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Uncovering the Network Complexity in Input-Output Linkages among Sectors in European Countries*

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Abstract

The global economic system is a highly interlinked network, comprised of heterogeneous industries in different countries. In such a complex system, a negative shock to the production of any industrial sector may have two distinct effects on the remaining industrial sectors: on the one hand by increasing/decreasing production it will demand more/less inputs from other sectors (i.e. "upstream" propagation); on the other hand it will be able to supply more/less output to the sectors that use its production as input to their own production process (i.e. "downstream" propagation). In this work, applying network analysis tools we explore the main topological properties of the input-output linkages among industrial sectors in 19 members of the Economic and Monetary Union. Among the other results, on the one hand, we find that intra-country linkages are generally much denser than inter-country linkages. This implies that in many cases, the propagation of a shock to an industry may first tend to fall more heavily on other domestic industries. On the other hand, after uncovering the complexity in the backbone of inter-country linkages, we can identify the main properties that are potentially important to cross-border spillover risks. In particular, first, the tendency to trade with sectors in neighboring countries indicates that geographic linkages could be an important channel in the transmission of negative shocks from one country to another. Second, a subset of sectors playing as hubs, which form a densely connected core among themselves and at the same time bridge sectors in different member countries, could potentially become quick transmitters of shocks to different economies.

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1 Introduction

Following several decades of rapid globalisation, the global economic system has become a highly interlinked network, comprised of heterogeneous industries in different countries. In such a complex system, local shocks to single industrial sectors may lead to a large disruption in the aggregate output. In particular, a negative shock to the production of any sector may have two distinct effects on the remaining sectors: on the one hand, by decreasing production, via "upstream" propagation it will reduce its demand from input-supplying sectors; on the other hand, via "downstream" propagation it will supply less to customer industries.

It has been widely suggested that input-output linkages play a crucial role in the propagation and amplification of idiosyncratic shocks throughout an economy. In particular, local shocks to single firms or sectors can propagate further through input-output interdependencies, and finally may lead to a large aggregate fluctuation with potentially significant implications for macroeconomic volatility and economic growth (e.g. Horvath (1998), Horvath (2000); Shea (2002); Gabaix (2011); Acemoglu et al. (2012); Acemoglu et al. (2016); Acemoglu et al. (2017); Jones (2013); Carvalho (2014); Cavallo et al. (2014); Contreras and Fagiolo (2014); Carvalho et al. (2016)). Therefore, understanding the network structure of inter-sectoral linkages can better explain the origins of aggregate fluctuations as well as the potential channels of shock diffusion. Furthermore, it is also useful for policymakers to propose effective policies to mitigate adverse shocks that disrupt the production system.

Whereas much of analysis has been focused on the network of interactions between industrial sectors within a closed economy, less attention has, however, been devoted to the network patterns that are potentially important in explaining the propagation of shocks across borders. In this report, using the World Input-Output Tables (WIOT) we analyze topological properties of the inter-country production network in 19 members of the Economic and Monetary Union (EMU). The main objectives are: (i) to uncover the network complexity and patterns of input-output linkages, and (ii) to identify the important patterns of inter-dependencies between industrial sectors in the EMU, which may create the potential channels that local shocks can be propagated through the whole network. Overall, the main findings from this report are the following:

- Dense connections among domestic sectors and the tendency to trade with sectors in neighboring countries imply that geographic linkages could be an important transmission path of negative shocks.
- Considering only external linkages among sectors in different countries, we find that there is the presence of a hierarchical structure in which a subset of key sectors with many links trade more intensely among themselves, and the less active peripheral sectors mostly trade with a small number of these key sectors. Under this structure, local shocks could be quickly propagated to other parts of the network.

The remainder of this report is structured as follows. In Section 2, we explain the dataset and provide a general framework for the network representations of the Input-Output Tables in 19 members of the EMU. Section 3 summarizes the main results. Section 4 provides concluding remarks. At the end of this report, the Appendix A provides additional details concerning the list of sectors, and the Appendix B provides analytical details for the measures as well as additional results of different network properties and centrality.

2 Data and Network Representations

2.1 Data

We analyze the network structure of linkages between industrial sectors in the 19 members of the EMU, using the World Input-Output Database (WIOD). Data are available at: http://www.wiod.org/database. In every year, the data set provides world input-output table (WIOT) in current prices, denoted in millions of dollars. Each country has 35 of industrial sectors, besides the final demand sectors. The table gives information on the economic transactions that sectors made by buying and selling inputs from other sectors. More details on how to construct this database can be found in the study of Dietzenbacher et al. (2013).

Furthermore, in our study, we use the Hypergeometric method to filter the data (e.g. see Micciche et al. (2011); Riccaboni et al. (2013)). The method is a stochastic benchmark for normalization purposes. The network after filtering will contain only those links that are sensibly high connection with respect to randomly chosen connections. Practically, for two countries, A and B, let N_A be the value of goods exported by country A and N_B the value of goods imported by country B. The total value of traded goods is N_k and the observed value of goods exported from A to B is N_{AB}. Under the null hypothesis of random co-occurrence, i.e. customers in country B are indifferent to the nationality of the exporter, the probability of observing X US dollars of goods traded is given by the hypergeometric distribution

$$H(X|N_k, N_A, N_B) = \frac{\binom{N_A}{X}\binom{N_k-N_A}{N_B-X}}{\binom{N_k}{N_B}} \ , \tag{1}$$

and we can associate a p-value with the observed N_{AB} as

$$p(N_{AB}) = 1 - \sum_{X=0}^{N_{AB}-1} H(X|N_k, N_A, N_B) \ . \tag{2}$$

Note that the described null hypothesis directly takes into account the heterogeneity of countries with respect to the total value of goods traded. For each pair of countries, we separately evaluate the p-value and then use a cutoff to select only those links that represent a significant departure from the hypergeometric benchmark ($p < .01$). The resulting filtered matrices can then be dichotomized or anyway contain only the links that pass the test.

2.2 Network Representations

In the following, we briefly introduce the mathematical expression of an international production network comprised of different industries in different countries. Consider an aggregate network of N countries indexed by $\alpha = 1, 2, ..., N$. Each country has M industrial sectors indexed by $i = 1, 2, ..., M$.[1] Mathematically, the aggregate production network in of N countries can be represented by a supra-weighted matrix $\mathcal{W}^a$

$$\mathcal{W}^a = \{w_{ij}\}_{NM\text{x}NM} = \left[\begin{array}{c|c|c|c|c} \mathbf{W}_{11} & W_{12} & W_{13} & \dots & W_{1N} \\ \hline W_{21} & \mathbf{W}_{22} & W_{23} & \dots & W_{2N} \\ \hline W_{31} & W_{32} & \mathbf{W}_{33} & \dots & W_{3N} \\ \hline \dots & \dots & \dots & \dots & \dots \\ \hline W_{N1} & W_{N2} & W_{N3} & \dots & \mathbf{W}_{NN} \end{array}\right] , \tag{3}$$

[1]Particularly, in our data set, N=19 and M=35.

