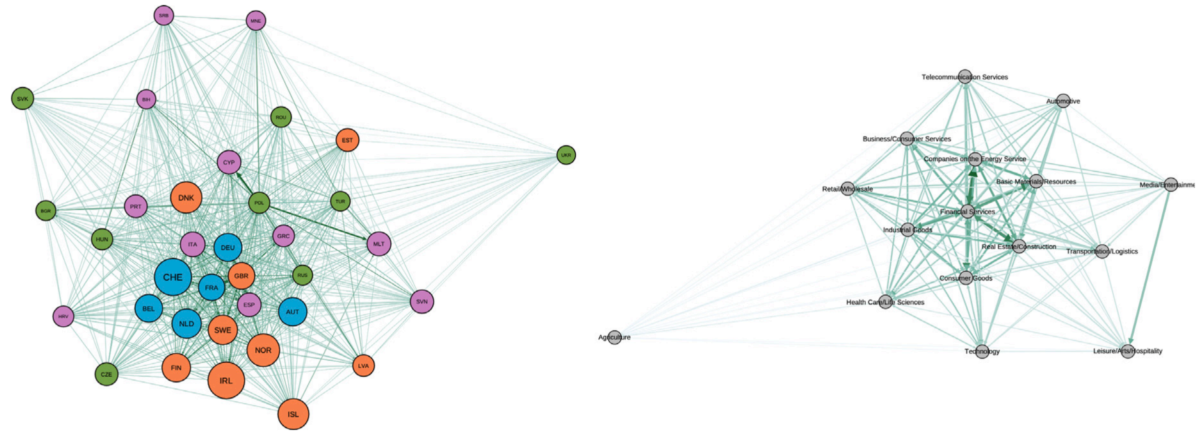

Fig. 4. Country (left) and sector (right) connectedness networks.

4.2. Country and sector membership attributes as connectedness drivers

Using Eq. (8), we calculate the individual connectedness indicators for countries and sectors. Recall that these indicators are constructed using firm level connectedness and that they represent the average of the directional volatility connectedness from all firms in the same group on any outsider firm. Tables 2 and 3 summarize the individual connectedness indicators. In Table 2, we present the summary statistics of the country indicators using country as the grouping variable. For example, if we consider the second column in this table, corresponding to the cross-country mean of the country connectedness indicators, we observe that, for firms listed in Ukraine ($Mean = 8.25$) or Serbia ($Mean = 4.58$), the influence of firms in the same country is far more important, on average, than it is, for example, for companies listed in Cyprus ($Mean = 0.18$), the United Kingdom ($Mean = 0.44$) or Malta ($Mean = 0.52$). Similarly, depending on the country, we also detect considerable variation within a country: for instance, firms in Ukraine ($Std.Dev. = 7.52$) and Slovakia ($Std.Dev. = 4.28$) are much more heterogeneous in terms of connectedness than their counterparts in the United Kingdom ($Std.Dev. = 0.07$) or France ($Std.Dev. = 0.05$).

Table 2
Summary statistics of firm individual spillovers from their own country grouped by country.

Country	Firms	Mean	Std.Dev.	Median	IQ Range	Skewness	Kurtosis
AUT	15	1.08	0.64	0.85	0.59	1.55	1.67
BEL	13	0.88	0.28	0.86	0.37	0.42	−1.38
BIH	13	2.14	2.37	0.15	4.62	0.14	−2.12
BGR	10	2.23	2.49	1.32	4.26	0.36	−1.75
HRV	12	3.20	1.28	3.36	1.79	0.03	−1.01
CYP	26	0.18	0.57	0.03	0.02	3.47	11.28
CZE	8	3.05	1.83	2.67	3.11	0.23	−1.85
DNK	13	1.57	0.87	1.47	0.77	1.29	1.14
EST	11	2.10	1.76	2.08	3.37	−0.03	−1.82
FIN	16	1.04	0.29	0.95	0.37	0.01	−0.95
FRA	32	0.55	0.05	0.55	0.07	−0.07	−0.86
DEU	20	0.67	0.11	0.64	0.14	0.43	−0.72
GRC	37	0.97	0.43	0.97	0.67	0.16	−1.26
HUN	10	2.19	1.77	1.47	1.94	0.64	−1.18
ISL	12	2.52	1.21	2.34	0.54	0.14	0.03
IRL	22	0.62	0.56	0.52	0.54	1.48	1.94
ITA	18	0.77	0.11	0.75	0.11	0.06	−0.49
LVA	12	0.71	1.58	0.03	0.10	1.74	1.40
MLT	16	0.52	1.38	0.02	0.02	2.11	2.70
MNE	7	2.22	3.84	0.00	3.24	0.84	−1.32
NLD	17	0.70	0.14	0.67	0.09	1.02	1.16
NOR	16	0.94	0.50	0.77	0.27	1.66	1.34
POL	19	1.17	0.51	1.17	0.70	0.57	−0.49
PRT	11	1.84	1.27	1.41	0.90	1.67	1.91
ROU	11	3.74	0.75	3.77	0.67	−0.30	−0.50
RUS	27	0.94	0.32	0.85	0.49	−0.10	−0.37
SRB	8	4.58	3.80	7.08	7.14	−0.40	−2.02
SVK	4	2.16	4.28	0.02	2.15	0.75	−1.69
SVN	7	3.20	2.61	3.56	2.36	0.26	−1.17
ESP	22	0.66	0.18	0.61	0.12	2.56	7.05
SWE	26	0.63	0.11	0.61	0.07	1.77	3.26
CHE	17	0.75	0.17	0.77	0.23	0.52	−0.57
TUR	61	1.13	0.16	1.16	0.18	−1.15	1.27
UKR	5	8.25	7.52	12.71	14.13	−0.28	−2.25
GBR	71	0.44	0.07	0.44	0.09	0.68	0.28

Table 3 presents the summary statistics of the indicators using sector as the grouping variable. Recall, sector indicators are constructed at the firm level and represent the average influence of all other firms in the same sector on any given firm. Accordingly, the influence is measured as the average of the directional volatility connectedness from all other firms in the same sector to any given firm. Unlike the country indicator, here the average value of connectedness remains relatively similar across sectors. For instance, if we consider the second column in this table, we observe that the sector with the largest average influence of all the categories on their risk dynamics is Media/Entertainment ($Mean = 1.78$), while the firms least influenced (in relative terms) by their peers in the same sector are those in Financial Services ($Mean = 0.30$) and Energy Services ($Mean = 0.33$). The Leisure/Arts/Hospitality sector, while presenting the second highest average ($Mean = 0.80$), presents quite disperse values. This is evident if we observe the difference between columns two (*Mean*) and four (*Median*), as the 0.50 quantile is significantly lower than its average ($Median = 0.09$). This outcome is also evident in the case of Agriculture ($Mean = 0.52$, $Median = 0.05$). The heterogeneity within sectors is shown in column four of Table 3. Again, the level of heterogeneity is lower by sector than it was by country. The greatest degree of heterogeneity is recorded in the Media/Entertainment sector ($Std.Dev. = 1.75$) and the lowest in Financial Services ($Std.Dev. = 0.10$).

The heterogeneities at the firm level can be further decomposed (see Fig. 5, panels A and B). The left panel compares three smoothed kernel density estimates of the ratios between the country and sector connectedness values for three different countries, while the right panel compares the densities of the ratios for three different sectors. Both cases present evidence of heterogeneities between groups. If we focus our attention first on panel A, while the great majority of firms listed on the stock market in Cyprus concentrate at values below 1 – indicating that for this set of firms the sector is more relevant as a source of connectedness than it is for other firms listed on the same national market – the opposite holds for firms listed in Turkey, where the ratio, in almost all cases, is much greater than 1. In this sense, Germany is more similar to Turkey than it is to Cyprus, that is, the country effect is, on average, more relevant than the sector effect.

If we now focus our attention on panel B, we can see the respective outcomes for the Automotive (Aut), Financial Services (Fin) and Leisure/Arts/Hospitality (LAH) sectors. It is evident that in the case of the Fin kernel of firms, country is a more relevant connectedness factor than is sector, with a distribution value well above 1. In contrast, a large fraction of LAH firms depends more on their sector than on their country, as its kernel is, in the main, below 1. Finally, in the case of Aut, the sector's firms fall equally into both camps, its distribution being situated around the value 1.

Table 3
Summary statistics of firm individual spillovers from their own sector grouped by sector.

Sector	Abbreviation	Firms	Mean	Std.Dev.	Median	IQ Range	Skewness	Kurtosis
Agriculture	Agr	4	0.52	0.94	0.05	0.48	0.75	−1.69
Automotive	Aut	20	0.76	0.34	0.72	0.58	−0.04	−1.07
Basic Materials/Resources	Mat	59	0.38	0.17	0.34	0.23	0.56	0.05
Business/Consumer Services	Bus	34	0.46	0.31	0.39	0.18	1.79	3.34
Companies on the Energy Service	Ene	75	0.33	0.16	0.30	0.10	1.48	3.16
Consumer Goods	Good	56	0.40	0.21	0.35	0.19	1.31	1.33
Financial Services	Fin	114	0.30	0.10	0.29	0.06	0.81	1.76
Health Care/Life Sciences	HCLF	35	0.61	0.33	0.53	0.29	1.10	0.38
Industrial Goods	Ind	46	0.49	0.31	0.39	0.24	1.66	2.42
Leisure/Arts/Hospitality	LAH	17	0.80	1.16	0.09	0.93	1.33	0.19
Media/Entertainment	ME	9	1.78	1.75	1.27	0.95	1.53	1.24
Real Estate/Construction	REC	70	0.36	0.23	0.27	0.27	1.10	0.37
Retail/Wholesale	RW	30	0.74	0.38	0.72	0.45	0.80	0.02
Technology	Tech	24	0.62	0.34	0.55	0.45	0.52	−0.36
Telecommunication Services	Tel	28	0.72	0.52	0.53	0.56	1.16	0.32
Transportation/Logistics	Trans	24	0.53	0.40	0.46	0.60	0.52	−1.08

