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EU FDI Network and Systemic Risks

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Abstract

Fragmentation of production certainly is a possible channel of economic contagion and could play a key role in the study of systemic risk. The investments abroad of firms implicitly create long range economic dependencies between investors and the economies of destination, possibly triggering contagion phenomena. Complex Network theory is a primary tool to highlight economic mutual relationships and paths of contagion, shedding light on intrinsic systemic risks. In this paper we reconstruct the networks of EU28 foreign direct investments and we study the networks' evolution from 2003 to 2015. Our analysis aims at detecting the change of topological properties of foreign direct investment network during the crisis, in order to assess its effect on the architecture of economic relationships. Trough a detailed study of correlations at different time lags between network measurements and macroeconomic variables, we assess systemic risks based on network topology. The main results are: (i) 2009 is a clear break in the network evolution, before the structure is characterized by only one or few very central nodes - countries - while after it emerges a set of connected key central nodes; (ii) an increasing heterogeneity is observed in link weights during the entire period analyzed 2003-2015; (iii) after 2009, a rewiring of investments is observed towards the EU28 countries considered more safe; (iv) time-lagged centrality measures and macro-economic variables show a clear correlation.

Key words: Foreign Direct Investment, Economic networks, Projected network, Systemic Risks

JEL codes: F23, D85

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1 Introduction

In modern economies, a major feature is the fragmentation of production: a process with visible and strong impact on the strategies of firms and countries (of origin and destination), due to the fact that they have to deal with an environment of strong competition. The firms capacity to innovate their processes and products, together with their ability of penetration into new markets, is the base of their surviving in the new context that the production's fragmentation creates. The reply of firms is to develop strategies with international orientation, as showed by the substantial increase of the quantity of firms involved in exports, global outsourcing and foreign direct investments (FDI).

FDIs have the characteristic of being medium-long term choices for companies. This is even more true when considering greenfield FDI as in our study. Furthermore, FDI overlaps with global value chains, intrinsically creating a network between various countries involved. The choices are therefore not random but involve the development of long-term strategies and their maintenance. Choosing a given country as the recipient depends on many factors both within the firm and more closely related to the country in which it is decided to build. In particular, for the latter macroeconomic variables (expected growth, per capita GDP, inflation etc.) can be considered as proxies of the environmental goodness, that firms must take into account. Considering these two elements (the FDI that constitute an implicit network and the macroeconomic variables proxy of the medium-long term reliability of a country), we believe it is worth analyzing how the structure of FDI network and its evolution may affect macroeconomic variables, correlating them with topological measures.

According to Schwarcz (2008), the various definitions of systemic risk have the domino effect as a common element. There is a cause that causes a series of negative economic effects. For this reason, in this paper, systemic risk refers to a situation in which instability in a country leads to instability in another one (see for example, Recchioni and Tedeschi 2017). In particular, we wonder if there is a correlation between the flow of foreign direct investments and the economic performance of European countries. We try to study the direction of causality, in particular if the changes in investment choices anticipate or are a consequence of the economic situation of a country. Finally, we believe that the network structure of economic relations can well explain the possible externalities (positive or negative) brought by direct investments. For this reason, we do not correlate directly FDI with other economic variables but, the latter, with the indexes calculated by the network.

Economic systemic risk is an issue linked to two kinds of phenomena widely studied in complex networks: propagation of failures/damages in a network and epidemic spreading. It has been shown that uncorrelated scale-free (SF) networks show an exceptional tolerance to random damages (Zhao et al. 2004) while they are highly vulnerable to intentional attacks. On the other hand, SF networks are also the ideal media for the propagation of infections, bugs, or unsolicited information (Pastor-Zatorras and Vespignani, 2001), while for homogeneous networks it is possible to distinguish between a healthy/inactive phase where the virus cannot propagate or it can be easily confined and an endemic/active phase where the virus propagates through the network. The above explained particular dynamics of both propagation of failures/damages and epidemic spreading in a SF network are due to the hierarchical dynamics typical of spreading on scale free networks: once the highly connected hubs are reached, the infection as well as damage pervades the network in a progressive cascade across smaller degree classes. These ideas arose more and more interest in Economics, to analyze how changes in the network structure, for example in credit-debit or in the interbank network (i.e. Berardi and Tedeschi, 2017; Lenzu and Tedeschi, 2012), customer-supplier relationship (Arata et al., 2018) as well as other financial networks (Hautsch et al., 2015; Acemoglu, 2015) generating a greater systemic risk, can explain the chain failures of the system. While these models are very well established in network field, in this paper, instead, we follow a different approach. We firstly analyze the evolution of the EU28 FDI network in the period 2003-2015, to understand if there was a structural change in the network around the crisis and, then, we study the cross-correlations with time lag between macroeconomic variable and network indexes (both in advance and delayed) with the intention to identify signals of systemic risk. However, it is worth noting that FDI are different from debt-credit relationships. If on the one hand a more connected network could lead us to imagine a systemic risk that spreads faster, on the other it could be the result of greater diversification of companies to limit the damage caused by a crisis. With a consequent reduction in systemic risk.

We follow the approach of complex network theory analyzed in Schweitzer et al. (2009). Since the last ten years, in various disciplines from natural (biology and physics) to social sciences (Dorogovtsev, Mendez 2003), the complex networks theory emerged, as a cross-cutting research field, aimed to the reconstruction and analysis of connections between different agents/individuals/businesses and to the study of their evolution. A great number of studies have been carried out, in particular, to better understand the mechanisms that underly communication networks: World Wide Web (WWW), Internet and e-mail networks (Vega-Redondo, 2007). Recently, also, the complex network theory has been applied to Economics, and it allows an identification and evaluation of the structures that underly the relationships between different economic units. The network analysis is mainly used, in the empirical literature, to study the structure of bank-firm credit market (De Masi et al., 2011; Battiston et al. 2007), interbank market (Iori et al., 2008), financial market investments (Garlaschelli et al., 2005), the world trade (Fagiolo et al., 2011; De Benedictis and Tajoli, 2011). Related with the fragmentation of production, Criscuolo and Timmis (2017) maps the global value chains, detecting the main hubs in terms of countries and sectors with a core-periphery approach. The application of network analysis to FDI is recently growing. Wall et al. (2011) analyze - in more than 2000 cities worldwide - the network of top 100 global multinational and ownership linkages, giving a distinction between producer service sector and all industrial sectors. More recently, Alfaro and Chen (2014) use measurements of network density to study agglomeration phenomena in order to analyze a worldwide establishment based database of multinationals. Garas et al. (2016) analyze the relation between the network of migrants and that of FDI, while Metulini et al. (2017) studies how the FDI network affects the trade network. Rungi et al. (2017) build the links between ownership and firms' control all over the world. Moving to European countries, then, network based analyses on Italian foreign investment data (De Masi et al., 2013) and on French data (Joyez, 2017 and 2019) have been performed.

In a recent work, De Masi and Ricchiuti (2018) reconstruct the *network* of the European (EU28) firms co-investing in the same countries, studying - separately - the years 2003 and 2015. Starting with a bipartite network model with two kinds of nodes (countries and investors), and studying the projections in investor space, they highlight the occurrence of heterogeneity in investment strategies between and within sectors, stressing the emergence of common strategies among firms. They detect the presence of subnets and main hubs (in terms of firms) also within specific sectors, and, analyzing qualitatively the main actors, they discover whether the choice to develop new projects is correlated to specific features of these actors.

The network of countries due to FDI has not been yet studied. However, since the primary aim of this paper is to study the role of network in systemic risk, and mutual dependencies among countries, due to FDIs, we use here a different definition of nodes and links. In particular, the network is defined as follows: two countries are linked if a firm belonging to the first one is investing in the second. This makes a network of countries naturally arising, with mutual economic relationships. We believe, this representation is particularly suitable for a study of systemic risk related to FDI. For this reason, in the present paper we study the evolution of EU28 country network emerging because of FDI within EU itself, along the entire period (2003-2015). We take data from 'fDi markets': a really rich global detailed database developed by the Financial

Times, which contains information on worldwide greenfield FDI. 38 networks have been analyzed, one for each industrial sector. Trough a detailed study of correlations at different time lags between network measurements -particularly centrality measurements- and macroeconomic variables, we assess systemic risks based on network topology. The main results are: (i) 2009 is a clear break in the network evolution, before the structure is characterized by only one or few very central nodes - countries - while after it emerges a set of connected key central nodes; (ii) an increasing heterogeneity is observed in link weights during the entire period analyzed 2003-2015; (iii) after 2009, a rewiring of investments is observed towards the EU28 countries considered more safe; (iv) time-lagged centrality measures and macro-economic variables show a clear correlation.