and a supra-adjacency matrix $\mathcal{A}^a$

$$\mathcal{A}^a = \{a_{ij}\}_{NMxNM} = \left[\begin{array}{c|c|c|c|c} \mathbf{A}_{11} & A_{12} & A_{13} & ... & A_{1N} \\ \hline A_{21} & \mathbf{A}_{22} & A_{23} & ... & A_{2N} \\ \hline A_{31} & A_{32} & \mathbf{A}_{33} & ... & A_{3N} \\ \hline ... & ... & ... & ... & ... \\ \hline A_{N1} & A_{N2} & A_{N3} & ... & \mathbf{A}_{NN} \end{array}\right], \tag{4}$$

where $\mathbf{W}_{\alpha\alpha}$ (or $\mathbf{A}_{\alpha\alpha}$) with size MxM represents intra-country weighted (or adjacency) block matrix capturing the interactions among domestic sectors in the country α, and $W_{\alpha\beta}$ (or $A_{\alpha\beta}$) with size MxM represents inter-country weighted (adjacency) block matrix capturing the interactions between sectors in the country α and sectors in the country β. Note that the aggregate weighted matrix, $\mathcal{W}^a$, and each of its block matrices represent directed networks with possible self-loops, in which each element indicates an economic flow from one sector to another sector.

Furthermore, the aggregate weighted matrix $\mathcal{W}^a$ can be decomposed into two distinct parts. The first part consists of only domestic inter-sectoral linkages–namely the domestic network, represented by

$$\mathcal{W}^d = \left[\begin{array}{c|c|c|c|c} \mathbf{W}_{11} & O & O & ... & O \\ \hline O & \mathbf{W}_{22} & O & ... & O \\ \hline O & O & \mathbf{W}_{33} & ... & O \\ \hline ... & ... & ... & ... & ... \\ \hline O & O & O & ... & \mathbf{W}_{NN} \end{array}\right], \tag{5}$$

and the second part consists of only external inter-sectoral linkages–namely the external network, represented by

$$\mathcal{W}^e = \left[\begin{array}{c|c|c|c|c} O & W_{12} & W_{13} & ... & W_{1N} \\ \hline W_{21} & O & W_{23} & ... & W_{2N} \\ \hline W_{31} & W_{32} & O & ... & W_{3N} \\ \hline ... & ... & ... & ... & ... \\ \hline W_{N1} & W_{N2} & W_{N3} & ... & O \end{array}\right], \tag{6}$$

where O stands for the matrix of size MxM with all elements are equal to zero. Similarly, in the binary version, we can also define $\mathcal{A}^d$ and $\mathcal{A}^e$ respectively as the domestic and external adjacency matrices.

Later we will see that in fact internal linkages among domestic sectors are generally much denser than the external linkages among sectors in different countries. In such a asymmetric structure, we focus the network properties of the external linkages (based on $\mathcal{A}^e$ and $\mathcal{W}^e$), which are more potentially relevant for a better understanding of the international diffusion of shocks. We provide analytical details for different measures of different network properties and centrality in the Appendix B.

3 Network properties

In this section, we summarize the main topological properties of the input-output (I-O) linkages among sectors in 19 member countries of the EMU. Additional results of the network properties and centrality are provided in Appendix B. Note that for the illustration purpose, in what follows we select the network in the two years 2005 and 2011 as examples.

Our starting point is to have a visualization for the structure of the aggregate network and its decomposition. In Figure (1) we show the structure of the supra adjacency matrix, $\mathcal{A}^a$, in which each blue dot represents a directed link between two sectors. The internal linkages in each country are represented by an associated block matrix located at the diagonal space of $\mathcal{A}^a$. In contrast, each block in the off-diagonal space shows the external linkages form sectors in a country to sectors in another country.

The visualizations of the aggregate network and only the external linkages are respectively shown in panels (a) and (b) of Figure (2).

Figures (1) and (2) lead us to a first glance at the network structure: in general, the network exhibits a very asymmetric structure between the internal and external linkages. In particular, intra-country linkages are generally much denser than the inter-country linkages, implying that many sectors in the members of the EMU are more internally integrated. Further details about the distributions of the degrees and strengths of sectors are provided in Figures (7), (8), (9), and (10) in the Appendix A, where we can see that the range of the distributions of degrees and strengths in the aggregate network is wider than in the external network, especially in the distributions of strengths. It is intuitive when a sector tend to trade more with other domestic sectors, since it can help to reduce transportation costs and facilitate information transfer (e.g. Fujita et al. (1999)). Denser and more intensive linkages among domestic sectors within each member country also reveal that the propagation of a shock to an industry may first tend to fall more heavily on other domestic industries, implying the potential effects of geographic spillovers (e.g. Acemoglu et al. (2017)).

In addition, examining the relationships between the degrees and strengths with the aggregate outputs, we find that large output sectors are not necessarily more active in trade with sectors in other member countries (see Figures (11), (12), (13), and (14) in the Appendix B). Similar results are also typically observed in other network centrality measures such as PageRanks, betweenness (see Figures (15), (16), (17), and (18) in the Appendix B).

Furthermore, when considering only the external linkages, we do also observe, however, the presence of key players trading with other sectors in different members of the EMU. These are, for instance, sectors in several countries such as Germany, France, Italy, Spain, Netherlands, and Belgium. Overall, we find that these key players are not only high degree or strength nodes, but also have a higher level of network centrality.

The first impression of the hierarchical structure of inter-country linkages motivates us to examine the tendency of interactions of different groups of sectors, for example, interactions among the highly connected sectors, interactions between highly connected and less active sectors, and interactions among less active sectors. This will help to identify whether there is the presence of potential (global) propagators in the network.

To do that, in the next steps, first, we analyze clusters formed by three sectors in different countries based on various types of directed clustering coefficients (e.g. Onnela et al. (2005); Fagiolo (2007)). As visualized in Figure (19) in the Appendix, each of inward, outward, middleman, and cyclic clusters in fact captures different direct and indirect exposures among three connected sectors (e.g. Tabak et al. (2014); Luu et al. (2017)). Second, at the intermediate-scale level (or "meso-scale" level), we investigate whether there is the presence of the core-periphery structure (e.g. Borgatti and Everett (2000); Rombach et al. (2014)) of the external network and then measure the averages of links and weights within and between different groups. In general, under this structure the network is composed by a dense core with a sparsely connected periphery. In addition, nodes in the core should also be well connected to peripheral nodes, thus the core also tends to be "central" to the network. Further details for the visualization as well as the analytical expression of the clustering coefficients, and the method to detect the core-periphery structure are provided in the Appendix B.

We show the results for four directed weighted clustering coefficients in Figure (4). All of these coefficients are plotted against the natural independent strengths or the combinations of them.[2] We find that in all types of coefficients, sectors with a higher level of strengths also have a higher level of weighted clustering coefficients. This indicates that indicating that sectors with larger total external trade tend to participate in more intense inter-country trade clusters.

[2]Notice that in the cases of cyclic and middleman types, the coefficients are plotted against $s^{in-out} = \sqrt{s^{in}s^{out}}$, since the clustering coefficients in these types depends on both incoming and outgoing link weights.