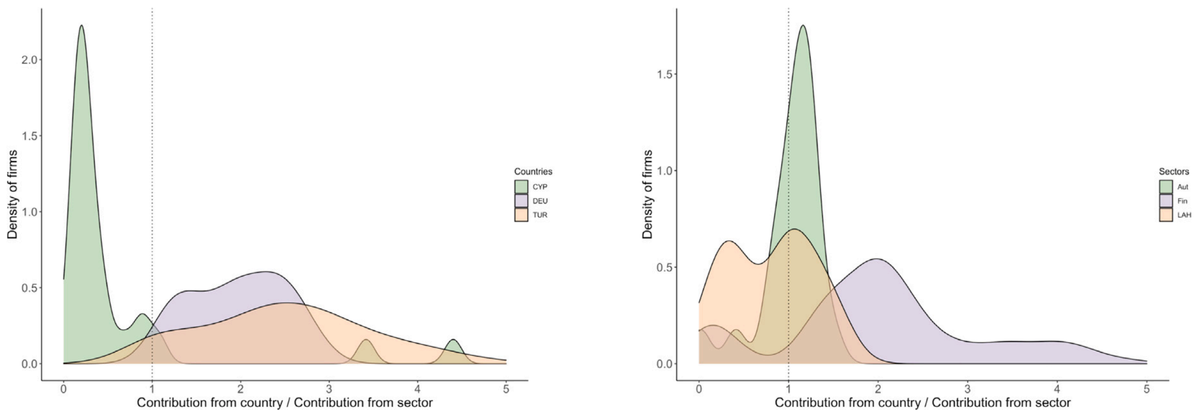

Fig. 5. Distribution of individual contributions to firms from their own countries for three countries (left): Cyprus (CYP), Deutschland (DEU) and Turkey (TUR), and from their own sectors for three sectors (right): Automotive (Aut), Financial Services (Fin), and Leisure/Arts/Hospitality (LAH).

In summary, we find heterogeneities at almost all levels when seeking to determine the relative importance of sector or country characteristics. Indeed, there are, in fact, more heterogeneities than those described up to this point. For instance, if we return to the question raised in the introduction: Which is more relevant, being an energy company or being listed in the UK? According to Tables 2 and 3, a preliminary answer is provided by the ratio between the average interconnectedness of UK firms (0.44) and the average interconnectedness of energy firms (0.33), which equals 1.33; thus, country is more important in relative terms to explain connectedness for UK Energy Service firms. Of course, this answer is conditional on the degree of connectedness of specific firms in this sector. Indeed, as we shall show, this answer does indeed vary, depending on whether the firm is British Petroleum, Shell or SSE Energy Services. To be able to arrive at a more precise answer, we need to analyze country and sector connectedness indicators at the firm level.

4.3. Country and sector effects at company level

The advantages of seeking to answer our research question by conducting this analysis at the firm level are illustrated in Fig. 6, panels A and B. The figure includes a country and a sector example, showing the values obtained from Eq. (8) for Germany (panel A) and for Energy Services (panel B). In the case of German companies, connectedness ranges between 0.51 and 0.90, while in the case of companies offering Energy Services, connectedness ranges between 0.08 and 0.97.

Additionally, Tables 4 and 5 show the sector and country connectedness indicators from Eq. (8) for the subsample of energy companies listed in the United Kingdom. Table 4 shows the top five countries in terms of their influence on each UK energy company in our sample, while Table 5 shows the top five firms in the sector worldwide. Here, to control for the estimated influence, we include uncertainty intervals, constructed by simulation.[4]

[4] More specifically, we calculate 100 times the value of the point statistic, after randomly removing 20% of the connections in each simulation step and, then, we select the value of the statistic for the 16th and 84th percentiles, which we include in the table.

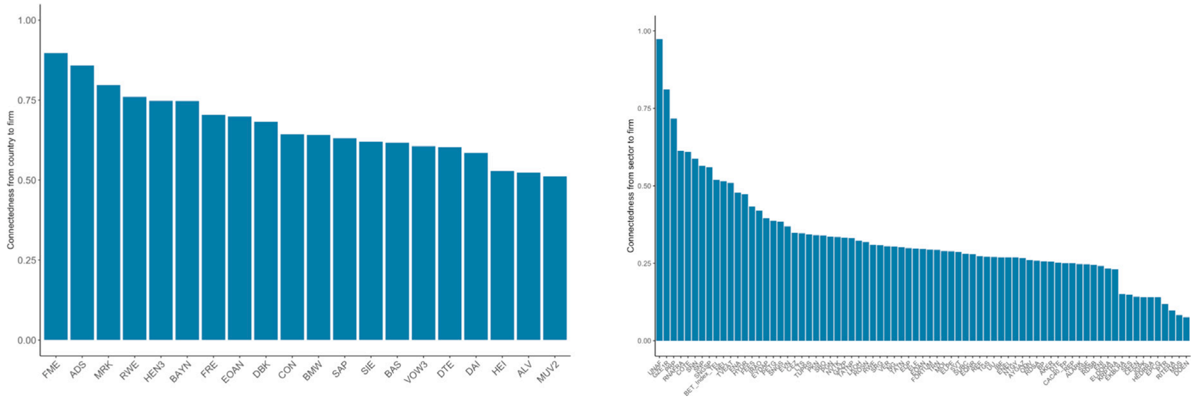

Fig. 6. Contribution from country Germany to its firms (left) and from sector Companies on the Energy Service to its firms (right).

Table 4
Top 5 country contributors to each of the 6 studied firms belonging to United Kingdom and Companies on the Energy Service. BP corresponds to British Petroleum, RDSB to Royal Dutch Shell, NG to National Grid, UU to United Utilities Group and SVT to Severn Trent.

Firm	Country				
	Top 1	Top 2	Top 3	Top 4	Top 5
BP	*FRA* 0.35 (0.33–0.36)	*GBR* 0.34 (0.28–0.36)	*NLD* 0.34 (0.30–0.36)	*ESP* 0.31 (0.28–0.33)	*BEL* 0.29 (0.26–0.32)
RDSB	*FRA* 0.36 (0.35–0.38)	*NLD* 0.35 (0.32–0.37)	*GBR* 0.31 (0.26–0.33)	*DEU* 0.31 (0.29–0.33)	*BEL* 0.30 (0.27–0.34)
NG	*GBR* 0.49 (0.37–0.53)	*CHE* 0.27 (0.26–0.28)	*ITA* 0.26 (0.24–0.28)	*NLD* 0.25 (0.24–0.27)	*ESP* 0.24 (0.23–0.25)
SSE	*GBR* 0.48 (0.39–0.52)	*FRA* 0.26 (0.25–0.26)	*ESP* 0.25 (0.24–0.27)	*NLD* 0.25 (0.23–0.26)	*CHE* 0.24 (0.23–0.26)
UU	*GBR* 0.48 (0.47–0.52)	*NLD* 0.29 (0.28–0.30)	*FRA* 0.26 (0.25–0.27)	*CHE* 0.25 (0.24–0.27)	*DEU* 0.25 (0.24–0.26)
SVT	*GBR* 0.51 (0.50–0.55)	*ITA* 0.25 (0.23–0.26)	*CHE* 0.25 (0.23–0.26)	*NLD* 0.24 (0.23–0.25)	*FRA* 0.24 (0.23–0.25)

Note that Tables 4 and 5 provide richer information than all the results presented up to this point. For instance, in relation to our original question, it is now evident that for British Petroleum (BP), the average impact of all other companies listed on the London Stock Exchange is 0.34 (Table 4), while the average impact of all other European firms in the energy sector is 0.26 (Table 5), with a ratio of 1.31. This means that BP's country membership is more relevant than that of its sector for understanding the company's market volatility variation over time. The same holds for Royal Dutch Shell (RDSB) – with values of 0.31 and 0.25, respectively, and a ratio of 1.24 – as well as for all other energy firms: National Grid (NG), SSE, United Utilities Group (UU) and Severn Trent (SVT), which present even more pronounced ratios of 1.63, 1.92, 1.78 and 1.76, respectively. This means that in the case of UU, the average transmission of the country characteristic is almost twice the average transmission of the sector characteristic; whereas in the case of BP, the two grouping variables assert almost the same influence. Interestingly, it is also evident that own market volatility for the United Kingdom (*GBR*), in Tables 4 and 5, is not even the most relevant, in terms of the average connection for BP or RDSB, whereas France (*FRA*) asserts a greater average influence (albeit, one that is very similar to the UK effect: 0.35 vs. 0.34, and 0.36 vs. 0.31, for BP and RDSB, respectively).

More examples of heterogeneities can be observed within a group. In the case of Financial Services, the connectedness of Raiff Bank Ava (BAVL), a Ukrainian company, presents a strong country dependence, with an average spillover index of 12.71, which is c. 21 times higher than the average for this sector of 0.59. An example in the opposite direction is presented by the firm Dunav Osiguranje (DNOS), a Serbian firm with a sector influence of 0.15, which is c. 15 times higher than the country average of 0.01. Finally, here, Table 6 shows the five non-Russian companies that are most connected to Russia, to exemplify a pre-crisis risk analysis that can be undertaken using this methodology. As mentioned, an interactive tool that allows analyses to be conducted by firm, country and/or sector is available online.[5]

[5] Individual Risk Spillovers App

Table 5
Top 5 sector contributors to each of the 6 studied firms belonging to United Kingdom and Companies on the Energy Service. BP corresponds to British Petroleum, RDSB to Royal Dutch Shell, NG to National Grid, UU to United Utilities Group and SVT to Severn Trent.