After a brief presentation of the data (section 2), in section 3, we present the methodology employed to build the network and the topology measures used, discussing the evolution of the network. Finally, we present heat-maps on the correlations between topology measures and economic variables and the results of an econometric model (section 5.1). Final remarks conclude.

2 The Dataset

fDi markets is one the main global database of FDI information. Since 2003, it monitor real-time investments made by companies worldwide. It now has information about more than 80,000 firms. It records only greenfield FDI and more than affiliates, it reports information (country of origin and destination, an estimation on capital investments, possible job creation) about firms' projects in investing abroad, the name used in fDi markets. Information are captured by media, industry organizations, investment agencies, and firms' official publications.

In this study, we focus on outward FDI from each of EU28 (countries of origin) to other EU28 countries in the period 2003 to 2015. Moreover, we do not use information about capital investments and number of workers because too disperse and with too many missing values. Using flow data, we can better analyze how firms' choices evolved and their impact on both countries of origin and destination. Finally, we use the World Development Indicator of the World Bank to get information on Domestic Credit (%GDP), Curren Account (%GDP), GDP growth, GDP per capita growth, Inflation (as % change of the GDP deflater), Trade (Import plus Export as %GDP), FDI net flows (as %GDP). While from Bloomberg we get the 10 years Yield of public bonds in the different EU28 countries.

3 Methodology

FDI dataset naturally allows to define a FDI network. Nodes are countries ($C = C_1, C_2, ...C_{N_C}$), in particular EU28 countries in the current study. A link between two countries C_i and C_j is drawn if a company based in country C_i is making an investment (i.e. opening an affiliate) in country C_j. A weight is associated to the links: it represents the number of investments from C_i to C_j countries. Since flows data of FDI are here analyzed, a completely new network is generated for each year. Flow data appear to be more suitable than Stock data for the study of relation between FDI and systemic risk, due to the effects on the balance of payment, the (real) exchange rate (i.e. the Dutch disease) and on GDP growth. The original network is both weighted and directed. FDIs build a mutual relationship between two countries where a static direction is easily defined (from the investing country to that of destination). However, dynamically, the role of direction is ambiguous. While in debt networks, a path of contagion has a clear direction, it is not the same for FDI networks. Indeed, a country slowdown can both reinforce the other one as well as make it weaker. In fact, companies can either decide invest abroad in order to respond at the deterioration of economic conditions, or not to do so to avoid a greater exposure to economic risk. For this reason, following Fagiolo (2009), after some basic statistics on the directed network, we decided to make the matrix symmetric as usually done for different kinds of similar networks, like trade networks.

More specifically, starting from the above described dataset, for each year for each industrial sector a network is defined [1]. Given that 13 years of data and 38 sectors are available, this leads to the generation of a total of 494 networks. A set of local-scale, meso-scale and large-scale network topological measurements are calculated. As local, the following have been investigated:

- at first order: degree and strength
- at second order: average neighbors degree
- at third order: clustering
- at fourth order: squared clustering

As higher order measurements, three measures of centrality have been compared:

- betweenness
- closeness
- eigen centrality
- eccentricity

These centrality measurements are considering binary networks, neglecting weights of links. Many definitions of 'centrality' have been proposed in network analysis. We consider three of them. A first measure of centrality of a node is the **degree centrality**, achieved dividing the degree by the number of nodes of the network:

$$dc_i = k_i/(N-1); \tag{1}$$

where N is the total number of nodes.
A second definition, the **betweenness centrality** (Brandes, 2001), is based on dynamical properties of the graph and is given by the number of times that one vertex k is crossed by minimal path from one vertex i to j. Let's define d_{ij}, the **distance** between two vertices i, j, as *the shortest* number of edges to go from i to j, that is:

$$d_{ij} = min\{\sum_{k,l \in \mathcal{P}_{ij}} a_{kl}\} \tag{2}$$

where $\mathcal{P}_{ij}$ is a path connecting vertex i and vertex j. Therefore, the betweenness centrality b_i is defined :

$$b_i = \sum_{\substack{j,l=1,N \\ i \neq j \neq l}} \frac{d_{jl}(i)}{d_{jl}} \tag{3}$$

where d_{jl} is the total number of different shortest paths (distances) going from j to l and $d_{jl}(i)$ is the subset of those distances passing through i. The sum runs over all pairs with $i \neq j \neq l$.

Another measure of centrality employed is the **closeness centrality** (see Freeman, 1977 and Sabidussi, 1966):

$$cl_i = \frac{N-1}{\sum_j d_{ij}} = \frac{1}{\bar{d}_i} \tag{4}$$

[1]The network definition is different from De Masi and Ricchiuti (2018), where the authors used the same dataset. In De Masi and Ricchiuti (2018), a bipartite was first defined, then projected on investors' and countries' spaces. This methodology was useful to detect common strategies among countries and investors.

which is the reciprocal of the average distance of one node from the other nodes. In order to be an hub, a country should not be very far from all the others.

The last measure of centrality employed is the **eigenvector centrality** [29] which measures the importance of a node based on the score of its neighbors. Differently from the previous measures, this measure is not based on distance among nodes, but it is intrinsically based on the spectral properties of adjacency matrix. So it provides a different approach to assess node centrality.

Finally the **eccentricity** of a node is the inverse of the maximum distance of that node from any other possible node of the network. So is strongly related to centrality.

As pointed out by Krackhardt (1990) different centrality measures identify distinct nodes as the most central ones, even if a certain correlation among the above measurements is observed. Within each sector, the evolution of above measurements is analyzed year by year, both at aggregated level (the mean values on all the nodes) and node by node. The centrality measurements (particularly closeness, betweenness and eigenvector centrality), typical of meso-scale level network analysis, can not be reduced to traditional statistical measurements. At this level, network analysis is showing its most explanatory power, giving an added value compared to traditional techniques. At large scale level, we have investigated the number of nodes (also called the order of the network), the number of links (also called the size of the network), the density (number of observed links normalized by the total possible links), diameter, radius, and connected components. We do not report all these analyses, but it is intrinsically related to the work presented. The contribution of network analysis to the study of systemic risk is at the mesoscopic scale, shedding light of the architecture of mutual dependencies between countries, where traditional statistics can not arrive.

Finally, for each specific network a null hypothesis model has been implemented. Starting from initial investments of each country, the destinations have been randomized. This is preserving the intention of each specific country to make an investment and only the destination is changed. Another approach to links' reshuffling has been also adopted: starting from initial investment project list, both origin and destination have been randomized.The first procedure is more strict: if the network looses the internal architecture by the first reshuffling procedure, this ia very strong proof of internal structure of real observed networks.

4 The evolution of the whole FDI Network

Considering all sectors, within the whole database there are around 1600 and 3000 investors in 2003 and 2015 respectively, and corresponding to almost 3100 and 5200 projects (Fig. 1). On average, an investor has 1.9 projects in 2003 and 1.7 in 2015, but we register large heterogeneity across sectors.

In Fig. 1(left panel), we report year by year the number of projects in the whole sample (black line) and in the EU countries (Grey line). The number of EU based investors is shown by the red line. There is a first growing trend until 2008 and, after a small decrease, the number has stabilized around 6000 projects per year. The pattern is similar, although more smooth for EU countries, after an increase in the first part of the last decade, there was a reduction suddenly after the crises. In the last years, the number of projects has been stabilized around 2000 EU28. Therefore almost half of the EU28 project are directed within the Union itself. More relevantly, from the point of view of the network structure, the density (defined as $\rho = 2L/[N(N-1)]$) is pretty constant despite the trend observed in investments. As clearly visible in Fig. 1(right panel), the density of EU28 FDIs is between 0.53 and 0.6. Fig.2 shows that the in-degree and out-degree of the EU countries most active in FDI are pretty constant. Strong economies (like Germany and UK) shows an increase of incoming degree after the crisis because they keep attracting FDI while other countries like Austria are less attractive. This can be explained by the fact that the number of links among countries is almost constant. However, a change is observed only in distribution of links (origin and destination countries) and values of weights (number of investments) which change relevantly during the period 2003-2015.