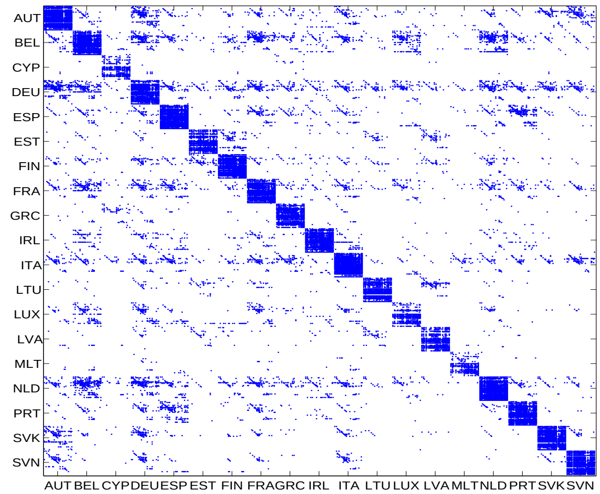
Regarding the core-periphery structure, we find that sectors in some countries such as Germany, France, Italy, Spain, Netherlands, and Belgium again dominantly appear in the core part.[3] Furthermore, the averages of links and weights within the core part are respectively larger than the averages of links and weights between the core and the periphery parts. Additionally, the interactions among sectors within the periphery part are negligible on average.

The results obtained from the analysis of the clustering behaviors as well as the core-periphery structure imply that some sectors (in a few member countries), which build up a more densely connected core, are the main actors in the inter-country production chains. The less active peripheral sectors (in other member countries) mostly trade with these core sectors.

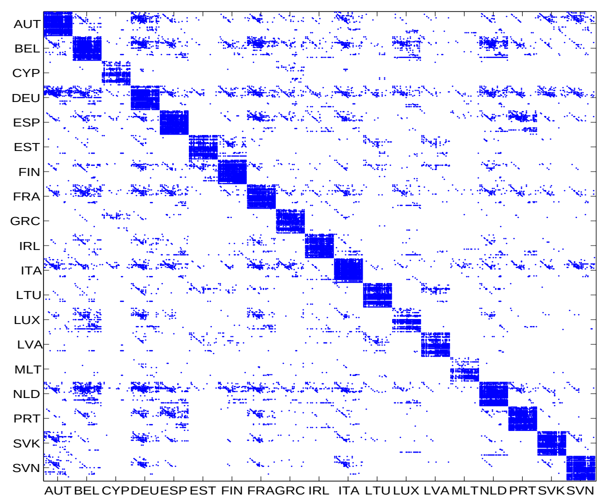
In order to evaluate the overall strength of the input-output tie for every pair of countries, we measure the inter-country average of connectivity and the inter-country average of intensity. In particular, the average of connectivity from one country to another country is based on the external (directed) links between sectors (represented by $\mathcal{A}^e$), and similarly the average of intensity is based on the external (directed) weights between sectors (represented by $\mathcal{W}^e$). Again, further analytical details for these measures are provided in the Appendix B.

In Figure (6), we show the color-coded matrices for the averages of connectivity and intensity between every two countries. Notice that each matrix is not necessarily symmetric, since the input-output network is directed. Our findings suggest that the overall input-output inter-dependencies are highly heterogeneous (see also Figure (20) in the Appendix B). In particular, while on average sectors in some countries are more intensely connected, the overall strength of the tie between sectors in other pairs of countries is very weak. This result is in harmony with what we obtained from the aforementioned analysis of clustering behaviors and the core-periphery structure, i.e. some sectors in several countries build up more intensely connected clusters but the rest mildly interact among themselves. In addition, we also find a tendency to connect to sectors in neighboring countries, especially for the case of small members of the EMU. This indicates that besides the presence of global hubs, geographic linkages could be also another important channel in the transmission of negative shocks across borders.

[3]Here we only analyze the core-periphery structure of external links between sectors in different countries. Since the internal links in the domestic layers are much denser, the aggregate network somewhat exhibits a block structure shown in Figure (1).

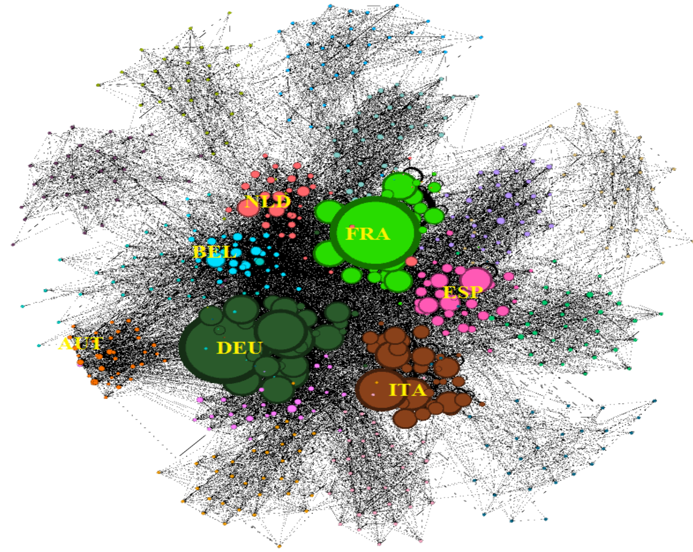


(a) adjacency matrix in 2005

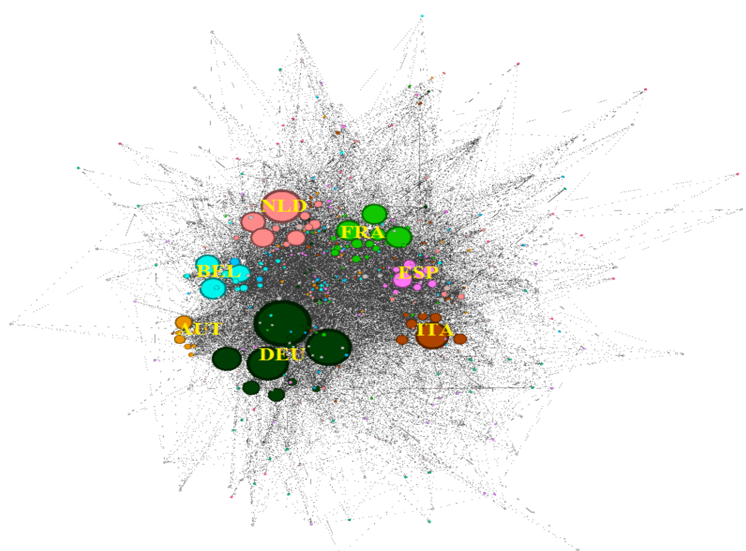


(b) adjacency matrix in 2011

Figure 1: The adjacency matrix of the aggregate production network in EMU in 2005 (panel (a)) and 2011 (panel (b)). In each panel, each blue dot represents a directed link between two sectors.