Firm	Sector				
	Top 1	Top 2	Top 3	Top 4	Top 5
BP	*Ene* 0.26 (0.21–0.29)	*Fin* 0.20 (0.19–0.21)	*Aut* 0.18 (0.16–0.21)	*Bus* 0.17 (0.16–0.18)	*Mat* 0.15 (0.14–0.17)
RDSB	*Ene* 0.25 (0.20–0.27)	*Fin* 0.22 (0.21–0.23)	*Bus* 0.18 (0.17–0.19)	*Aut* 0.16 (0.14–0.18)	*Tech* 0.15 (0.13–0.17)
NG	*Ene* 0.30 (0.20–0.35)	*Fin* 0.18 (0.17–0.19)	*ME* 0.17 (0.13–0.20)	*RW* 0.16 (0.14–0.18)	*Tel* 0.16 (0.14–0.17)
SSE	*Ene* 0.25 (0.16–0.28)	*Fin* 0.19 (0.18–0.20)	*ME* 0.19 (0.14–0.23)	*Bus* 0.16 (0.16–0.18)	*Tel* 0.16 (0.15–0.18)
UU	*Ene* 0.27 (0.18–0.31)	*Fin* 0.19 (0.18–0.20)	*Ind* 0.16 (0.15–0.17)	*RW* 0.16 (0.15–0.18)	*REC* 0.15 (0.14–0.16)
SVT	*Ene* 0.29 (0.18–0.33)	*RW* 0.18 (0.16–0.19)	*Ind* 0.17 (0.16–0.18)	*Fin* 0.16 (0.16–0.17)	*Bus* 0.16 (0.15–0.17)

Table 6
Top 5 non-Russian firms with higher connectedness from Russia.

Full name	Ticker	Country	Sector
LCP Holdings & Investments	LI	Cyprus	Financial Services
Donegal Investment Group	DQ7A	Ireland	Consumer Goods
CD Projekt	CDR	Poland	Consumer Goods
BHP Group	BHP	United Kingdom	Basic Materials/Resources
Norsk Hydro	NHY	Norway	Basic Materials/Resources

4.4. Network dynamics at different levels of aggregation

Frequently, a country or a sector analysis is sufficient to satisfy immediate research needs. For instance, a central bank may be interested in determining which countries are responsible for the shocks affecting the rest of the markets in a certain region from a macroeconomic perspective or a researcher might be interested in testing the hypothesis that the financial sector amplifies the shocks to the rest of the economy, as has been suggested by the recent macrofinance literature. In such cases, aggregation is clearly justified, as our unit of analysis is not at the individual level (the same applies here to traditional portfolio allocation problems); yet, this is true primarily from a regulator's point of view. The specific question we explore in this section is how our results change depending on the particular aggregation we opt to employ. There are two options: (1) "estimating–aggregating" or E–A, that is, we estimate the connectedness in our sample and, then, aggregate across the unit of analysis (i.e. the sector or country), following the guidelines in the previous sections; or, (2) "aggregating–estimating" or A–E, that is, we aggregate individual dynamics (e.g. using country or sectoral indices) and then estimate the connectedness indicators, which is the traditional approach taken by the literature.

In what follows we show that estimated connectedness between countries or between sectors following the E–A or the A–E pathways differs depending on this methodological choice, an outcome that the literature typically fails to acknowledge. Additionally, the size of the specific country or sector in which we are interested is crucial for understanding these changes in the connectedness indicators. In general, the larger the group (measured in terms of the number of companies from which it is comprised), the more the A–E approach tends to underestimate the own variance shares and, therefore, to overestimate cross-spillovers (taking as its point of reference the estimates taken from the volatilities at the level of the individual company). In contrast, for countries or sectors made up from a relatively small number of firms, cross-spillovers are larger when we adopt the E–A approach than when we employ the A–E approach. In future research, it will be possible to deepen into the overestimation produced by no disaggregating, especially for larger groups.

Table 7, corresponds to the spillover table by country, when adopting the E–A method, while Table 8, shows the spillover table obtained when employing the second method (A–E). The first pattern to emerge is that, for the smaller countries in terms of sample size, the values in the main diagonal of Table 7 are lower than those in the main diagonal of Table 8 – e.g. Slovakia (SVK) 8.6 vs. 80.1; Ukraine (UKR) 41.3 vs. 97.1 – while the situation is reversed for the larger countries – e.g. Turkey (TUR) 69.1 vs. 27.0; United Kingdom (GBR) 31.5 vs. 8.4. The values in the main diagonal are associated with the percentage of the variance share that can be explained by the own variance in each market, that is, with the connectedness we assume to be produced within a given country and which does not result from international cross-spillovers. It is impossible to determine, a priori, whether cross-spillovers are being underestimated or overestimated, but there is a strong correlation with market size (measured as the number of firms in each country).

A summary statistic – the aggregate cross-spillover statistic – is included in the last column, last row entry for each of the tables. In Tables 7 and 8, the statistic presents values of 77.9 and 73.9, respectively, showing that the importance of cross-spillovers is understated (on average) when we opt to aggregate before estimating market connectedness (A–E), compared that is to an approach

Table 7
Country spillover table using method E–A.