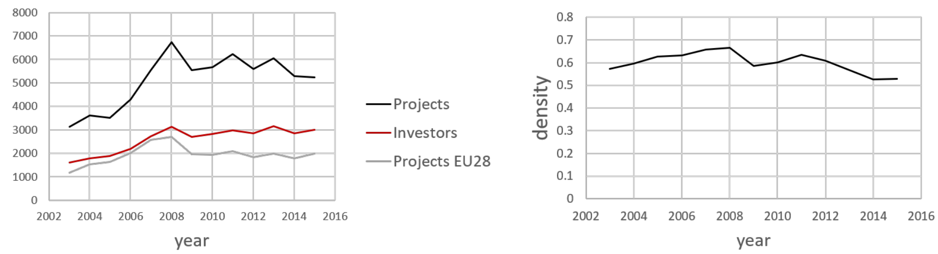


Figure 1: Evolution of number of investors (red line) in the whole sample and number of projects towards the world (black line) and inside EU countries (grey line) during the period 2003-2015 (left panel). Evolution of density of country network during the period 2003-2015 (right panel)

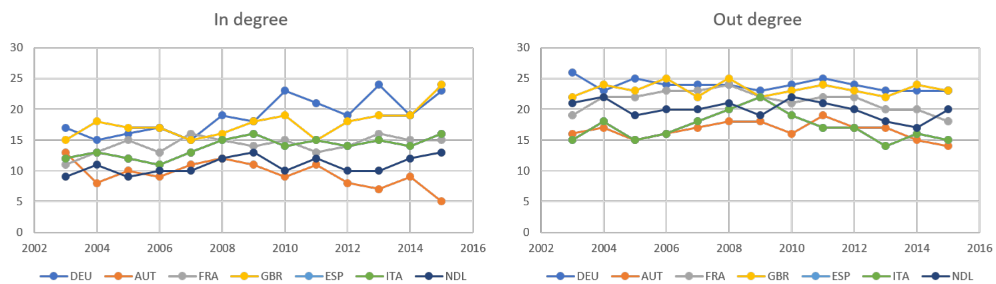


Figure 2: Evolution of in-degree (left panel) and indegree (right panel) for the EU countries most active in FDI.

This is evident from a qualitative point of view from the three graphs reported in Fig.3. Here the EU28 FDI country networks for all sectors together are reported for year 2003, 2009 and 2015. The procedure employed to visualized the graphs is the Kamada-Kawai algorithm (Kamada and Kawai, 1989): it is based on the idea that the geometric length between two countries (our nodes) show the topological distance between them in the graph. Therefore countries that are closer in the graph are more strongly connected. The size of nodes represents the weighted degree centrality, while the thickness of the link is showing the weight of the link[2]. While the number of nodes is constant, a big change of links can be observed. Some channels of FDI become relatively more important than others: in the first network links are quite homogeneous, while moving forward along the period 2003-2015, the heterogeneity within the same network of both node sizes and links keeps increasing.

More quantitatively, the change in weights in evident from Fig.4. Weights' distribution is moving to higher values of w, with even stronger emergence of heterogeneity. The heterogeneity is increasing very fast during the period 2003-2009, while after 2009 it seems the curves slow down their shift to higher values. Curves start to become closer showing that heterogeneity is not growing anymore. This could be due to a smaller tendency to invest only in some preferred countries. Looking to the graph, Germany, France, Great

[2]Only for visualization reasons, given the heterogeneity of the values, authors chose to use as size of nodes and links the square root of degree centrality and of real weight respectively in order to reduce the variability of values that would make the graph not clearly readable.

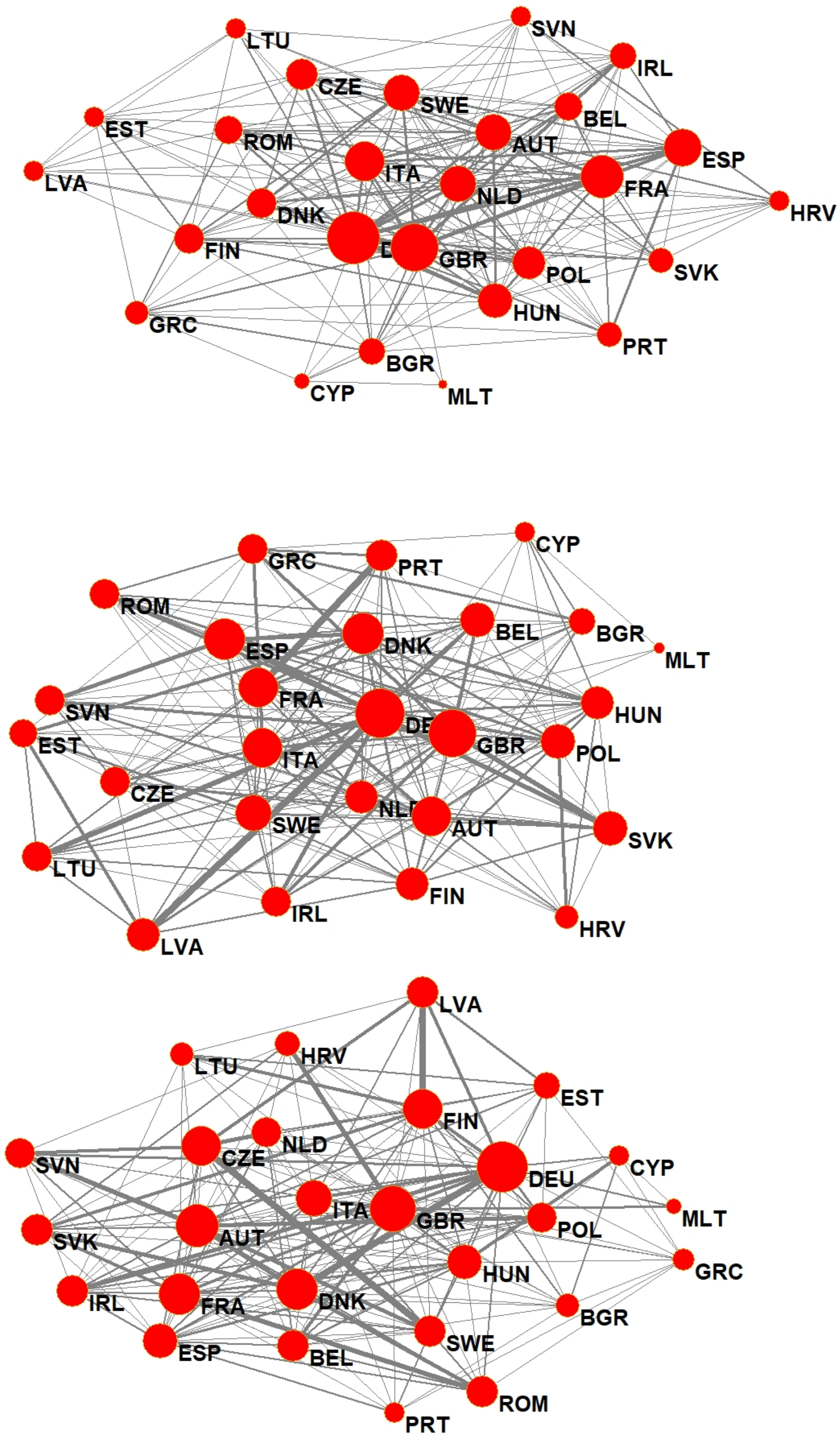


Figure 3: Graphs of EU28 FDI network for 2003 (top panel), 2009 (middle panel) and 2015 (bottom panel). While the number of nodes is constant, a big change of links can be observed.

Britain and Netherlands become progressively the most important actors of FDI, as already observed in Fig.2.

In Fig.5 the four centrality measurements, namely degree, betweenness, closeness and eigenvector centrality distributions, are reported from 2003 to 2015, in order to shed light on the change of structure of the network. The cumulative degree distribution shows that curves are moving towards higher values of k, so to large heterogeneity of countries' degree. In 2009 a strong bending of the distribution curve to lower value is observed. There is no more a dominant hub but many main actors are more connected. The betweenness distribution starts from heavy tails in 2003, bending abruptly in 2009 towards lower values tail and then relaxing again to heavy tails after 2009. A similar trend is observed for closeness centrality and eigencentrality: around 2009 the distribution is the steepest, with lowest maximum value of centrality, like a cut-off value.

We explain this change in the number of links as follows: in 2009, as a reaction to the crisis, firms tried to reduce the heterogeneity, in particular avoiding to have few nodes with high centrality because of the activation of alternative channels of investments. In the year after the system relaxed to a structure which privilege some few investment countries. Eigenvector centrality instead show the 2009 curve (in the region of high values) is the most external, meaning that in 2009 the highest values are observed as well as the highest number of nodes with high values. This could be explained with higher presence of several nodes with similar high degree, without a main role of one or very few nodes. The same conclusion can be get from closeness distribution where in 2009 is observed the lowest maximum value of closeness with several nodes populating the right part of the distribution. To sum up, while before 2009 there were few key nodes, starting with the crises many nodes emerge but with a lower value of centrality. So, there is a change in the network structure. At the same time, looking at weights, heterogeneity continues to grow throughout the entire period but at a lower rate.