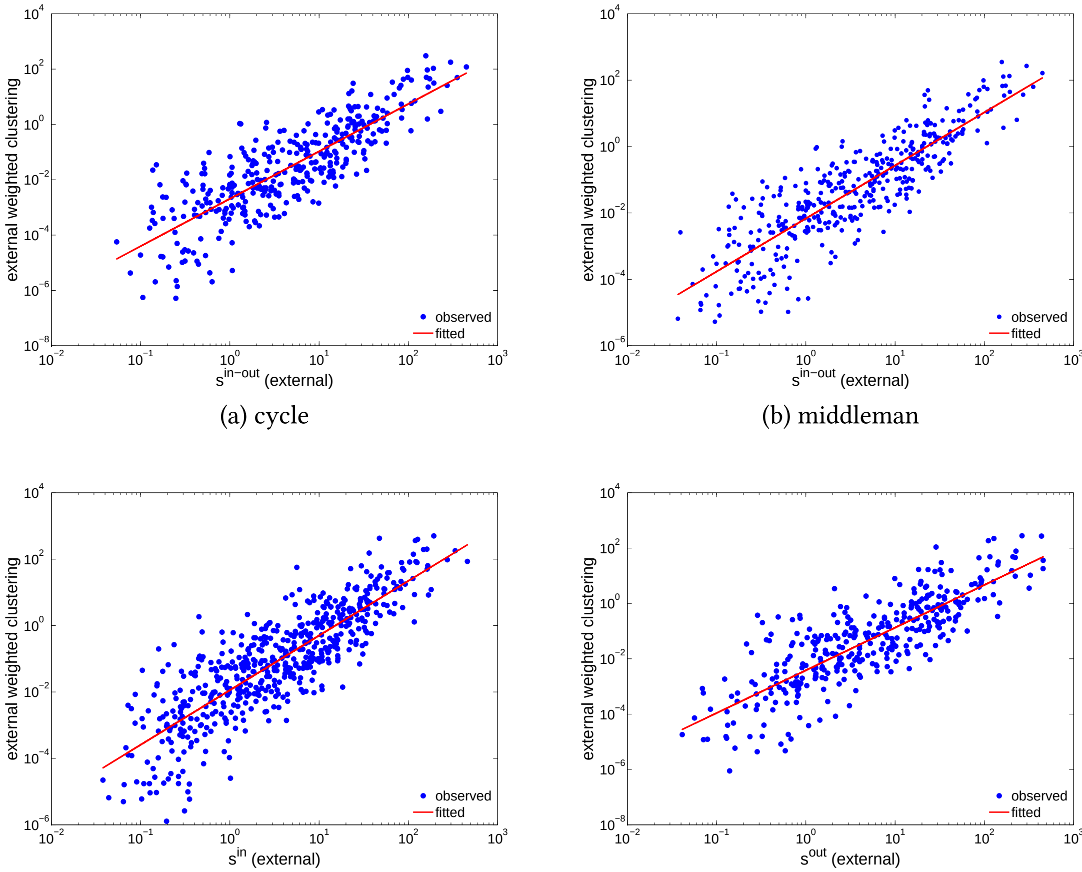


(a) both domestic and external links



(b) only external links

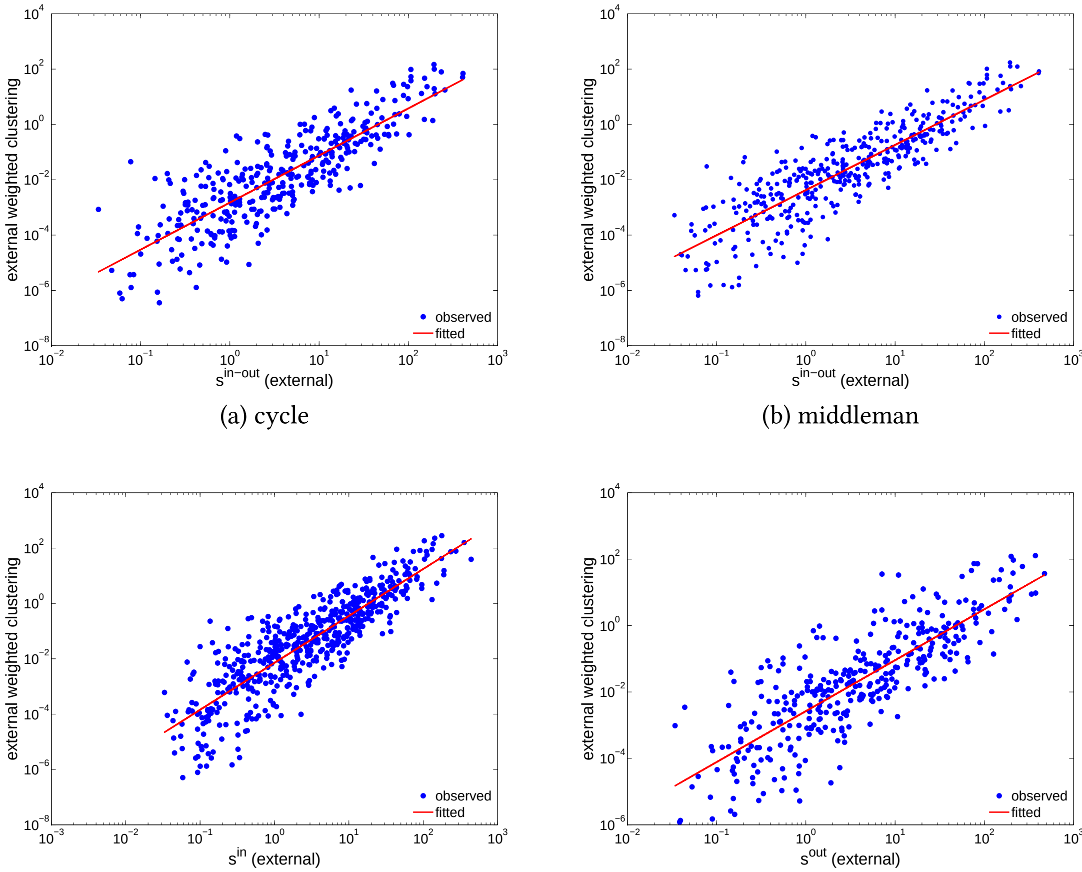
Figure 2: The visualization of the production network in EMU in 2011. Panel (a) shows the visualization for the domestic as well as external linkages among sectors. Panel (b) shows the visualization for the partial network consisting of only external linkages among sectors. Different colors represent sectors in different countries and the size of each node is proportional to its out-strength. Large sectors in six countries DEU, FRA, EPS, ITA, NLD, and BEL are located at the center of each graph. They play as hubs bridging industrial sectors in different members of the EMU.