	AUT	BEL	BIH	BGR	HRV	CYP	CZE	DNK	EST	FIN	FRA	DEU	GRC	HUN	ISL	IRL	ITA	LVA	MLT	MNE	NLD	NOR	POL	PRT	ROU	RUS	SRB	SVK	SVN	ESP	SWE	CHE	TUR	UKR	GBR	*Contribution from*
AUT	16.2	3.0	0.1	0.3	0.7	0.4	1.0	1.5	0.4	2.2	8.6	4.8	3.9	1.2	0.6	2.3	4.2	0.2	0.2	0.1	3.7	3.2	2.4	1.5	0.5	3.3	0.1	0.1	0.4	5.0	5.0	4.0	3.3	0.1	15.4	83.8
BEL	2.6	11.4	0.1	0.1	0.5	0.2	0.8	1.7	0.3	3.0	10.2	5.9	2.8	1.0	0.3	2.4	4.7	0.1	0.1	0.0	5.1	3.3	2.0	1.3	0.3	2.9	0.0	0.0	0.3	5.7	6.4	4.8	2.4	0.0	17.2	88.6
BIH	1.6	1.3	27.8	0.8	0.7	5.0	1.1	0.9	0.6	1.5	3.6	2.2	2.6	5.5	1.2	1.7	2.1	0.4	0.6	1.9	1.7	1.5	7.0	0.9	4.7	1.7	1.3	1.4	0.5	2.4	2.2	1.8	2.9	0.1	6.7	72.2
BGR	1.9	1.5	0.9	22.3	1.0	1.5	1.6	1.3	0.8	2.3	4.0	2.5	3.0	6.2	2.1	1.7	2.3	0.7	0.4	0.4	1.9	1.8	8.8	4.0	1.2	2.1	0.4	0.4	0.6	3.3	2.5	2.0	3.9	0.2	8.7	77.7
HRV	1.9	1.7	0.4	0.7	38.4	1.2	1.0	1.1	1.2	1.9	4.0	2.5	4.0	1.1	1.2	1.7	2.4	0.4	0.4	0.4	1.9	1.8	2.0	1.2	0.9	2.7	0.3	0.3	0.6	3.1	2.8	2.0	3.9	0.1	8.9	61.6
CYP	3.3	2.0	0.3	0.6	2.0	4.8	1.7	2.4	0.8	2.1	5.8	3.3	5.2	0.9	2.5	1.8	3.7	0.3	0.3	0.1	2.5	2.2	14.3	1.4	2.6	3.6	0.1	0.1	1.0	3.6	3.3	3.2	6.8	0.1	10.8	95.2
CZE	2.6	2.5	0.8	0.6	0.9	0.7	24.4	1.4	0.8	2.2	6.1	3.3	4.4	1.1	0.7	2.1	3.4	0.4	0.3	0.3	2.9	2.3	2.4	1.3	1.2	2.7	0.3	0.3	0.5	4.0	3.7	3.3	3.4	0.0	12.7	75.6
DNK	2.2	2.9	0.1	0.3	0.5	0.4	0.8	20.4	0.5	3.1	7.2	4.3	3.2	1.0	0.9	2.5	4.1	0.3	0.2	0.1	3.4	2.7	1.9	1.6	0.5	2.4	0.1	0.1	0.2	4.6	5.5	3.7	3.5	0.1	14.6	79.6
EST	2.1	2.1	0.3	0.5	1.2	0.6	1.1	1.5	23.1	2.3	4.8	3.1	3.7	1.2	0.6	2.0	3.0	0.4	0.3	0.2	2.3	2.0	5.3	1.2	3.5	2.4	0.2	0.1	0.6	3.5	3.6	2.8	9.0	0.1	9.3	76.9
FIN	2.1	3.3	0.1	0.3	0.6	0.2	0.8	2.1	0.4	16.6	9.4	5.0	2.3	0.7	0.5	2.2	3.6	0.1	0.1	0.0	4.5	3.3	1.6	1.5	0.4	2.3	0.1	0.0	0.2	4.7	8.7	4.4	2.5	0.1	15.2	83.4
FRA	2.7	3.7	0.1	0.1	0.4	0.1	0.7	1.5	0.2	2.8	17.5	6.3	2.5	0.9	0.2	2.3	4.8	0.1	0.1	0.0	5.4	3.5	2.0	1.1	0.2	3.0	0.0	0.0	0.2	6.0	6.9	4.9	2.1	0.0	17.6	82.5
DEU	2.6	3.8	0.1	0.1	0.4	0.2	0.7	1.6	0.2	2.6	10.8	13.4	2.7	1.0	0.2	2.2	4.8	0.1	0.1	0.0	5.1	3.4	2.1	1.3	0.2	3.1	0.0	0.0	0.2	6.0	6.4	5.0	2.9	0.0	16.8	86.6
GRC	2.4	2.0	0.4	0.4	0.9	1.0	1.0	1.3	0.6	1.6	4.9	3.1	35.9	1.0	0.8	1.9	3.5	0.3	0.3	0.2	2.4	2.0	2.0	1.4	1.0	2.5	0.3	0.1	0.4	3.6	3.0	2.6	3.3	0.1	11.7	64.1
HUN	2.6	2.5	0.3	0.4	1.0	0.5	1.0	1.6	0.6	1.9	6.5	4.0	3.5	21.9	0.6	2.0	3.7	0.2	0.3	0.1	2.8	2.5	4.6	1.4	0.7	2.9	0.2	0.2	0.5	4.3	3.8	3.2	4.3	0.1	13.2	78.1
ISL	2.6	1.9	0.3	0.5	1.4	0.4	1.0	2.5	0.7	2.8	4.4	2.5	4.6	1.0	30.2	2.0	2.1	0.3	0.4	0.2	2.2	2.2	3.2	1.4	1.6	2.0	0.2	0.1	0.4	3.0	3.8	2.5	3.3	0.1	12.2	69.8
IRL	2.4	2.8	0.3	0.3	0.7	0.4	1.0	1.7	0.5	2.3	7.2	4.2	4.4	1.5	2.0	13.6	3.8	0.2	0.2	0.1	4.0	2.4	3.5	1.4	0.8	2.7	0.1	0.1	0.3	4.7	4.6	3.5	4.2	0.1	17.9	86.4
ITA	2.7	3.7	0.1	0.1	0.4	0.2	0.8	1.8	0.3	2.3	10.2	5.7	3.6	1.1	0.2	2.3	13.9	0.1	0.1	0.0	4.5	3.1	2.2	1.6	0.3	2.9	0.0	0.0	0.3	6.4	5.6	4.6	2.0	0.0	16.9	86.1
LVA	5.6	1.9	0.3	1.0	0.9	1.0	1.0	1.9	0.7	2.2	4.8	2.9	6.6	2.4	2.0	2.5	2.8	8.5	0.4	0.2	2.4	3.2	6.8	1.4	3.2	2.6	0.2	0.2	0.9	3.4	3.6	2.4	10.1	0.1	10.1	91.5
MLT	2.0	1.9	0.5	0.5	0.8	0.8	0.9	2.1	0.6	1.8	4.0	2.6	3.9	1.7	4.6	1.8	3.1	0.4	8.4	0.2	1.9	1.9	14.3	1.4	2.8	2.6	0.3	0.2	0.5	2.8	3.1	2.2	12.4	0.1	10.9	91.6
MNE	1.9	1.5	2.1	0.4	0.7	3.2	0.7	1.0	0.5	1.5	4.1	2.7	2.6	0.7	0.5	1.3	2.6	0.3	0.4	15.5	2.1	1.6	11.0	0.9	0.8	2.2	1.0	1.0	0.5	2.7	2.6	2.3	19.7	0.1	7.5	84.5
NLD	2.4	3.8	0.1	0.1	0.4	0.1	0.7	1.6	0.2	2.8	11.1	6.0	2.5	0.9	0.2	2.3	4.3	0.1	0.1	0.0	11.8	3.4	1.9	1.2	0.2	3.1	0.0	0.0	0.2	5.8	6.8	5.0	2.4	0.0	18.4	88.2
NOR	2.7	3.3	0.1	0.2	0.5	0.2	0.7	1.7	0.4	2.8	9.4	5.2	2.8	1.0	0.4	2.0	3.9	0.1	0.2	0.0	4.4	15.1	2.0	1.3	0.4	3.7	0.1	0.1	0.3	5.2	6.7	4.5	2.6	0.0	16.0	84.9
POL	2.7	2.8	0.2	0.3	0.8	0.4	1.1	1.5	0.5	1.9	7.1	4.4	3.8	1.3	0.6	1.9	4.0	0.2	0.2	0.1	3.4	2.6	22.3	1.4	0.7	3.6	0.1	0.1	0.5	4.7	4.3	3.3	3.4	0.1	13.7	77.7
PRT	2.6	2.8	0.2	0.5	0.7	0.5	0.9	1.9	0.5	2.7	6.9	4.1	3.7	1.1	0.6	2.2	4.5	0.2	0.3	0.1	3.4	2.7	1.9	20.3	0.7	2.5	0.1	0.1	0.4	4.8	4.3	3.6	3.0	0.1	15.2	79.7
ROU	1.6	1.6	0.8	0.7	0.9	1.1	1.2	1.3	0.8	1.7	3.3	1.9	4.7	0.9	1.3	1.5	2.4	0.6	0.6	0.4	1.7	1.7	1.9	1.3	41.1	2.0	0.4	0.4	0.7	2.5	3.0	1.9	2.5	0.2	9.5	58.9
RUS	2.6	2.8	0.2	0.2	0.7	0.3	0.8	1.2	0.4	1.8	7.6	4.6	3.3	1.0	0.4	1.7	3.7	0.2	0.2	0.1	3.7	3.4	3.8	1.1	0.4	25.3	0.1	0.1	0.3	3.8	4.4	3.8	3.9	0.1	12.3	74.7
SRB	3.4	1.3	2.9	0.6	0.9	4.0	1.0	1.0	0.7	1.2	3.0	1.8	5.8	0.7	0.7	1.3	2.0	0.4	0.5	2.4	1.4	1.2	4.5	0.8	0.9	1.8	36.7	0.9	0.6	1.9	2.0	2.1	3.5	0.2	5.9	63.3
SVK	6.6	2.9	2.2	1.9	0.9	3.7	1.6	1.5	0.7	2.7	5.8	4.3	2.7	6.5	1.0	1.7	3.0	0.3	0.4	1.5	2.7	2.3	2.3	1.3	1.2	2.5	0.9	8.6	0.8	3.6	3.9	2.8	4.3	0.1	10.7	91.4
SVN	2.7	2.3	0.4	0.5	0.9	1.6	1.0	1.3	0.9	1.8	5.2	3.2	3.5	1.2	0.5	1.9	3.3	0.4	0.5	0.3	2.6	2.2	9.1	1.5	0.8	2.4	0.4	0.3	22.4	4.1	3.4	3.0	3.6	0.2	10.5	77.6
ESP	2.7	3.5	0.1	0.1	0.5	0.2	0.8	1.7	0.3	2.4	10.1	5.7	3.1	1.1	0.3	2.4	5.0	0.1	0.1	0.0	4.7	3.2	2.1	1.4	0.3	2.5	0.0	0.0	0.3	14.6	6.0	4.6	2.1	0.0	17.9	85.4
SWE	2.3	3.4	0.1	0.1	0.4	0.2	0.6	1.8	0.3	3.9	10.3	5.6	2.2	0.8	0.3	2.2	4.0	0.1	0.1	0.0	4.9	3.7	1.7	1.1	0.3	2.6	0.0	0.0	0.2	5.3	16.5	5.0	1.8	0.0	18.2	83.5
CHE	2.7	3.6	0.1	0.1	0.4	0.2	0.7	1.7	0.3	2.9	10.3	5.9	2.6	1.0	0.3	2.3	4.5	0.1	0.1	0.0	5.0	3.5	1.9	1.3	0.3	3.1	0.0	0.0	0.3	5.7	7.0	12.7	1.8	0.0	17.9	87.3
TUR	1.0	1.1	0.2	0.3	0.4	0.3	0.4	0.8	0.3	0.9	2.8	2.1	1.7	0.6	0.3	0.8	1.2	0.1	0.2	0.1	1.5	1.0	1.1	0.7	0.2	1.8	0.1	0.0	0.1	1.5	1.5	1.1	69.1	0.1	4.5	30.9
UKR	1.1	1.2	0.4	0.3	0.4	0.9	0.3	1.0	0.5	1.2	3.3	1.8	1.7	0.7	0.6	1.4	1.4	0.5	0.6	0.3	1.6	1.1	1.2	0.7	0.5	1.3	0.4	0.1	0.4	2.1	2.2	1.5	18.1	41.3	8.0	58.7
GBR	2.4	3.1	0.1	0.1	0.5	0.2	0.7	1.6	0.3	2.4	9.0	4.9	3.0	0.9	0.3	2.7	4.1	0.1	0.1	0.0	4.6	3.0	1.8	1.4	0.4	2.5	0.0	0.0	0.2	5.4	6.2	4.4	1.8	0.0	31.5	68.5
Contribution to	87.2	85.4	15.6	14.1	24.9	31.7	31.3	52.5	18.0	75.6	225.6	132.3	116.8	50.8	29.8	67.0	115.9	8.7	9.2	10.2	108.3	84.8	136.6	45.5	35.0	87.5	8.3	7.1	14.1	139.3	149.0	111.8	160.9	2.7	433.3	2726.6
Contribution to with own	103.4	96.8	43.4	36.4	63.3	36.5	55.7	72.9	41.1	92.2	243.1	145.7	152.8	72.7	60.0	80.6	129.7	17.2	17.6	25.8	120.1	99.8	158.9	65.8	76.1	112.8	44.9	15.7	36.4	153.9	165.4	124.5	230.0	44.0	464.8	**77.9**

Table 8
Country spillover table using method A–E.