4.1 Sectorial networks

While this evidence emerge from the network including all sectors, some differences emerge sector by sector. In particular we selected a new sector (IT) and a traditional one (Industrial machinery), which are among the sectors characterized by higher number of investment projects. In Fig.7 and Fig.8 the network of Industrial machinery and IT sectors are reported for year 2003, 2009 and 2015. In Fig.6 it is evident different adaptation of the two sectors to crisis. In the traditional sector (Industrial machinery), the maximum heterogeneity is observed in 2009 in a progressive growth. After 2009 a strong trend reversal is observed towards lower values of weights. On the contrary, for the emerging sector (IT), the heterogeneity keeps increasing also after 2009, moving the distribution towards higher values of tails. This is also evident from Fig. 8 where the size of nodes is proportional to the strength of countries. The same results emerges also from the analysis of underlying network structure, particularly from the betweenness distribution. The topology of Industrial Machinery network initially evolve towards a configuration with few very central nodes. After crisis, starting in 2009, the topology moves back to a more connected structure with a set of nodes sharing similar centrality because of their mutual links. For IT sector instead, there is a continuous trend from a topology with few central nodes towards a more connected net with a set of countries sharing high centrality. So we can conclude that IT sector is less affected by the crisis. The trend is clear and without of structural break.

In Fig. 9 we report a reshuffled graph for the sector IT. As evident the heterogeneity is removed by reshuffling: the graph approaches a random graph. This result is confirmed for all sectors. The other graphs are available upon request. It should be noted that the nodes have a more homogeneous size between them and this is due to the fact that FDI are randomly distributed on the possible links. Thus, this is a strong demonstration of presence of main privileged channels in the true network.

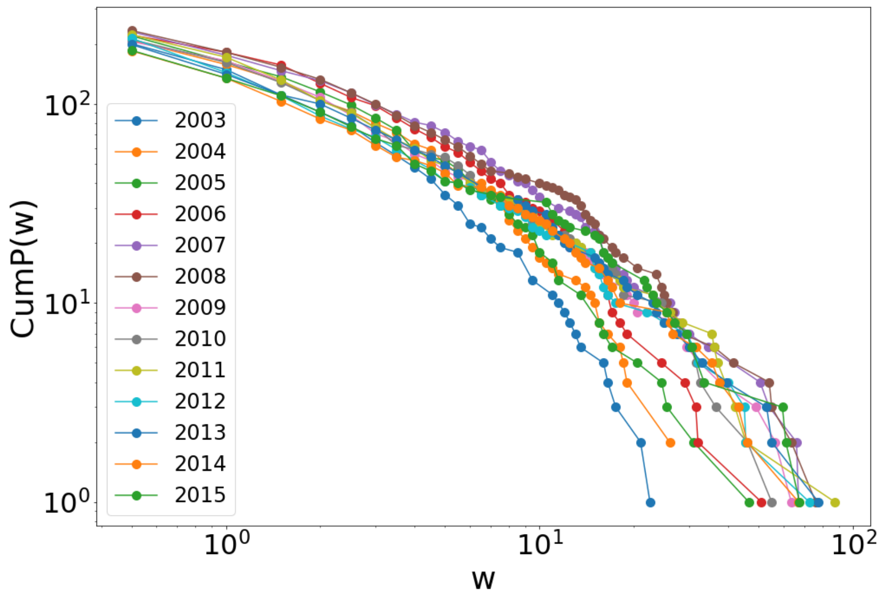


Figure 4: Evolution of cumulative distribution of weights on loglog scale during the period 2003-2015

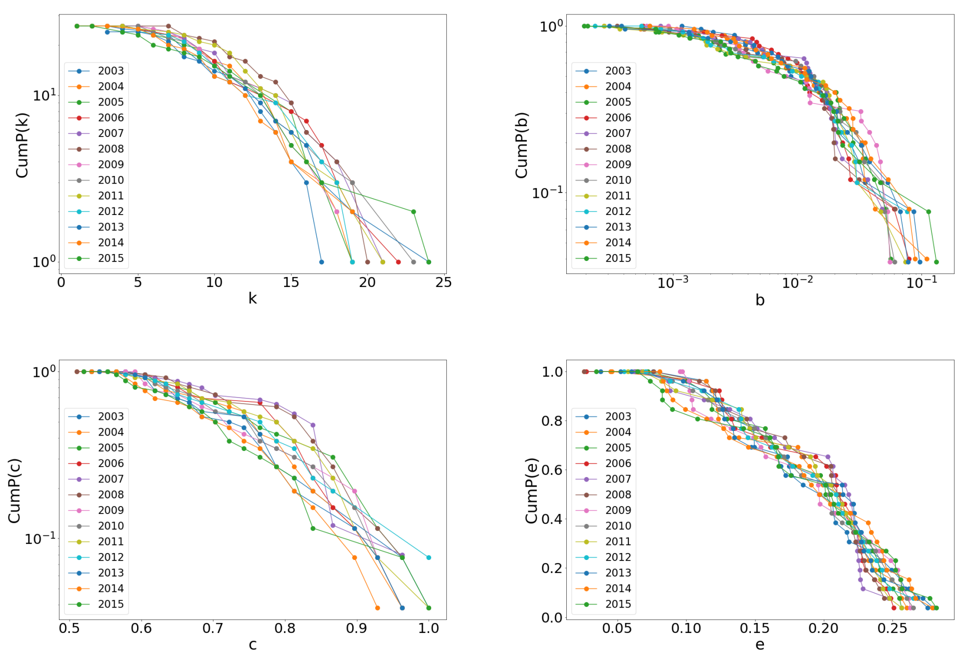


Figure 5: Evolution of cumulative distribution of degree (top left panel), betweenness (top right panel), closeness (bottom left panel) and eigenvector centrality (bottom right panel) during the period 2003-2015

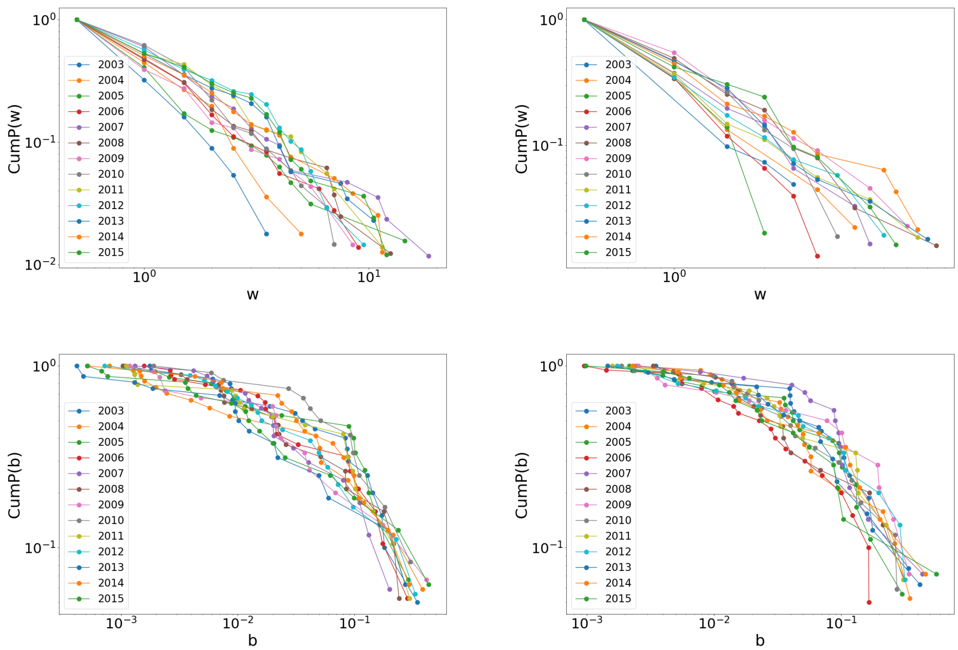


Figure 6: Evolution of cumulative distribution of weight (top) and betweenness (bottom), for two sectors: IT (left) and Industrial Machinery (right) during the period 2003-2015

5 Aggregated Indexes and Heat-maps

The networks have been built sector by sector. Therefore, in order to analyze the most central destination countries, we aggregate the topological measures as follows:

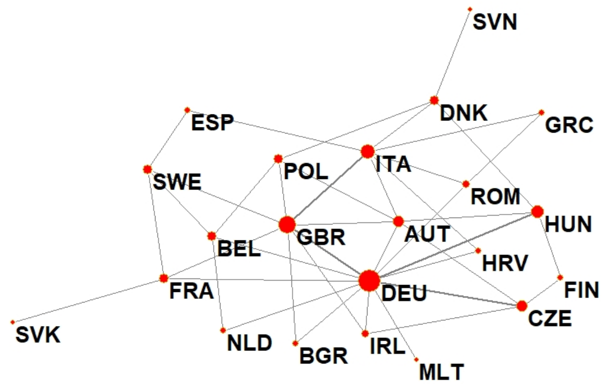
$$Index_{it}X = \frac{1}{N}\sum \lambda_{ijt} Index_{ijt} \tag{5}$$

where X is one of the indexes described above, N is the number of sector and λ_{ijt} is, for each country i, the ratio between number of projects in sector j over the total number of projects in the year t. While $Index_{ijt}$ is the $Index$ of sector j of country i in the year t.