(a) cycle (b) middleman

(c) inward (d) outward

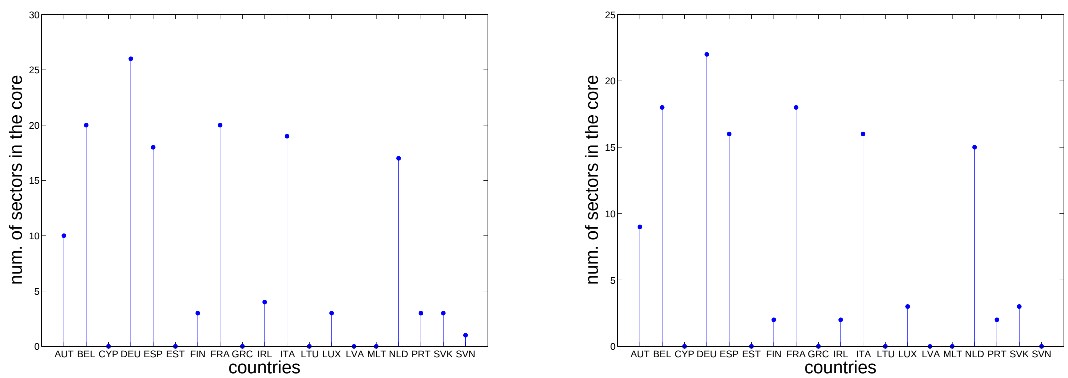
Figure 3: Inter-country weighted clustering coefficients vs. external strengths in 2005.



(a) cycle (b) middleman

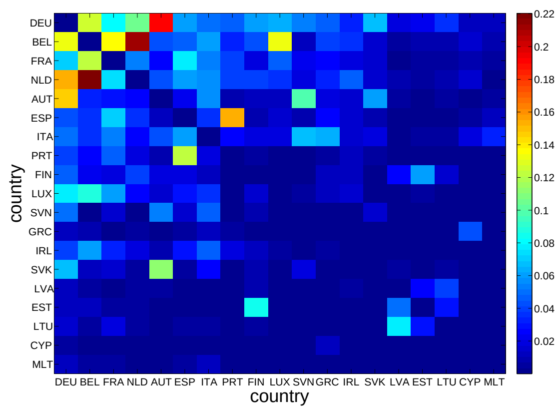
(c) inward (d) outward

Figure 4: Inter-country weighted clustering coefficients vs. external strengths in 2011.

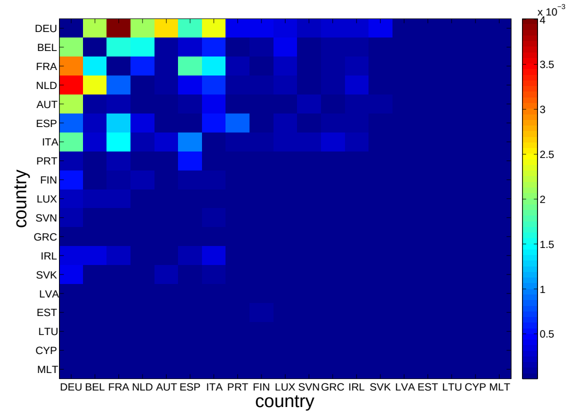


(a) in 2005 (b) in 2011

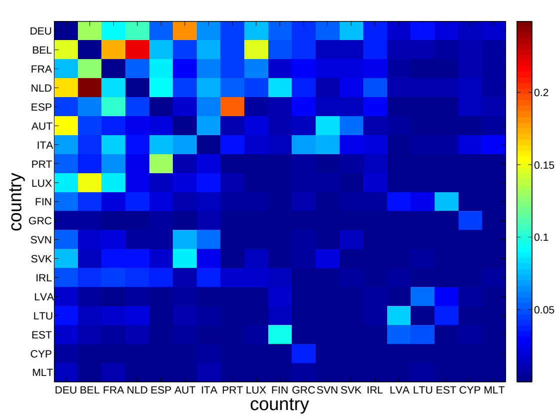
Figure 5: Number of sectors in each country belongs to the core in the inter-country linkages in EMU.



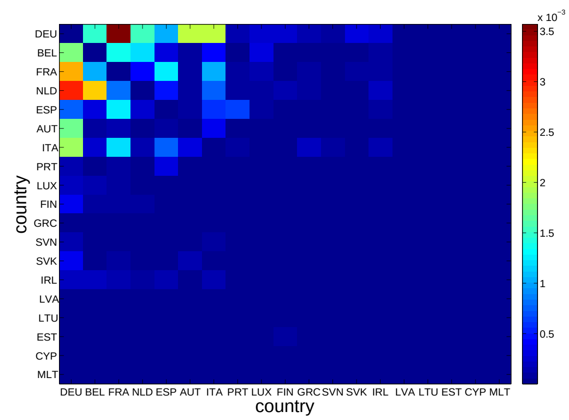
(a) averages of connectivity, in 2005



(b) averages of intensity, in 2005



(c) averages of connectivity, in 2011



(d) averages of intensity, in 2011

Figure 6: The averages of connectivity and intensity between countries in 2005 and 2011. The average of connectivity between each pair of countries is based on the external (directed) links. The average of intensity between each pair of countries is based on the external (directed) weights. Note that each matrix is not necessarily symmetric. Diagonal elements are equal to zero, since we exclude the domestic linkages in this case. In each panel, countries are sorted in the descending order of the average of out-going links of each country.

4 Conclusions

In a complex system, shocks propagate by following paths on the network of inter-dependencies among the system's units. Network analysis, therefore, provides important information for inferring shock diffusion in the system.

In this report, we explored the important topological properties of the inter-country production network in 19 members of the EMU. Among other results, we find that intra-country linkages are generally much denser than inter-country linkages. This implies that, the propagation of a shock to an industry may first tend to fall more heavily on other domestic industries. In addition, there is also a tendency to connect to sectors in neighboring countries, suggesting that geographic spillovers may also play an important role in explaining how local shocks can be transmitted from one country to another.

Furthermore, our findings suggest that some sectors belonging to several countries play as hubs bridging industrial sectors in different members of the EMU. Additionally, these sectors tend to build-up densely connected clusters among themselves. The presence of this hierarchical structure creates potential channels of the quick transmission of shocks to different countries.

We suggest that the role of various network properties in explaining the propagation of shocks under different diffusion models should be studied further. For example, one interesting question is to examine how the network structure among industries affects the possible emergence of a large aggregate fluctuation at a national or international level. It is also important to investigate which network properties are relevant under different propagation mechanisms, i.e. upstream effects (to input-supplying industries), the downstream effects (to customer industries), or both of them. We believe that these further analyses can provide useful information for designing more effective strategies to mitigate cascades in the EMU.