	AUT	BEL	BIH	BGR	HRV	CYP	CZE	DNK	EST	FIN	FRA	DEU	GRC	HUN	ISL	IRL	ITA	LVA	MLT	MNE	NLD	NOR	POL	PRT	ROU	RUS	SRB	SVK	SVN	ESP	SWE	CHE	TUR	UKR	GBR	*Contribution from*
AUT	8.7	5.4	0.1	1.2	1.4	0.3	4.3	3.1	1.4	4.6	5.9	5.4	2.7	2.5	1.1	2.0	4.9	0.2	0.2	0.1	5.5	4.8	3.2	4.4	2.1	2.7	0.1	0.0	0.5	5.6	4.5	4.8	1.2	0.0	5.0	91.3
BEL	5.0	8.1	0.1	1.1	1.3	0.2	3.5	3.8	1.3	4.9	6.4	5.7	2.6	2.1	1.2	1.8	5.2	0.2	0.2	0.1	6.0	4.3	2.9	4.3	2.0	2.2	0.1	0.0	0.4	5.6	5.3	5.7	1.1	0.0	5.4	91.9
BIH	0.6	0.8	74.3	1.0	1.4	1.4	1.3	0.5	1.3	0.2	0.4	0.2	0.8	1.0	0.7	0.6	0.3	0.0	1.0	2.2	0.5	0.3	1.6	0.6	1.5	0.0	1.9	0.5	1.3	0.5	0.4	0.3	0.1	0.1	0.4	25.7
BGR	4.2	3.6	0.3	24.5	3.5	0.9	3.9	2.2	2.3	3.0	3.5	3.2	3.2	3.0	1.7	1.6	2.8	0.4	0.8	0.6	3.3	2.9	2.6	2.8	3.3	0.8	0.6	0.2	1.6	3.2	2.5	3.1	1.1	0.0	3.0	75.5
HRV	3.7	3.6	0.4	3.3	22.5	0.9	4.3	2.5	2.5	2.9	3.6	3.1	2.7	2.9	2.2	1.7	3.2	0.6	0.8	0.5	3.3	3.4	3.3	2.5	3.4	1.4	0.7	0.1	1.4	3.4	2.6	3.1	0.7	0.1	2.7	77.5
CYP	1.9	1.7	0.9	2.2	2.2	48.8	3.5	1.8	2.7	1.5	1.5	1.5	1.9	3.1	1.4	1.1	1.5	0.3	1.0	1.5	1.4	1.7	2.1	1.3	2.0	0.4	1.3	0.4	1.5	1.6	1.2	1.4	0.5	0.2	1.3	51.2
CZE	5.5	4.7	0.2	1.7	2.0	0.7	10.4	2.8	2.4	4.1	4.9	4.7	2.9	3.5	1.5	2.0	4.3	0.4	0.3	0.3	4.5	4.1	3.3	3.8	3.3	2.3	0.4	0.0	0.8	4.8	3.8	4.0	1.2	0.0	4.3	89.6
DNK	4.1	5.3	0.1	1.1	1.3	0.4	3.0	11.3	1.1	4.9	5.6	5.3	2.2	2.4	0.9	1.8	4.5	0.3	0.2	0.1	5.8	4.8	3.2	3.9	2.2	2.1	0.2	0.0	0.4	4.5	5.6	5.5	1.1	0.0	4.8	88.7
EST	4.0	3.9	0.4	2.5	2.8	1.2	5.5	2.4	23.0	3.0	3.1	2.7	2.4	3.0	2.5	1.6	2.8	0.6	0.8	0.5	3.0	2.9	2.6	2.7	3.3	1.2	0.7	0.1	1.5	3.2	2.9	3.2	1.2	0.0	2.8	77.0
FIN	4.8	5.5	0.0	1.1	1.2	0.2	3.4	3.9	1.1	9.0	5.9	6.0	2.1	2.2	0.9	2.1	4.4	0.2	0.1	0.1	5.9	5.0	2.9	4.1	1.9	2.7	0.1	0.0	0.4	4.9	6.5	5.4	1.0	0.0	5.2	91.0
FRA	5.0	5.9	0.0	1.0	1.2	0.2	3.4	3.6	0.9	4.9	7.5	6.3	2.6	2.1	1.1	1.9	5.2	0.2	0.1	0.1	6.6	4.4	2.7	4.3	1.8	2.6	0.1	0.0	0.4	6.0	5.5	5.8	1.1	0.0	5.8	92.5
DEU	5.0	5.6	0.0	1.0	1.1	0.2	3.5	3.7	0.9	5.2	6.7	7.9	2.2	2.3	0.9	1.8	5.4	0.2	0.1	0.0	6.3	4.4	3.0	4.1	2.0	2.5	0.1	0.0	0.3	5.7	5.5	5.7	1.2	0.0	5.5	92.1
GRC	4.6	4.9	0.2	1.8	1.7	0.5	4.0	2.9	1.4	3.4	5.1	4.2	14.8	2.0	1.7	1.6	4.4	0.3	0.4	0.0	4.7	4.3	3.2	4.2	2.7	1.5	0.3	0.0	0.6	4.9	3.7	4.6	1.1	0.0	4.4	85.2
HUN	4.5	4.1	0.2	2.1	2.0	0.9	5.1	3.2	1.9	3.8	4.4	4.5	2.1	14.8	1.2	2.0	3.4	0.3	0.3	0.3	4.3	3.9	3.9	3.5	3.2	2.0	0.5	0.1	1.1	4.2	3.4	3.7	1.4	0.0	3.8	85.2
ISL	3.5	4.1	0.2	2.0	2.6	0.7	3.8	2.1	2.8	2.7	3.9	3.2	3.2	2.2	26.2	1.1	3.1	0.2	0.6	0.1	3.3	3.2	2.7	2.7	2.5	1.2	0.7	0.1	1.1	3.7	3.0	3.2	0.9	0.0	3.2	73.8
IRL	4.5	4.4	0.2	1.3	1.6	0.4	3.6	3.2	1.3	4.5	5.0	4.4	2.1	2.5	0.9	18.9	3.7	0.1	0.4	0.1	4.4	3.6	2.3	3.5	1.9	2.0	0.2	0.0	0.4	4.3	4.1	3.9	1.1	0.0	5.0	81.1
ITA	5.0	5.8	0.0	0.9	1.2	0.2	3.6	3.5	1.0	4.3	6.3	6.1	2.7	2.0	1.0	1.7	9.0	0.2	0.1	0.1	5.9	4.4	2.9	4.2	2.0	2.5	0.1	0.0	0.3	6.4	4.8	5.5	1.0	0.0	5.2	91.0
LVA	1.6	1.9	0.0	0.9	1.5	0.3	2.0	1.6	1.6	1.4	1.5	1.4	1.2	1.2	0.6	0.5	1.7	63.9	0.2	0.1	1.3	1.1	1.2	1.4	1.4	0.6	0.0	0.1	0.6	1.5	1.6	2.0	0.5	0.0	1.3	36.1
MLT	2.4	2.2	0.7	2.7	2.3	1.1	2.8	1.5	2.3	1.6	2.0	1.9	2.0	1.8	1.5	0.8	1.7	0.3	45.8	1.1	2.1	1.9	2.3	1.7	2.0	0.8	1.8	0.2	1.1	2.1	1.4	1.7	1.0	0.0	1.7	54.2
MNE	1.5	1.1	1.9	1.9	1.9	1.8	2.0	0.9	1.6	1.1	1.1	0.9	0.5	1.4	0.3	0.5	0.8	0.1	1.3	64.2	1.1	0.8	1.1	1.3	1.2	0.3	1.4	0.1	1.2	1.0	0.8	1.0	0.4	0.3	1.0	35.8
NLD	4.8	5.7	0.0	0.9	1.1	0.2	3.2	3.9	0.9	4.9	6.8	6.1	2.4	2.1	0.9	1.7	5.1	0.1	0.1	0.1	7.7	4.7	2.8	4.2	1.9	2.8	0.1	0.0	0.4	5.6	5.7	5.9	1.2	0.0	5.8	92.3
NOR	5.1	4.9	0.0	1.0	1.3	0.3	3.5	3.9	1.1	5.1	5.5	5.1	2.7	2.3	1.0	1.7	4.5	0.1	0.2	0.0	5.6	9.2	3.2	4.2	2.2	3.3	0.1	0.0	0.4	5.1	5.7	5.3	1.1	0.0	5.2	90.8
POL	4.6	4.6	0.3	1.4	1.9	0.5	3.9	3.5	1.4	4.0	4.7	4.8	2.7	3.3	1.3	1.5	4.2	0.2	0.4	0.2	4.7	4.5	12.4	3.8	2.5	3.0	0.3	0.1	0.6	4.8	4.2	4.3	1.4	0.0	4.0	87.6
PRT	5.1	5.4	0.1	1.0	1.1	0.2	3.5	3.4	1.1	4.6	5.8	5.2	2.9	2.3	1.0	1.8	4.7	0.2	0.2	0.1	5.6	4.6	3.0	10.2	2.0	2.6	0.1	0.0	0.5	5.9	4.6	5.0	1.1	0.0	5.1	89.8
ROU	4.0	4.0	0.3	2.2	2.5	0.6	5.1	3.2	2.0	3.4	4.1	4.1	3.0	3.4	1.5	1.6	3.6	0.4	0.6	0.2	4.2	4.0	3.1	3.3	16.3	1.9	0.4	0.0	1.1	3.9	3.3	4.0	1.1	0.0	3.5	83.7
RUS	4.8	4.2	0.0	0.3	0.8	0.1	3.3	2.9	0.7	4.6	5.5	4.8	1.6	1.9	0.7	1.5	4.1	0.1	0.1	0.0	5.7	5.5	3.7	3.9	1.7	15.5	0.0	0.0	0.1	4.9	5.1	4.8	1.8	0.0	4.9	84.5
SRB	2.1	2.0	1.4	2.4	2.4	1.4	3.4	1.4	2.1	1.6	1.9	1.7	1.8	2.4	1.6	1.0	1.4	0.1	1.8	1.5	1.7	1.7	2.0	1.6	2.3	0.7	45.2	0.2	1.3	1.8	1.5	1.6	0.9	0.3	1.8	54.8
SVK	0.4	0.6	0.6	1.1	0.5	0.8	0.4	0.3	0.4	0.4	0.4	0.4	0.2	0.5	0.5	0.2	0.3	0.1	0.4	0.8	0.4	0.3	0.7	0.5	0.3	0.1	0.6	86.1	0.3	0.3	0.4	0.4	0.1	0.0	0.3	13.9
SVN	2.4	2.4	0.8	2.7	2.7	1.3	3.3	1.6	2.5	2.0	2.4	2.0	1.7	3.0	1.8	0.9	1.6	0.4	1.2	0.8	2.2	2.1	2.3	2.2	2.7	0.8	1.1	0.1	41.0	2.1	1.7	2.1	0.4	0.0	1.9	59.0
ESP	5.2	5.6	0.1	0.9	1.2	0.2	3.6	3.2	1.1	4.4	6.5	5.9	2.7	2.2	1.1	1.8	5.9	0.2	0.2	0.1	5.9	4.5	3.0	4.8	1.9	2.6	0.1	0.0	0.4	8.2	4.8	5.2	1.1	0.0	5.7	91.8
SWE	4.4	5.6	0.0	0.8	1.0	0.2	3.0	4.2	1.0	6.1	6.3	6.0	2.1	1.9	0.9	1.8	4.6	0.2	0.1	0.1	6.3	5.3	2.8	3.9	1.7	2.8	0.1	0.0	0.3	5.1	8.6	6.2	1.0	0.0	5.6	91.4
CHE	4.6	5.8	0.0	0.9	1.1	0.2	3.0	4.0	1.0	4.9	6.4	6.0	2.5	2.0	1.0	1.6	5.0	0.2	0.1	0.1	6.4	4.8	2.8	4.0	2.0	2.6	0.1	0.0	0.4	5.3	6.0	8.3	1.0	0.0	5.8	91.7
TUR	4.0	3.8	0.2	1.1	0.8	0.2	3.0	2.8	1.4	3.2	4.2	4.1	2.2	2.6	1.0	1.6	3.2	0.2	0.4	0.1	4.3	3.2	3.0	3.0	1.8	3.3	0.3	0.0	0.2	3.8	3.3	3.3	27.0	0.0	3.4	73.0
UKR	0.2	0.0	0.1	0.0	0.4	0.3	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.1	0.4	0.1	0.1	0.1	0.0	0.0	0.1	0.2	0.0	0.0	0.1	0.0	0.0	0.1	97.1	0.0	2.9
GBR	4.8	5.6	0.0	0.9	1.0	0.2	3.3	3.5	0.9	4.7	6.6	5.8	2.5	2.1	1.0	2.1	4.9	0.2	0.1	0.1	6.4	4.8	2.7	4.2	1.8	2.7	0.1	0.0	0.3	5.8	5.5	5.9	1.0	0.0	8.4	91.6
Contribution to	127.8	134.9	10.0	48.5	53.9	19.1	112.4	90.9	49.2	115.9	143.9	132.5	73.2	75.2	38.7	49.1	116.6	7.8	14.9	12.2	138.7	115.8	88.2	104.9	70.4	61.0	15.2	2.7	23.2	131.5	121.1	127.5	32.5	1.2	125.2	2585.4
Contribution to with own	136.6	142.9	84.3	73.0	76.4	67.9	122.7	102.2	72.2	124.9	151.3	140.4	88.1	90.0	64.9	67.9	125.5	71.7	60.7	76.4	146.4	125.0	100.6	115.0	86.6	76.5	60.3	88.8	64.2	139.7	129.7	135.8	59.5	98.2	133.6	**73.9**