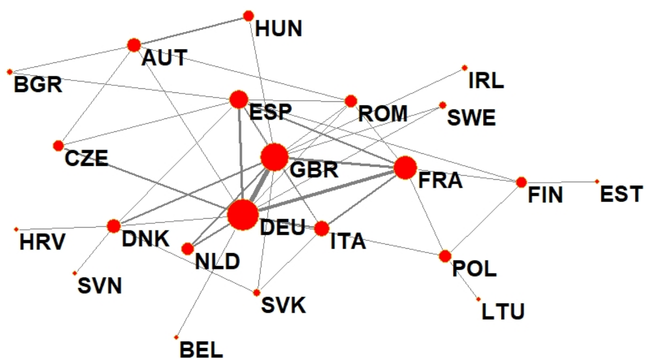
In table 1 the main descriptive statistics of the calculated indexes are shown for all the years considered. Values are very small because the index takes all sectors into consideration. Moreover, there is not much dispersion in distributions, because investments in all sectors do not take place in all countries.

In the table 2 we have reported, year by year, the hubs (countries) of the network emerged using the degree as Index. It is worth noting that, countries with the highest degree are also the most important (in terms of population and GDP) EU countries: UK, Germany, France. They are mainly followed by Italy, Austria, the Netherlands, Spain and Sweden. Like evident from Fig.2, these countries are both origin and destination of investments. However, while the outgoing links seem to keep a stable structure during the period 2003-2015, the number of incoming links is increasing after the crisis, particularly for Germany and Great Britain, showing that they are attracting more investments.

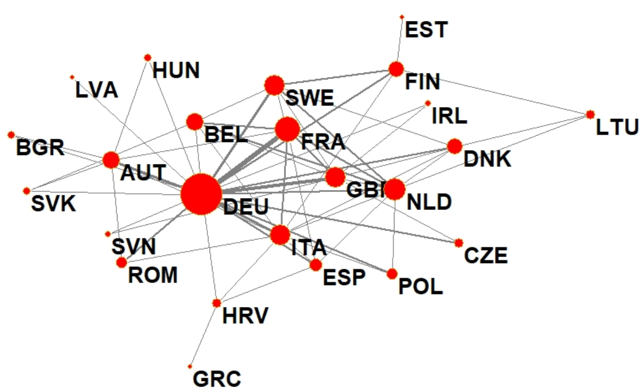
Finally, figures 10 and 11 show, at the European level and for 2003-2009-2015, the sum of projects per country and the values of in the index based on the eigenvector centrality, respectively. The countries are divided into quartiles. Visually, the projects are concentrated - in the period considered - in the central EU countries (Germany first of all), but they move from more peripheral countries (in 2009) to the founding



2003

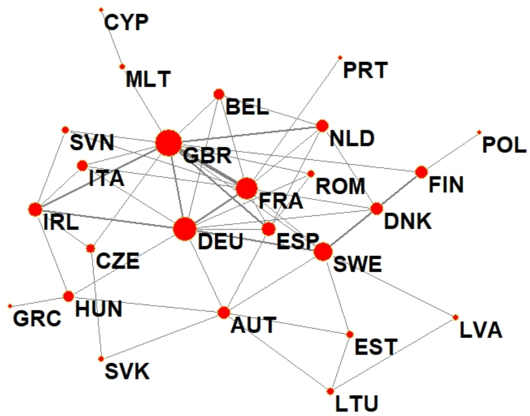


2009

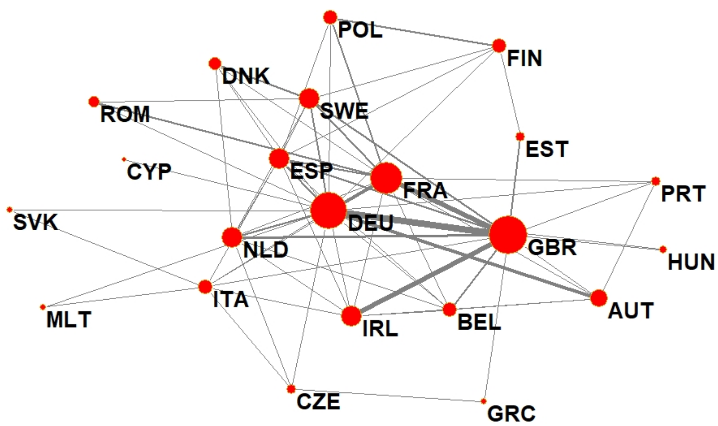


2015

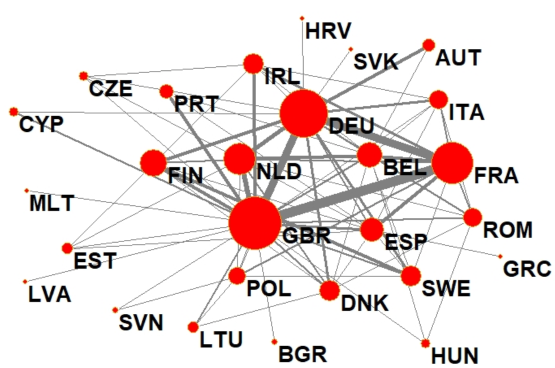
Figure 7: Industrial machinery Network. The size of nodes is proportional to degree centrality. The thickness of links to number of investments between the two countries



2003



2009



2015

Figure 8: Software and IT Network. The size of nodes is proportional to degree centrality. The thickness of links to number of investments between the two countries.

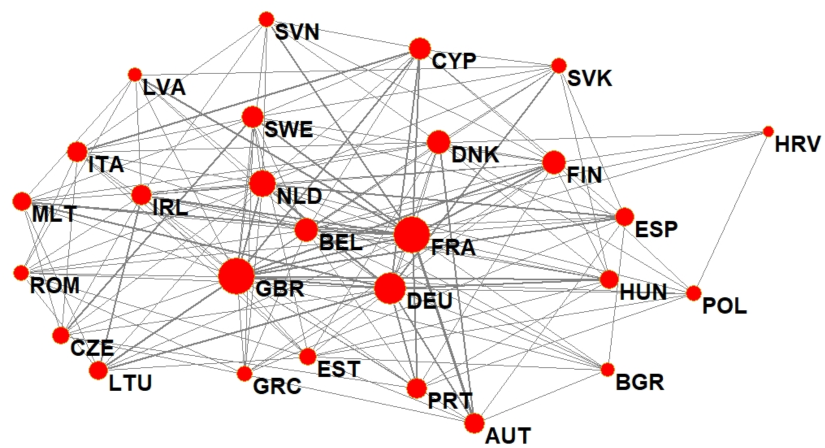


Figure 9: Reshuffled graph for Software and IT network (2015). The size of nodes is proportional to degree centrality, while the thickness of links to number of investments between the two countries. As evident, the heterogeneity is removed by reshuffling and the graph approaches a random graph.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Indexdegree	0.107	0.07	0.026	0.348
Indexavneighbourdegree	0.196	0.055	0.063	0.507
Indexclustering	0.009	0.005	0	0.025
Indexclustering2	0.006	0.003	0	0.025
Indexbetweenness	0.001	0.002	0	0.011
Indexcloseness	0.012	0.002	0.003	0.018
Indexeingencentrality	0.005	0.003	0.001	0.016
Indexeccentricity	0.091	0.012	0.037	0.143

Table 2: Highest Index Degree for EU Countries

2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
DEU	GBR	GBR	DEU	GBR	GBR	GBR	GBR	DEU	DEU	DEU	DEU	GBR
GBR	DEU	DEU	FRA	DEU	DEU	DEU	DEU	GBR	GBR	GBR	GBR	DEU
ITA	NLD	SWE	GBR	FRA	FRA	FRA	FRA	ESP	ESP	NLD	FRA	NLD
FRA	FRA	FRA	SWE	POL	NLD	NLD	ESP	FRA	FRA	FRA	ITA	FRA
AUT	AUT	AUT	AUT	AUT	AUT	ESP	AUT	ITA	NLD	ESP	SWE	BEL

ones (in 2015). On the other hand, looking at the eigenvector centrality index, it is clear that the map has concentric circles. The core are EU founding countries plus Spain and the UK. A second and third circle are also highlighted as you move away from the center.