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Appendices

A Lists of sectors and countries

Full Name	WIOD Code	3-Letter Code
Agriculture, Hunting, Forestry and Fishing	c1	Agr
Mining and Quarrying	c2	Min
Food, Beverages and Tobacco	c3	Fod
Textiles and Textile Products	c4	Tex
Leather, Leather and Footwea	c5	Lth
Wood and Products of Wood and Cork	c6	Wod
Pulp, Paper, Paper , Printing and Publishing	c7	Pup
Coke, Refined Petroleum and Nuclear Fuel	c8	Cok
Chemicals and Chemical Products	c9	Chm
Rubber and Plastics	c10	Rub
Other Non-Metallic Mineral	c11	Omn
Basic Metals and Fabricated Metal	c12	Met
Machinery, Nec	c13	Mch
Electrical and Optical Equipment	c14	Elc
Transport Equipment	c15	Tpt
Manufacturing, Nec; Recycling	c16	Mnf
Electricity, Gas and Water Supply	c17	Ele
Construction	c18	Cst
Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	c19	Sal
Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	c20	Whl
Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	c21	Rtl
Hotels and Restaurants	c22	Htl
Inland Transport	c23	Ldt
Water Transport	c24	Wtt
Air Transport	c25	Ait
Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	c26	Otr
Post and Telecommunications	c27	Pst
Financial Intermediation	c28	Fin
Real Estate Activities	c29	Est
Renting of M&Eq and Other Business Activities	c30	Obs
Public Admin and Defence; Compulsory Social Security	c31	Pub
Education	c32	Edu
Health and Social Work	c33	Hth
Other Community, Social and Personal Services	c34	Ocm
Private Households with Employed Persons	c35	Pvt

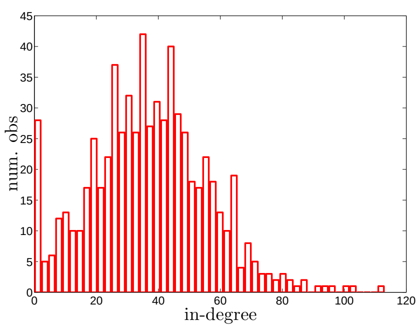
Table 1: List of WIOD industries.

B Additional results for network properties

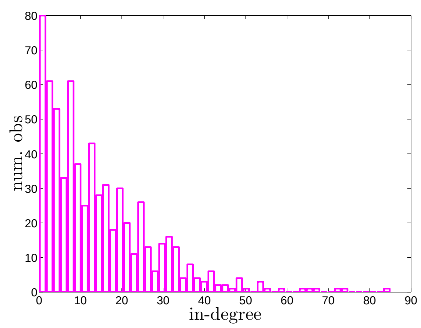
Distributions of degrees and strengths

As we mentioned in the main text, the aggregate network can be decomposed into two separate subnetworks, i.e. the domestic and the external ones. Therefore, we can define different degree and strength sequences in the aggregate network (based on $\mathcal{A}^a$ and $\mathcal{W}^a$) and the external network (based on $\mathcal{A}^e$ and $\mathcal{W}^e$). Mathematically, for every node i, its in-degree (k_i^{in}) and in-strength (s_i^{in}) are respectively defined as the sums of all elements in the column i^{th} of the adjacency and weighted matrices. Similarly, the out-degree (k_i^{out}) and out-strength (s_i^{out}) are respectively defined as the sums of all elements in the row i^{th} of the adjacency and weighted matrices. In the context of the production network under consideration, the degree and strength sequences represent the distributions of the number of connections and of the magnitude of trade across sectors. In addition, it should be emphasized that the out-strength of each sector is smaller than its aggregate output if a part of the output is destined to final demand.

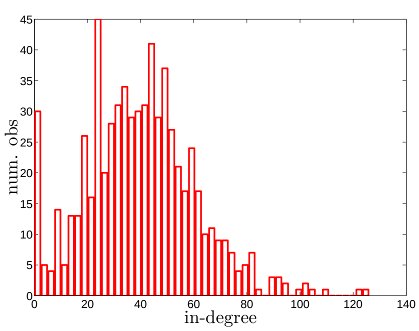
The histograms of the degrees and strengths of sectors are shown in Figures (7), (8), (9), and (10). The ranges of the distributions of degrees and strengths in the aggregate network are wider than those in the external network. In addition, while the mass of the distributions of degrees and strengths is concentrated on the left (positive skewness), we observe the presence of larger outlines on the right. Furthermore, in the binary version, the skewness of the distributions of degrees in external networks is higher than in the aggregate network. These results evidence the presence of hubs in the input-output linkages in the EMU.



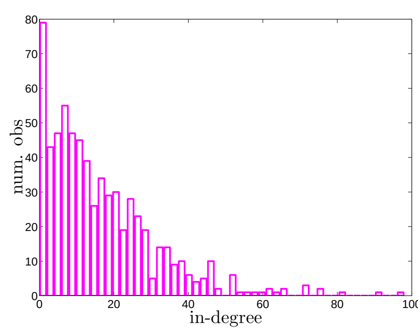
(a) in aggregate network, 2005



(b) in external network, 2005

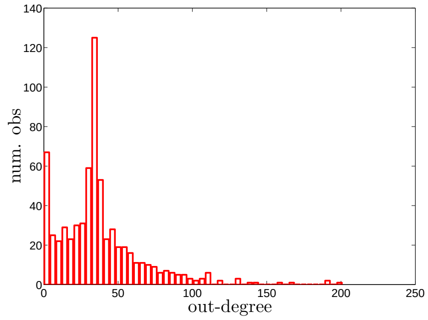


(c) in aggregate network, 2011

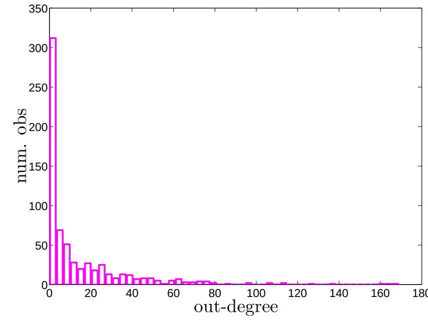


(d) in external network, 2011

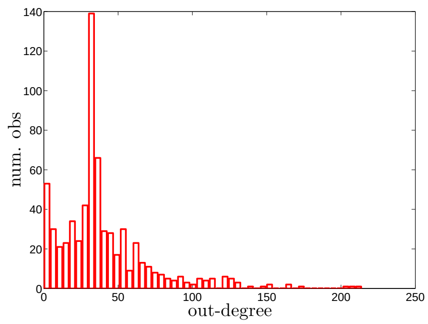
Figure 7: Distributions of in-degrees in the aggregate and in the external networks, in 2005 and 2011.



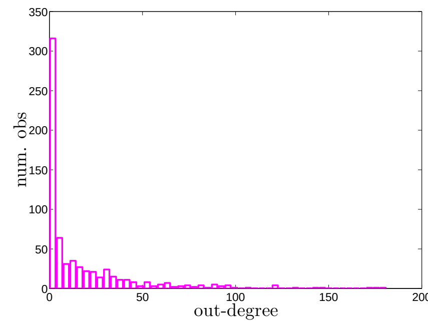
(a) in aggregate network, 2005



(b) in external network, 2005

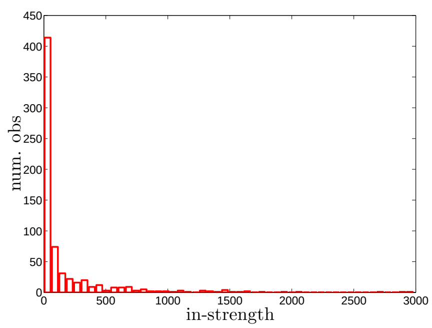


(c) in aggregate network, 2011

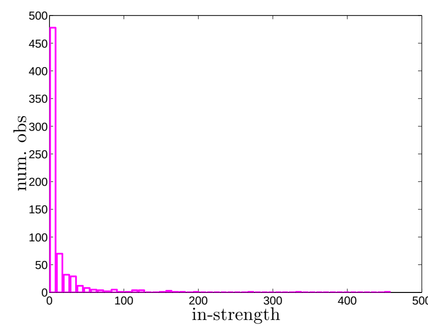


(d) in external network, 2011

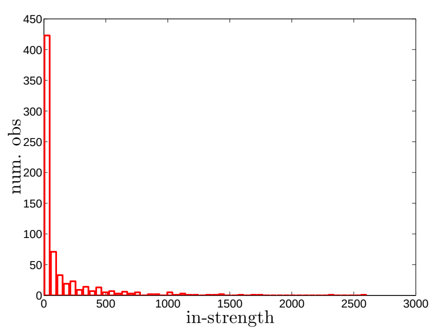
Figure 8: Distributions of out-degrees in the aggregate and in the external networks, in 2005 and 2011.