Table 9
Sector spillover table using method E–A.

	Agr	Aut	Mat	Bus	Ene	Good	Fin	HCLF	Ind	LAH	ME	REC	RW	Tech	Tel	Trans	*Contribution from*
Agr	2.1	2.5	6.1	5.6	11.0	6.7	19.3	10.9	12.4	1.0	1.1	9.0	3.1	2.9	3.4	2.9	97.9
Aut	0.2	15.3	10.2	4.6	8.5	8.0	20.1	3.7	6.6	1.0	0.8	9.1	3.0	3.3	2.5	2.9	84.7
Mat	0.2	4.1	22.4	4.8	9.6	7.1	18.1	3.5	6.7	1.1	1.3	8.7	3.5	3.1	3.3	2.3	77.6
Bus	0.2	3.0	7.0	15.6	9.9	6.7	19.8	4.0	7.1	0.9	2.7	10.0	4.5	3.4	3.3	2.1	84.4
Ene	0.2	2.8	7.0	4.8	24.8	6.8	19.2	4.4	6.2	1.0	1.9	8.5	3.2	2.8	4.1	2.4	75.2
Good	0.2	3.2	7.6	4.8	9.5	22.1	17.9	4.0	6.3	1.2	1.8	8.7	3.7	3.2	3.6	2.3	77.9
Fin	0.2	3.1	7.1	4.9	10.1	6.4	33.9	3.9	6.3	1.0	1.8	8.5	4.1	2.8	3.7	2.2	66.1
HCLF	0.2	2.7	6.5	5.0	9.3	7.2	17.8	21.4	6.5	1.0	1.8	8.4	3.3	3.3	3.4	2.2	78.6
Ind	0.3	3.2	7.4	5.2	8.7	7.0	18.4	3.8	22.5	1.1	1.7	8.6	3.4	3.3	3.1	2.3	77.5
LAH	0.2	2.9	7.9	4.1	10.9	6.6	16.0	4.2	6.6	13.5	6.4	8.5	3.7	3.1	3.1	2.4	86.5
ME	0.2	2.9	6.9	4.9	10.4	7.2	18.4	4.3	6.4	1.0	16.0	8.9	3.9	3.0	3.4	2.2	84.0
REC	0.2	3.0	7.8	4.7	9.2	6.6	17.4	3.7	6.1	1.2	1.8	25.2	3.6	3.2	3.7	2.5	74.8
RW	0.2	2.6	6.2	4.7	9.0	6.7	17.9	4.0	6.3	1.1	1.5	9.0	22.2	3.0	3.2	2.4	77.8
Tech	0.2	3.6	8.4	5.6	9.0	7.7	18.7	4.5	7.5	1.0	1.5	8.6	3.4	14.9	3.1	2.4	85.1
Tel	0.2	2.4	6.5	4.7	10.9	6.5	18.7	3.7	6.3	1.1	2.3	8.2	3.4	2.7	20.0	2.4	80.0
Trans	0.2	3.1	7.2	4.3	9.8	6.3	19.5	3.8	6.0	1.2	3.0	10.2	5.4	3.1	4.2	12.8	87.2
Contribution to	3.1	44.9	109.7	72.4	145.8	103.4	277.2	66.5	103.2	16.1	31.5	132.8	55.3	46.4	51.1	35.7	1295.2
Contribution to with own	5.2	60.2	132.1	88.0	170.6	125.5	311.2	88.0	125.7	29.6	47.5	157.9	77.5	61.3	71.1	48.5	**80.9**

Table 10
Sector spillover table using method A–E.

	Agr	Aut	Mat	Bus	Ene	Good	Fin	HCLF	Ind	LAH	ME	REC	RW	Tech	Tel	Trans	*Contribution from*
Agr	65.8	1.5	1.8	2.1	2.3	3.1	2.5	2.0	2.4	2.0	1.7	2.5	3.3	1.6	2.9	2.4	34.2
Aut	0.3	14.3	7.8	6.8	5.4	7.3	7.5	4.5	7.0	3.9	3.9	7.5	6.5	6.0	5.1	6.0	85.7
Mat	0.3	6.2	11.2	7.5	6.8	7.4	7.5	4.8	8.0	3.8	4.7	7.4	7.1	6.1	5.5	5.7	88.8
Bus	0.3	5.0	6.8	10.3	6.2	7.4	7.5	5.4	8.1	4.1	5.6	7.8	7.4	6.5	5.9	5.8	89.7
Ene	0.4	4.6	7.2	7.3	12.0	7.2	7.4	5.0	7.4	4.0	5.5	7.2	6.9	5.4	6.9	5.7	88.0
Good	0.5	5.4	6.9	7.5	6.3	10.5	6.6	6.0	7.0	4.4	5.2	7.7	7.7	6.3	6.2	5.9	89.5
Fin	0.4	5.7	7.1	7.8	6.6	6.7	10.7	4.3	7.7	4.5	5.3	8.0	7.4	5.4	6.3	6.3	89.3
HCLF	0.4	4.5	6.0	7.4	5.8	8.2	5.6	14.2	7.2	3.3	5.3	6.8	7.2	7.2	6.2	4.6	85.8
Ind	0.4	5.2	7.4	8.2	6.4	7.0	7.5	5.3	10.4	4.1	5.4	7.5	7.2	6.5	5.7	5.8	89.6
LAH	0.5	4.8	5.7	6.7	5.6	7.1	7.0	4.1	6.4	15.6	5.2	7.3	6.9	4.9	5.6	6.6	84.4
ME	0.4	3.9	5.7	7.5	6.3	6.9	6.9	5.1	7.2	4.3	13.7	6.8	7.4	6.0	6.4	5.4	86.3
REC	0.4	5.5	6.8	7.8	6.2	7.6	7.7	5.0	7.4	4.4	5.1	10.4	7.5	5.9	6.0	6.3	89.6
RW	0.5	4.9	6.6	7.6	6.1	7.8	7.3	5.4	7.3	4.4	5.7	7.7	10.6	5.7	6.5	5.9	89.4
Tech	0.3	5.3	6.7	7.9	5.6	7.5	6.3	6.4	7.9	3.7	5.4	7.1	6.8	12.6	5.2	5.3	87.4
Tel	0.6	4.5	6.1	7.2	7.1	7.3	7.3	5.5	6.8	3.8	5.8	7.2	7.6	5.2	12.5	5.4	87.5
Trans	0.5	5.4	6.3	7.1	6.0	7.2	7.4	4.2	7.0	5.1	5.0	7.8	7.2	5.5	5.7	12.6	87.4
Contribution to	6.2	72.5	94.9	106.1	88.6	105.7	102.1	73.0	104.8	59.9	74.8	106.3	104.2	84.2	86.1	83.2	1352.6
Contribution to with own	72.0	86.8	106.1	116.4	100.5	116.2	112.8	87.2	115.2	75.5	88.5	116.7	114.8	96.8	98.6	95.8	**84.5**

that estimates connectedness first and then aggregates (E–A). Our results for the aggregate cross-spillover statistic are, therefore, driven by the fact that there are more relatively small countries in our sample than there are large countries.