To sum up, even if we are analyzing FDI flows, the network structure is very compact and its leaders do not change from year to year. However, the distribution of both links and weights show significant changes around 2009. The crisis has stopped the evolution of the network, changing the firms' strategies. These seem concentrated in few countries to diversify the risk. Our idea is that an FDI - more compact - network could transmit weaknesses/strengths in the economic system from one country to another, increasing/reducing the systemic risk. Indeed, it is difficult to understand whether network evolution has or has not favored the contagion or, instead, was a stabilizing element for the countries (both of origin and destination) themselves. For this reason, in the next section, we analyze if there is, and in which direction, a correlation between the network evolution (proxied by its indexes) and macroeconomic variables.

5.1 Heatmaps

All countries are linked through the trade as well as the capital flow channel (including the FDI). For this reason we believe that the FDI network can help us understand how weaknesses/strengths are transmitted between the various economic systems (countries). Therefore, we run correlations (using also delayed variables) the network indexes to some macroeconomic variables, in order to understand sign and magnitude of them.

In the Figures 12-14, we report the heat-maps of correlations between our indexes and macroeconomic variables for EU countries[3]. The least correlated index with the macroeconomic variables chosen are clustering and the squared clustering. This is not surprising, because the index is an indirect measure of centrality. On the other hand, the betweenness and eigenvector centrality present the maximum values for correlations.

Looking at the macro variables, the strongest correlations are between our indexes and the trade variables (import, export, the current account and trade). And this is true in both directions: import/export are (negatively) correlated with the current values of the indexes, as well as its delays; but at the same time delayed trade variables have a (negative) correlation with our indexes. Also it emerges that centrality measures are positively correlated to the current account balance, while they are negatively correlated to Yield10. Finally GDP growth and GDP per capita growth, inflation and deficit are weakly or not correlated. Two considerations are important. First, we made the correlations on the whole sample, assuming that there are no relevant country fixed effects. However, taking into account single countries some correlations show stronger magnitude. Moreover, it is to be considered our indexes are the weighted averages of the indexes of the various sectors. By correlating the values of the individual sectors could give us different indications. To sum-up the most interesting results are the following:

[3] all correlations are significant at 5%

- the three centrality measurements, that is closeness, betweenness and eigen-centrality have a similar pattern
- they are negatively correlated to export, import and trade, yield, while they are positively correlated to the current account.

We could say that the changes of topological measures anticipate and follow, in many cases, the trends of macroeconomic variables. It is clear these variables are strongly correlated and we should analyze them with an analysis of co-integration or a var analysis. However, the number of observation per country is too small to achieve robust regressions. And, therefore, we consider our results exploratory, even if they indicate a clear direction.

6 Conclusions

In the last decades, FDI became a key mode of internationalization changing the geography of production. The mutual economic relationships naturally arising after internationalization strategies create possible path of economic contagion, being a source of intrinsic systemic risks.

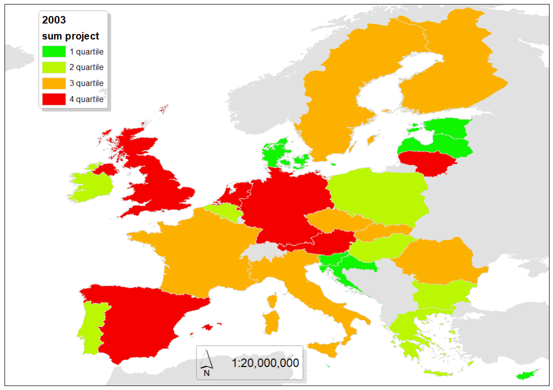
Differently from the traditional theoretical models of failure propagation or epidemic spreading, in this paper, we follow an empirical approach with the intention to identify signals of systemic risk based on a double approach: (i) monitoring the evolution of specific topological properties of the network (like centrality measurements), highlighting the signs of structural changes during crisis period and (ii) studying the correlations between macroeconomic variable and early and delayed network indexes.

The network of investments of EU firms investing in EU28 itself is generated. In this paper, we focus on the country space, where countries are linked if a firm of the first country is investing in the second one. For 38 different economic sectors, we reconstruct and discuss the networks of countries of investments by European (EU28) investors during the period 2003-2015. Without ex-ante priors, the evolution of network's structure is monitored, highlighting the topological changes by complex network analysis methods. Then, a cross-correlations between the centrality measures and some macroeconomic variables have been calculated, in order to detect forward or backward relations among them. In particular, a certain cross-correlation between specific lagged topological measurements and export, import, trade and yield emerge, giving us an indication that they can anticipate changes in these variables.

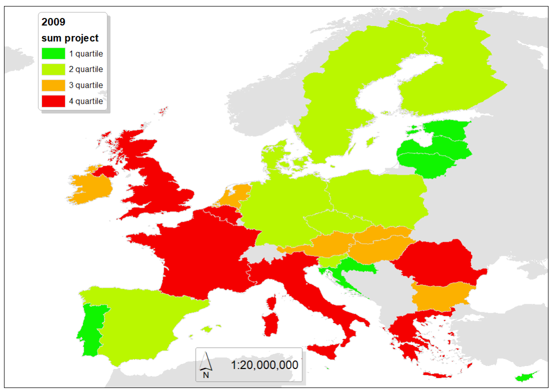
We explain our findings in the following way. At the beginning of the century the process of globalization and the augmented fragmentation of production have trigger firms to invest, at the same time, in many countries. However, after the emergence of the US crisis, EU firms started to move their investments in groups of countries like Germany, Great Britain, Netherlands. Feeling Eastern Europe markets more risky than the quite established ones, they tried to reduce the risk investing into main central EU countries. Also, the phenomenon is slightly different sector by sector. In a traditional sector like Industrial Machinery the trend here explained is very evident together with a reduction of number of investments, while in an emerging sector like Software and IT after a short term effect of crisis, we observe again expansion to an increased number of diversified investments.

This information is very relevant for systemic risk for two reasons. First of all, we have to expect that during crisis the relationships of mutual dependence between countries become stronger. So policy measures have to be taken to protect the traditional markets, much more than to try to intervene on new markets that most probably will not be chosen for new investments during crisis periods.

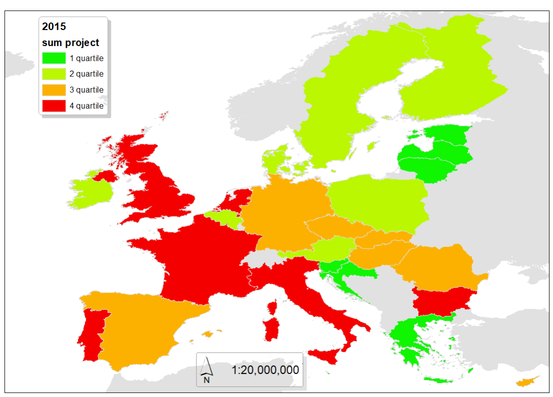
Then, we observe that the EU-FDI network self-organizes itself during crisis, in order to reduce the overall Systemic Risk, through rewiring of links towards the most safe nodes. Contagion would have become more likely if a central country faced a large idiosyncratic shock, like the structure we observe before 2009. The emergence of a set of central nodes, with a centrality slightly lower than the initial one facilitate diversification. From this point of view, even if an increased number of links in principle is creating more paths of economic contagion, in fact the rewiring of connection towards strong economies make the system more safe and less prone to systemic risk.