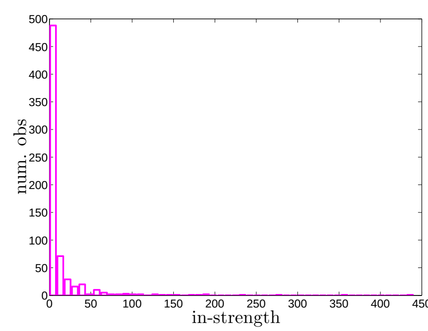
(a) in aggregate network, 2005



(b) in external network, 2005

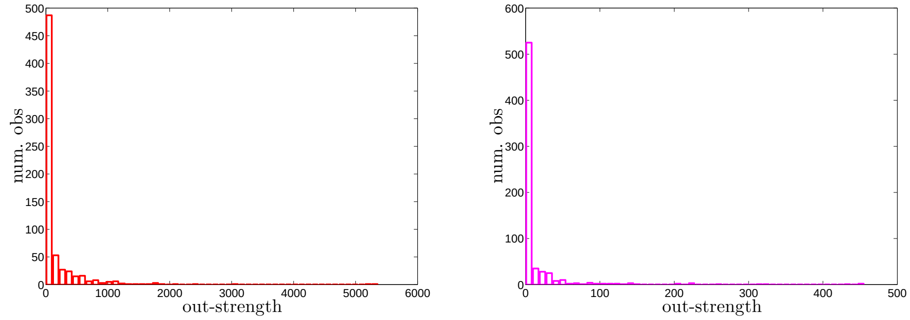


(c) in aggregate network, 2011

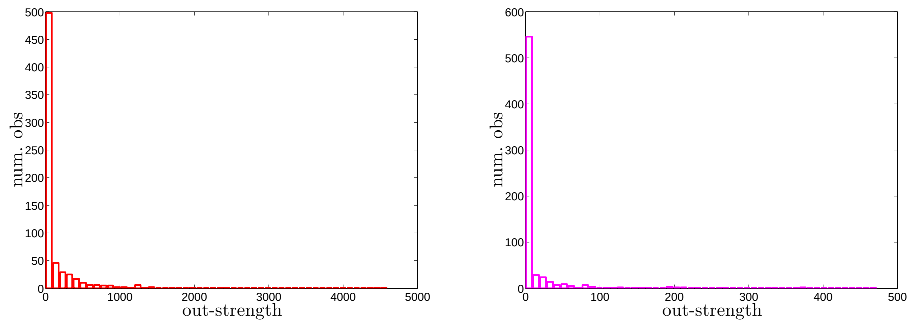


(d) in external network, 2011

Figure 9: Distributions of in-strengths in the aggregate and in the external networks, in 2005 and 2011.



(a) in aggregate network, 2005 (b) in external network, 2005

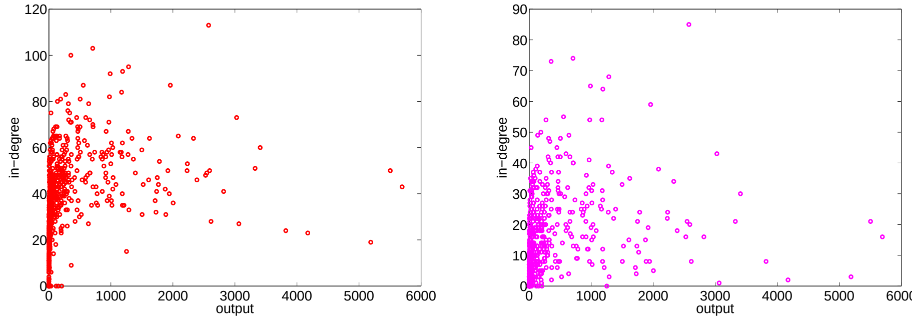


(c) in aggregate network, 2011 (d) in external network, 2011

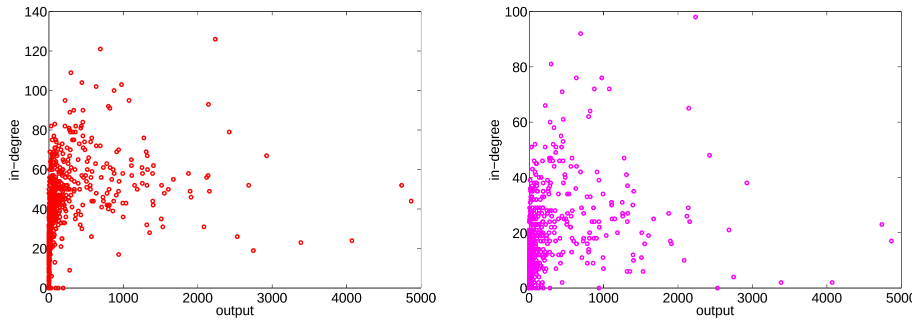
Figure 10: Distributions of out-strengths in the aggregate and in the external networks, in 2005 and 2011.

Degrees and strengths vs. outputs

In Figures (11), (12), (13), and (14), we provide the scatter plots showing the relationships between degrees and strengths with the outputs. We observe that some sectors with a high level of outputs are associated with a low level of degrees and strengths. This can be interpreted from the perspective of the concentration of the sectoral inputs and outputs. More specifically, if the output of a sector is used for further productions of many other sectors, its out degree and strength tend to be higher. Similarly, if a sector use the outputs of many other sectors for its production, its in degree and strength also tend to be higher. Furthermore, the difference between the aggregate strengths and the external strengths shown in Figures (13) and (14) indicates that some sectors including the large ones are actually more internally integrated. This again confirms the asymmetry between the domestic linkages and external linkages mentioned in the main text.