Tables 9 and 10 show the results when conducting the same exercise but this time using the sector as the unit of analysis. Here, the cross-spillover statistic is lower when adopting the E–A approach (80.9) (Table 9) than when using the A–E approach (84.5) (Table 10). Only in the cases of the Agriculture and Leisure/Arts/Hospitability sectors, which are relatively small (Agr is the smallest sector in the sample and LAH the third smallest) does the traditional A–E approach – which is based on indices – overestimate the own variance shares (Agr: 2.1 vs. 65.8; LAH: 13.5 vs. 15.6). In all other sectors, the reverse is the case, e.g., Telecommunication Services (20.0 vs. 12.5), Energy Services (24.8 vs. 12.0), and Financial Services (33.9 vs. 10.7).

It is worth stressing that the number of sectors in our study (16) is considerably smaller than the number of countries (35); thus, in general, each sector tends to have a larger number of firms than each country. One notable exception to this pattern, however, is Agriculture, which comprises just four companies, which may account for the vast overestimation of changes in own variance when using the traditional method of aggregation (A–E).

We calculated the Pearson's correlation between the differences in the values in the main diagonals of the two tables for each unit of analysis, Tables 7 and 8, and Tables 9 and 10, and the number of firms in each subgroup. In the first case, the correlation presents a coefficient of 0.47, while in the second it climbs to 0.61. This means that the A–E approach tends to produce larger own variance shares for larger groups of firms, either by sector or by country. In contrast, negative differences – corresponding to overestimations of connectedness and underestimation of own variance shares – tend to be associated with smaller groups, again either by sector or by country. Inevitably, the association is not perfect ($\rho = 1$), so it is impossible to know, a priori, with any certainty the sign of the under(over) estimation for large (small) groups.

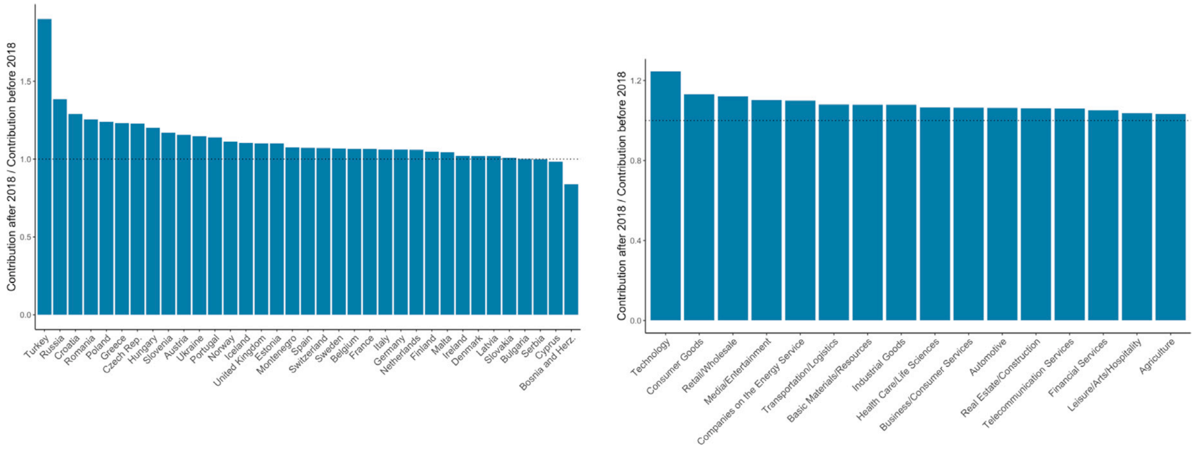

Fig. 7. Ratio of spillover indexes (crisis period over pre-crisis period) for countries (left) and sectors (right).

4.5. How does the network structure change during a crisis?

Interconnectedness effects play a prominent role in international finance, resulting in significant increases in the connectedness between different international markets or, similarly, a reduction in the diversification of benefits as observed during periods of crisis.

For comparative purposes, we split our sample into two equally sized parts and, then, estimated the network and the statistics developed above for each subsample. The first subsample runs from October 2, 2015, to December 31, 2018 ($T = 847$) and is representative of a period of stability, while the second subsample runs from January 1, 2018 to March 26, 2021 ($T = 845$) and includes the Covid-19 pandemic, a period of turmoil. We included 2018 in both samples so as to ensure minimum required information to run the connectedness algorithms. For future research, and to deepen the understanding of the interconnectedness of the system during different periods, a generation of time series using rolling windows could be applied, resulting in a bigger dataset in which this analysis could be performed year by year. In line with previous studies, the cross-spillover statistic increased in our general network from 83.4 to 89.9%, presenting evidence of a clearly stronger connectedness attributable to the Covid-19 crisis (see, for example, Akhtaruzzaman et al., 2021; Li et al., 2021; Bouri et al., 2021; Mensi et al., 2021). Moreover, this increase can be tracked down to individual sectors and countries. Fig. 7, panels A and B, shows the ratio between the “Contribution from” each country in the second subsample and the “Contribution from” the same country in the first subsample. For greater specification, this corresponds to the last column of the spillover tables (such as Tables 7 and 9) but using different periods instead of aggregation methods. Here, a statistic greater than 1 indicates that connectedness has increased from the period of stability to the times of crisis. With the exceptions of Bosnia and Herzegovina and Cyprus, the ratio was greater than 1 for all countries, indicating that connectedness increased as a result of the pandemic. This same situation is documented in panel B of the same figure, where a value greater than 1 is recorded in all cases, with Technology and Consumer Goods being the sectors with the highest increases. This is consistent with the greater need for digitization and the evident interdependence of these two sectors for the commercialization and distribution of goods of primary need during the pandemic.

Finally, Fig. 8 shows the same information as that included in panel A of Fig. 7, but leveraging a geographical perspective. A comparison of the two subsamples highlights a marked increase in connectedness in the European network attributable to firms in the Eastern European countries. For more detailed information, find Table A.11 in the Appendix A, which presents the weighted indegree and outdegree of connectedness of each country calculated with Gephi. We also calculated the spillover indexes on the two periods for the countries' network, and until 2018 renders a 76.11, while from 2018 renders an 83.36, which evidences the main point of this section: the network of European countries becomes more interconnected during turmoil periods.

5. Conclusions

The literature to date has studied volatility connectedness between firms listed on the stock market by using country or sector indices as their unit of analysis. In general, these studies have tended to identify county membership as the main determinant of volatility co-movement in global financial markets and sector membership as a secondary determinant. Here, we have defined a stock market network structure at the level of the individual firm and have proposed statistics that enable us to quantify the contribution of sector and country membership attributes for explaining international stock market connectedness. We show that the country category is, overall, more frequently relevant than the sector category. However, a number of caveats have to be added to that statement, because heterogeneities are found at the individual level; indeed, for quite a large fraction of companies the sector is more relevant than the country category. Results show that a dependence on indices as opposed to information at the individual level results in notable biases, as the dominance of the sector or country attributes is highly heterogeneous across individual companies.

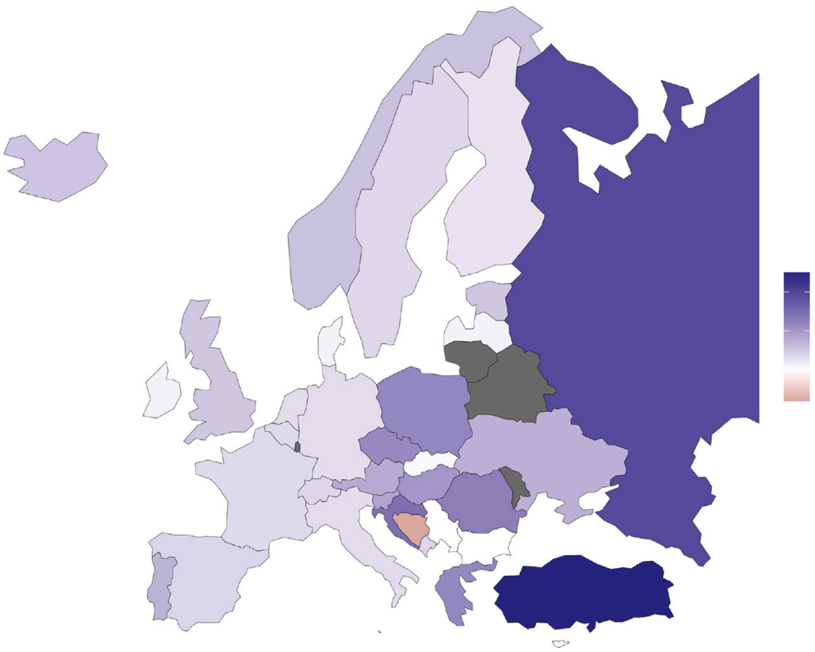

Fig. 8. Geographical map of the ratio of spillover indexes (Covid-19 crisis period over pre-Covid-19 crisis period) for countries.

Our results also show a higher ratio of connectedness during the Covid-19 outbreak in comparison with a previous period of relative stability, above all in Eastern Europe. It seems apparent that only by undertaking individual risk analyses can we begin to understand the complex picture presented by connectedness in international financial markets. Here, we have deployed new statistics that specifically speak of the importance of any given sector or country for any given company in the market, and this should prove useful for quantifying losses before periods of turmoil, such as those associated with the Covid-19 pandemic and the conflict in Ukraine.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A

See Table A.11.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.intfin.2022.101696.

Table A.11
Indegree and Outdegree of connectedness of the countries until 2018 and from 2018, obtained via Gephi.