2003

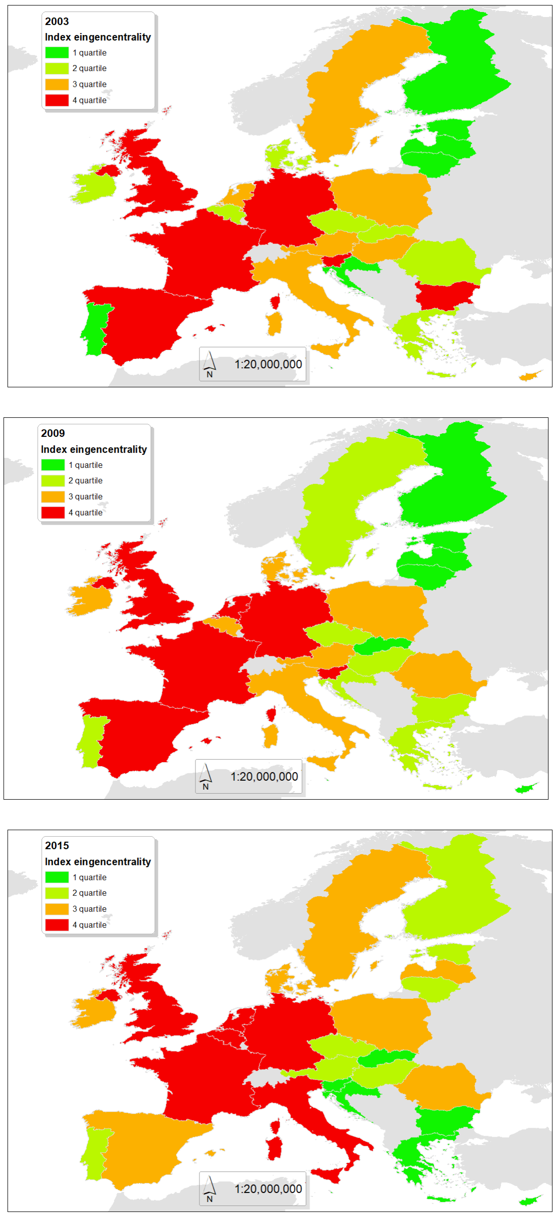


2009



2015

Figure 10: Sum of projects in 2003, 2009, 2015



2003

2009

2015

Figure 11: Maps of Eigen-Centrality in 2003, 2009, 2015

Figure 12: Actual Indexes and Actual Macro Variables

	Index_degree	Index_avneighbourdegree	Index_clustering	Index_clustering2	Index_betweenness	Index_closeness	Index_eingencentrality	Index_eccentricity	FDI net Inflows (%GDP)	Export (%GDP)	Import (%GDP)	Trade (%GDP)	CA (%GDP)	Domestic Credit	GDPgrowth	GDPpcgrowth	Inflation	Deficit	Yield10
Index_degree	1.00	-0.29	0.31	0.21	0.83	0.90	0.81	-0.59	-0.13	-0.34	-0.42	-0.38	0.27	0.17	-0.06	-0.10	-0.10	0.05	-0.25
Index_avneighbourdegr	-0.29	1.00	0.22	0.17	-0.45	0.04	-0.49	-0.06	0.21	0.40	0.42	0.41	0.01	-0.05	-0.07	-0.08	-0.14	-0.16	0.15
Index_clustering	0.31	0.22	1.00	0.66	-0.03	0.44	0.20	-0.33	-0.13	-0.02	-0.08	-0.05	0.13	-0.08	-0.04	-0.05	-0.05	-0.02	-0.17
Index_clustering2	0.21	0.17	0.66	1.00	-0.02	0.34	0.05	-0.18	-0.15	-0.01	-0.05	-0.03	0.09	-0.10	-0.08	-0.09	-0.05	-0.01	-0.04
Index_betweenness	0.83	-0.45	-0.03	-0.02	1.00	0.71	0.77	-0.41	-0.11	-0.34	-0.40	-0.37	0.24	0.10	-0.02	-0.04	-0.07	0.08	-0.21
Index_closeness	0.90	0.04	0.44	0.34	0.71	1.00	0.60	-0.58	-0.12	-0.23	-0.32	-0.27	0.29	0.10	-0.09	-0.13	-0.18	0.00	-0.26
Index_eingencentrality	0.81	-0.49	0.20	0.05	0.77	0.60	1.00	-0.62	-0.10	-0.35	-0.44	-0.40	0.28	0.12	-0.05	-0.09	-0.05	0.03	-0.27
Index_eccentricity	-0.59	-0.06	-0.33	-0.18	-0.41	-0.58	-0.62	1.00	0.02	0.10	0.18	0.14	-0.29	-0.18	0.18	0.22	0.16	0.06	0.26
FDI net Inflows (%GDP	-0.13	0.21	-0.13	-0.15	-0.11	-0.12	-0.10	0.02	1.00	0.39	0.42	0.41	-0.05	0.07	0.08	0.06	0.03	-0.07	-0.01
Export (%GDP)	-0.34	0.40	-0.02	-0.01	-0.34	-0.23	-0.35	0.10	0.39	1.00	0.97	0.99	0.23	-0.11	0.18	0.15	-0.09	-0.01	-0.12
Import (%GDP)	-0.42	0.42	-0.08	-0.05	-0.40	-0.32	-0.44	0.18	0.42	0.97	1.00	0.99	0.02	-0.15	0.23	0.21	0.04	-0.02	-0.06
Trade (%GDP)	-0.38	0.41	-0.05	-0.03	-0.37	-0.27	-0.40	0.14	0.41	0.99	0.99	1.00	0.13	-0.13	0.20	0.18	-0.03	-0.01	-0.09
CA (%GDP)	0.27	0.01	0.13	0.09	0.24	0.29	0.28	-0.29	-0.05	0.23	0.02	0.13	1.00	0.08	-0.22	-0.25	-0.53	0.12	-0.35
Domestic Credit	0.17	-0.05	-0.08	-0.10	0.10	0.10	0.12	-0.18	0.07	-0.11	-0.15	-0.13	0.08	1.00	-0.30	-0.40	-0.30	-0.09	-0.04
GDPgrowth	-0.06	-0.07	-0.04	-0.08	-0.02	-0.09	-0.05	0.18	0.08	0.18	0.23	0.20	-0.22	-0.30	1.00	0.98	0.46	0.33	-0.26
GDPpcgrowth	-0.10	-0.08	-0.05	-0.09	-0.04	-0.13	-0.09	0.22	0.06	0.15	0.21	0.18	-0.25	-0.40	0.98	1.00	0.49	0.31	-0.22
Inflation	-0.10	-0.14	-0.05	-0.05	-0.07	-0.18	-0.05	0.16	0.03	-0.09	0.04	-0.03	-0.53	-0.30	0.46	0.49	1.00	0.28	0.03
Deficit	0.05	-0.16	-0.02	-0.01	0.08	0.00	0.03	0.06	-0.07	-0.01	-0.02	-0.01	0.12	-0.09	0.33	0.31	0.28	1.00	-0.32
Yield10	-0.25	0.15	-0.17	-0.04	-0.21	-0.26	-0.27	0.26	-0.01	-0.12	-0.06	-0.09	-0.35	-0.04	-0.26	-0.22	0.03	-0.32	1.00

1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
-0.80
-1.00

Figure 13: Actual Indexes and Lagged Macro Variables

	Index_degree	Index_avneighbourdegree	Index_clustering	Index_clustering2	Index_betweenness	Index_closeness	Index_eingencentrality	Index_eccentricity	Lag FDI net Inflows (%GDP)	Lag Export (%GDP)	Lag Import (%GDP)	Lag Trade (%GDP)	Lag CA (%GDP)	Lag Domestic Credit	Lag GDPgrowth	Lag GDPpcgrowth	Lag Inflation	Lag Deficit	Lag Yield10
Index_degree	1.00	-0.29	0.31	0.21	0.83	0.90	0.81	-0.59	-0.13	-0.35	-0.44	-0.39	0.29	0.17	-0.04	-0.09	-0.12	0.08	-0.26
Index_avneighbour	-0.29	1.00	0.22	0.17	-0.45	0.04	-0.49	-0.06	0.26	0.38	0.40	0.39	-0.02	-0.09	-0.04	-0.05	-0.09	-0.19	0.22
Index_clustering	0.31	0.22	1.00	0.66	-0.03	0.44	0.20	-0.33	-0.12	-0.04	-0.09	-0.07	0.15	-0.11	-0.05	-0.07	-0.05	0.05	-0.16
Index_clustering2	0.21	0.17	0.66	1.00	-0.02	0.34	0.05	-0.18	-0.12	-0.02	-0.06	-0.04	0.11	-0.12	-0.05	-0.07	-0.07	0.04	-0.16
Index_betweenness	0.83	-0.45	-0.03	-0.02	1.00	0.71	0.77	-0.41	-0.11	-0.33	-0.40	-0.36	0.27	0.12	-0.06	-0.07	-0.10	0.08	-0.18
Index_closeness	0.90	0.04	0.44	0.34	0.71	1.00	0.60	-0.58	-0.08	-0.27	-0.36	-0.31	0.31	0.09	-0.06	-0.10	-0.17	0.02	-0.26
Index_eingencentra	0.81	-0.49	0.20	0.05	0.77	0.60	1.00	-0.62	-0.19	-0.33	-0.42	-0.38	0.31	0.15	-0.06	-0.10	-0.09	0.09	-0.28
Index_eccentricity	-0.59	-0.06	-0.33	-0.18	-0.41	-0.58	-0.62	1.00	0.14	0.11	0.19	0.15	-0.28	-0.21	0.10	0.14	0.11	-0.02	0.26
Lag FDI net Inflows	-0.13	0.26	-0.12	-0.12	-0.11	-0.08	-0.19	0.14	1.00	0.40	0.43	0.42	-0.06	0.07	0.05	0.03	0.02	-0.07	0.01
Lag Export (%GDP	-0.35	0.38	-0.04	-0.02	-0.33	-0.27	-0.33	0.11	0.40	1.00	0.97	0.99	0.21	-0.09	0.12	0.10	-0.11	-0.03	-0.09
Lag Import (%GDP	-0.44	0.40	-0.09	-0.06	-0.40	-0.36	-0.42	0.19	0.43	0.97	1.00	0.99	-0.01	-0.14	0.19	0.18	0.03	-0.03	-0.04
Lag Trade (%GDP)	-0.39	0.39	-0.07	-0.04	-0.36	-0.31	-0.38	0.15	0.42	0.99	0.99	1.00	0.11	-0.11	0.16	0.14	-0.04	-0.03	-0.07
Lag CA (%GDP)	0.29	-0.02	0.15	0.11	0.27	0.31	0.31	-0.28	-0.06	0.21	-0.01	0.11	1.00	0.09	-0.30	-0.32	-0.55	0.11	-0.34
Lag Domestic Cred	0.17	-0.09	-0.11	-0.12	0.12	0.09	0.15	-0.21	0.07	-0.09	-0.14	-0.11	0.09	1.00	-0.31	-0.41	-0.30	-0.09	-0.05
Lag GDPgrowth	-0.04	-0.04	-0.05	-0.05	-0.06	-0.06	-0.06	0.10	0.05	0.12	0.19	0.16	-0.30	-0.31	1.00	0.98	0.47	0.34	-0.26
Lag GDPpcgrowth	-0.09	-0.05	-0.07	-0.07	-0.07	-0.10	-0.10	0.14	0.03	0.10	0.18	0.14	-0.32	-0.41	0.98	1.00	0.51	0.32	-0.21
Lag Inflation	-0.12	-0.09	-0.05	-0.07	-0.10	-0.17	-0.09	0.11	0.02	-0.11	0.03	-0.04	-0.55	-0.30	0.47	0.51	1.00	0.29	0.03
Lag Deficit	0.08	-0.19	0.05	0.04	0.08	0.02	0.09	-0.02	-0.07	-0.03	-0.03	-0.03	0.11	-0.09	0.34	0.32	0.29	1.00	-0.39
Lag Yield10	-0.26	0.22	-0.16	-0.16	-0.18	-0.26	-0.28	0.26	0.01	-0.09	-0.04	-0.07	-0.34	-0.05	-0.26	-0.21	0.03	-0.39	1.00

1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
-0.80
-1.00

Figure 14: Lagged Indexes and Actual Macro Variables

	Lag Index_degree	Lag Index_avneighbourdegree	Lag Index_clustering	Lag Index_clustering2	Lag Index_betweenness	Lag Index_closeness	Lag Index_eingencentrality	Lag Index_eccentricity	FDI net Inflows (%GDP)	Export (%GDP)	Import (%GDP)	Trade (%GDP)	CA (%GDP)	Domestic Credit	GDPgrowth	GDPpcgrowth	Inflation	Deficit	Yield10
Lag Index_degree	1.00	-0.28	0.32	0.24	0.83	0.91	0.81	-0.59	-0.14	-0.35	-0.44	-0.39	0.28	0.17	-0.12	-0.16	-0.13	-0.02	-0.26
Lag Index_avneighbour	-0.28	1.00	0.22	0.14	-0.45	0.05	-0.49	-0.06	0.31	0.36	0.37	0.37	0.03	-0.03	-0.17	-0.17	-0.20	-0.20	0.18
Lag Index_clustering	0.32	0.22	1.00	0.63	-0.02	0.45	0.21	-0.33	-0.13	-0.05	-0.10	-0.08	0.10	-0.07	-0.10	-0.12	-0.06	-0.09	-0.10
Lag Index_clustering2	0.24	0.14	0.63	1.00	-0.01	0.34	0.07	-0.16	-0.12	-0.05	-0.09	-0.07	0.08	-0.08	-0.12	-0.13	-0.09	-0.05	-0.08
Lag Index_betweenness	0.83	-0.45	-0.02	-0.01	1.00	0.71	0.77	-0.42	-0.11	-0.34	-0.40	-0.37	0.24	0.10	-0.01	-0.02	-0.06	0.07	-0.23
Lag Index_closeness	0.91	0.05	0.45	0.34	0.71	1.00	0.59	-0.57	-0.05	-0.25	-0.34	-0.30	0.31	0.10	-0.16	-0.20	-0.20	-0.08	-0.25
Lag Index_eingencentra	0.81	-0.49	0.21	0.07	0.77	0.59	1.00	-0.63	-0.19	-0.36	-0.45	-0.40	0.26	0.13	-0.04	-0.07	-0.08	0.03	-0.26
Lag Index_eccentricity	-0.59	-0.06	-0.33	-0.16	-0.42	-0.57	-0.63	1.00	0.03	0.13	0.22	0.17	-0.33	-0.18	0.22	0.24	0.26	0.13	0.20
FDI net Inflows (%GDP	-0.14	0.31	-0.13	-0.12	-0.11	-0.05	-0.19	0.03	1.00	0.39	0.42	0.41	-0.05	0.07	0.08	0.06	0.03	-0.07	-0.01
Export (%GDP)	-0.35	0.36	-0.05	-0.05	-0.34	-0.25	-0.36	0.13	0.39	1.00	0.97	0.99	0.23	-0.11	0.18	0.15	-0.09	-0.01	-0.12
Import (%GDP)	-0.44	0.37	-0.10	-0.09	-0.40	-0.34	-0.45	0.22	0.42	0.97	1.00	0.99	0.02	-0.15	0.23	0.21	0.04	-0.02	-0.06
Trade (%GDP)	-0.39	0.37	-0.08	-0.07	-0.37	-0.30	-0.40	0.17	0.41	0.99	0.99	1.00	0.13	-0.13	0.20	0.18	-0.03	-0.01	-0.09
CA (%GDP)	0.28	0.03	0.10	0.08	0.24	0.31	0.26	-0.33	-0.05	0.23	0.02	0.13	1.00	0.08	-0.22	-0.25	-0.53	0.12	-0.35
Domestic Credit	0.17	-0.03	-0.07	-0.08	0.10	0.10	0.13	-0.18	0.07	-0.11	-0.15	-0.13	0.08	1.00	-0.30	-0.40	-0.30	-0.09	-0.04
GDPgrowth	-0.12	-0.17	-0.10	-0.12	-0.01	-0.16	-0.04	0.22	0.08	0.18	0.23	0.20	-0.22	-0.30	1.00	0.98	0.46	0.33	-0.26
GDPpcgrowth	-0.16	-0.17	-0.12	-0.13	-0.02	-0.20	-0.07	0.24	0.06	0.15	0.21	0.18	-0.25	-0.40	0.98	1.00	0.49	0.31	-0.22
Inflation	-0.13	-0.20	-0.06	-0.09	-0.06	-0.20	-0.08	0.26	0.03	-0.09	0.04	-0.03	-0.53	-0.30	0.46	0.49	1.00	0.28	0.03
Deficit	-0.02	-0.20	-0.09	-0.05	0.07	-0.08	0.03	0.13	-0.07	-0.01	-0.02	-0.01	0.12	-0.09	0.33	0.31	0.28	1.00	-0.32
Yield10	-0.26	0.18	-0.10	-0.08	-0.23	-0.25	-0.26	0.20	-0.01	-0.12	-0.06	-0.09	-0.35	-0.04	-0.26	-0.22	0.03	-0.32	1.00

1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
-0.80
-1.00

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