Country	Indegree_Until2018	Outdegree_Until2018	Indegree_Since2018	Outdegree_Since2018
AUT	75.53	58.27	87.30	91.25
BEL	84.34	70.73	89.91	91.75
BIH	95.27	24.36	79.79	11.77
BGR	87.26	14.55	87.34	14.13
HRV	58.56	20.39	75.61	36.00
CYP	96.23	35.62	94.63	26.04
CZE	67.09	24.66	82.41	39.13
DNK	80.00	61.55	81.66	61.06
EST	73.68	19.10	81.10	23.30
FIN	80.31	85.58	84.23	73.82
FRA	78.75	185.61	83.94	244.55
DEU	82.76	109.70	87.83	141.10
GRC	58.88	329.67	72.58	134.75
HUN	70.29	45.91	84.40	57.06
ISL	68.00	25.52	75.12	29.21
IRL	83.93	67.37	85.73	71.07
ITA	81.85	107.35	86.91	122.78
LVA	91.54	13.74	93.38	9.88
MLT	92.26	17.94	96.42	10.82
MNE	86.27	9.63	92.74	8.62
NLD	84.29	98.32	89.32	119.00
NOR	78.22	67.55	86.98	98.21
POL	66.32	117.57	82.24	133.67
PRT	76.22	43.91	86.92	50.51
ROU	52.97	21.54	66.53	38.49
RUS	58.06	56.01	80.46	115.87
SRB	85.55	10.53	85.61	8.31
SVK	91.48	8.64	92.30	5.59
SVN	70.76	15.94	82.74	16.72
ESP	81.00	120.08	86.92	143.75
SWE	79.68	152.48	85.21	146.93
CHE	82.66	94.53	88.53	127.55
TUR	21.26	127.33	40.41	165.62
UKR	78.19	5.45	89.67	3.63
GBR	64.36	396.73	70.88	445.79

References

Akhtaruzzaman, M., Boubaker, S., Sensoy, A., 2021. Financial contagion during COVID-19 crisis. Finance Res. Lett. 38, 101604.
Allen, L., Bali, T.G., Tang, Y., 2012. Does systemic risk in the financial sector predict future economic downturns? Rev. Financ. Stud. 25 (10), 3000–3036.
Bai, J., Wang, P., 2016. Econometric analysis of large factor models. Ann. Rev. Econ. 8, 53–80.
Balcilar, M., Ozdemir, Z.A., 2013. The causal nexus between oil prices and equity market in the US: A regime switching model. Energy Econ. 39, 271–282.
Barigozzi, M., Brownlees, C., 2019. Nets: Network estimation for time series. J. Appl. Econom. 34 (3), 347–364.
Barigozzi, M., Hallin, M., Soccorsi, S., von Sachs, R., 2021. Time-varying general dynamic factor models and the measurement of financial connectedness. J. Econom. 222 (1), 324–343.
Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. J. Financ. Econom. 16 (2), 271–296.
Baumöhl, E., Shahzad, S.J.H., 2019. Quantile coherency networks of international stock markets. Finance Res. Lett. 31, 119–129.
Bekaert, G., Harvey, C.R., Lundblad, C.T., Siegel, S., 2011. What segments equity markets? Rev. Financ. Stud. 24 (12), 3841–3890.
Bekaert, G., Hodrick, R.J., Zhang, X., 2009. International stock return comovements. J. Finance 64 (6), 2591–2626.
BenSaïda, A., 2019. Good and bad volatility spillovers: An asymmetric connectedness. J. Financ. Mark. 43, 78–95.
Bouri, E., Demirer, R., Gabauer, D., Gupta, R., 2021. Financial market connectedness: The role of investors' happiness. Finance Res. Lett. 44, 102075.
Bracker, K., Docking, D.S., Koch, P.D., 1999. Economic determinants of evolution in international stock market integration. J. Empir. Finance 6 (1), 1–27.
Chen, R., Yang, D., Zhang, C.-H., 2022. Factor models for high-dimensional tensor time series. J. Amer. Statist. Assoc. 117 (537), 94–116.
Chuliá, H., Fernández, J., Uribe, J.M., 2018. Currency downside risk, liquidity, and financial stability. J. Int. Money Finance 89, 83–102.
Corsetti, G., Pericoli, M., Sbracia, M., 2005. 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. J. Int. Money Finance 24 (8), 1177–1199.
Demirer, M., Diebold, F.X., Liu, L., Yilmaz, K., 2018. Estimating global bank network connectedness. J. Appl. Econom. 33 (1), 1–15.
Di Giovanni, J., Hale, G., 2021. Stock Market Spillovers Via the Global Production Network: Transmission of US Monetary Policy. Technical Report, National Bureau of Economic Research.
Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119 (534), 158–171.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.
Diebold, F.X., Yilmaz, K., 2015. Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring. Oxford University Press, USA.
Du, X., Cindy, L.Y., Hayes, D.J., 2011. Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. Energy Econ. 33 (3), 497–503.
Dutt, P., Mihov, I., 2013. Stock market comovements and industrial structure. J. Money Credit Bank. 45 (5), 891–911.
Elyasiani, E., Mansur, I., Odusami, B., 2011. Oil price shocks and industry stock returns. Energy Econ. 33 (5), 966–974.

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econom.: J. Econom. Soc. 50, 987–1007.
Ewing, B.T., Thompson, M.A., 2007. Dynamic cyclical comovements of oil prices with industrial production, consumer prices, unemployment, and stock prices. Energy Policy 35 (11), 5535–5540.
Ferreira, M.A., Santa-Clara, P., 2011. Forecasting stock market returns: The sum of the parts is more than the whole. J. Financ. Econ. 100 (3), 514–537.
Forbes, K.J., Chinn, M.D., 2004. A decomposition of global linkages in financial markets over time. Rev. Econ. Stat. 86 (3), 705–722.
Forbes, K.J., Rigobon, R., 2002. No contagion, only interdependence: measuring stock market comovements. J. Finance 57 (5), 2223–2261.
Freyberger, J., Höppner, B., Neuhierl, A., Weber, M., 2021. Missing data in asset pricing panels. Available at SSRN, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3932438.
Fukunaga, I., Hirakata, N., Sudo, N., et al., 2011. the Effects of Oil Price Changes on the Industry-Level Production and Prices in the United States and Japan, Vol. 20. University of Chicago Press, Chicago, IL, pp. 195–231.
Gelfand, A.E., Sahu, S.K., Carlin, B.P., 1995. Efficient parametrisations for normal linear mixed models. Biometrika 82 (3), 479–488.
Hamdi, B., Aloui, M., Alqahtani, F., Tiwari, A., 2019. Relationship between the oil price volatility and sectoral stock markets in oil-exporting economies: Evidence from wavelet nonlinear denoised based quantile and Granger-causality analysis. Energy Econ. 80, 536–552.
Hamilton, J.D., 2009. Causes and Consequences of the Oil Shock of 2007-08. National Bureau of Economic Research.
Hoerl, A.E., Kennard, R.W., 1970. Ridge regression: Biased estimation for nonorthogonal problems. Technometrics 12 (1), 55–67.
Jacomy, M., Venturini, T., Heymann, S., Bastian, M., 2014. ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the gephi software. PloS One 9 (6), e98679.
Jacquier, E., Polson, N.G., Rossi, P.E., 2002. Bayesian analysis of stochastic volatility models. J. Bus. Econom. Statist. 20 (1), 69–87.
Kastner, G., 2019. Dealing with stochastic volatility in time series using the R package stochvol. ArXiv Preprint arXiv:1906.12134.
Kastner, G., Frühwirth-Schnatter, S., 2014. Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models. Comput. Stat. Data Anal. 76, 408–423.
Kim, S., Shephard, N., Chib, S., 1998. Stochastic volatility: likelihood inference and comparison with ARCH models. Rev. Econ. Stud. 65 (3), 361–393.
Le, T.-H., Chang, Y., 2015. Effects of oil price shocks on the stock market performance: Do nature of shocks and economies matter? Energy Econ. 51, 261–274.
Lewis, K.K., 2011. Global asset pricing. Ann. Rev. Financ. Econ. 3 (1), 435–466.
Li, X., Li, B., Wei, G., Bai, L., Wei, Y., Liang, C., 2021. Return connectedness among commodity and financial assets during the COVID-19 pandemic: Evidence from China and the US. Resour. Policy 73, 102166.
Lin, S., Chen, S., 2021. Dynamic connectedness of major financial markets in China and america. Int. Rev. Econ. Finance 75, 646–656.
Lyócsa, Š., Vỳrost, T., Baumöhl, E., 2019. Return spillovers around the globe: A network approach. Econ. Model. 77, 133–146.
Mensi, W., Nekhili, R., Vo, X.V., Suleman, T., Kang, S.H., 2021. Asymmetric volatility connectedness among US stock sectors. N. Am. J. Econ. Finance 56, 101327.
Pitt, M.K., Shephard, N., 1999. Analytic convergence rates and parameterization issues for the gibbs sampler applied to state space models. J. Time Series Anal. 20 (1), 63–85.
Raddant, M., Kenett, D.Y., 2021. Interconnectedness in the global financial market. J. Int. Money Finance 110, 102280.
Reboredo, J.C., 2011. How do crude oil prices co-move?: A copula approach. Energy Econ. 33 (5), 948–955.
Reboredo, J.C., 2012a. Do food and oil prices co-move? Energy Policy 49, 456–467.
Reboredo, J.C., 2012b. Modelling oil price and exchange rate co-movements. J. Policy Model. 34 (3), 419–440.
Reboredo, J.C., Ugolini, A., 2016. Quantile dependence of oil price movements and stock returns. Energy Econ. 54, 33–49.
Rigobon, R., 2002. Contagion: how to measure it? In: Preventing Currency Crises in Emerging Markets. University of Chicago Press, pp. 269–334.
Roll, R., 1992. Industrial structure and the comparative behavior of international stock market indices. J. Finance 47 (1), 3–41.
Salisu, A.A., Oloko, T.F., 2015. Modeling oil price–US stock nexus: A VARMA–BEKK–AGARCH approach. Energy Econ. 50, 1–12.
Taylor, S.J., 1982. Financial returns modelled by the product of two stochastic processes-a study of the daily sugar prices 1961-75. Time Series Anal.: Theory Practice 1, 203–226.
Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. J. R. Stat. Soc.: Ser. B 58 (1), 267–288.
Yu, H., Du, D., Fang, L., Yan, P., 2018. Risk contribution of crude oil to industry stock returns. Int. Rev. Econ. Finance 58, 179–199.
Zou, H., Zhang, H.H., 2009. On the adaptive elastic-net with a diverging number of parameters. Ann. Stat. 37 (4), 1733.