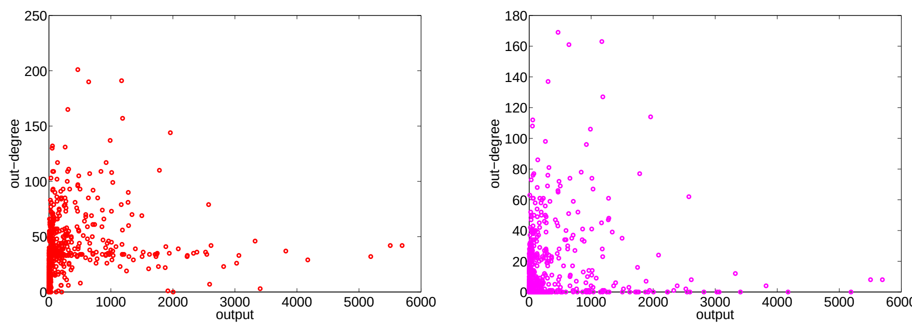


(a) in aggregate network, 2005 (b) in external network, 2005

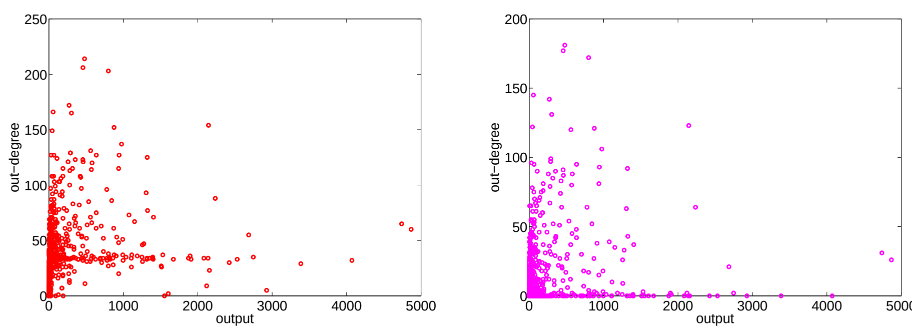


(c) in aggregate network, 2011 (d) in external network, 2011

Figure 11: In-degrees in the aggregate and in external networks vs. outputs, in 2005 and 2011.

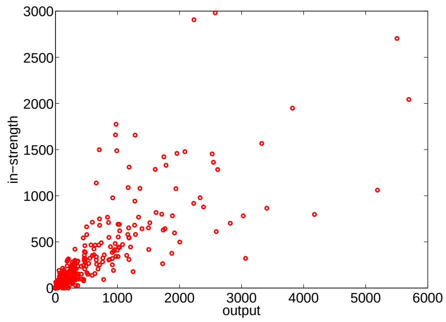


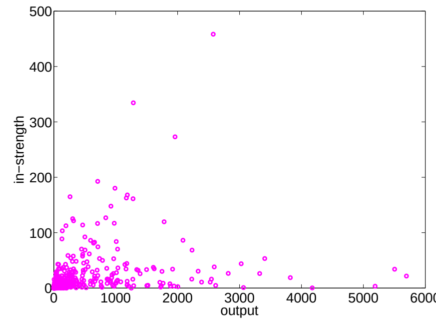
(a) in aggregate network, 2005 (b) in external network, 2005



(c) in aggregate network, 2011 (d) in external network, 2011

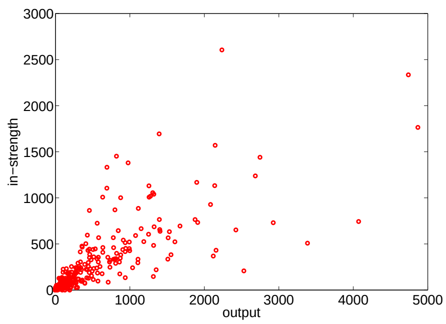
Figure 12: Out-degrees in the aggregate and in external networks vs. outputs, in 2005 and 2011.

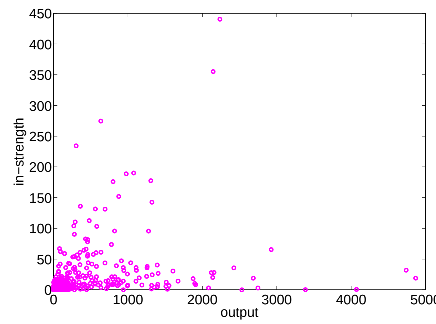




(a) in aggregate network, 2005

(b) in external network, 2005

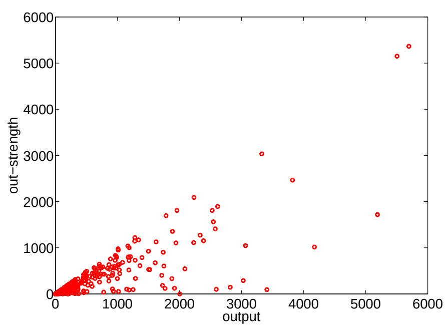


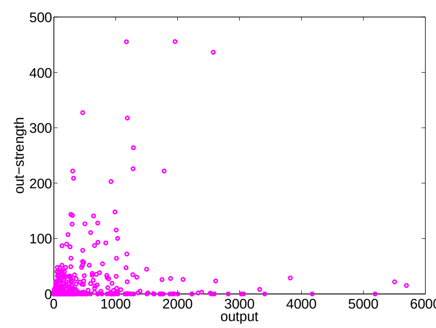


(c) in aggregate network, 2011

(d) in external network, 2011

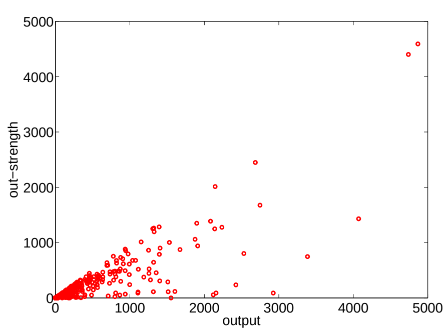
Figure 13: In-strengths in the aggregate and in external networks vs. outputs, in 2005 and 2011.

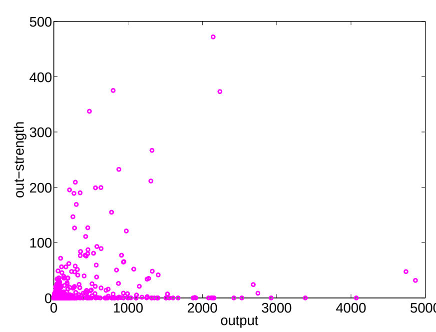




(a) in aggregate network, 2005

(b) in external network, 2005





(c) in aggregate network, 2011

(d) in external network, 2011

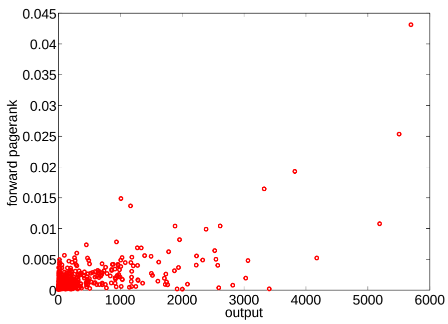
Figure 14: Out-strengths in the aggregate and in external networks vs. outputs, in 2005 and 2011.

PageRank centrality vs. outputs

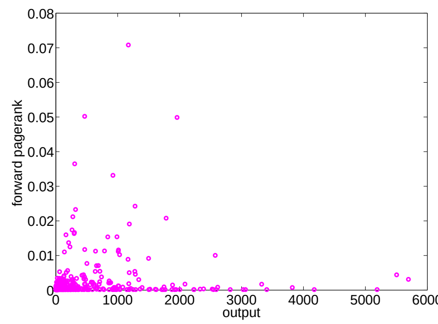
Broadly speaking, PageRank algorithm is used to evaluate the relative popularity of a node in a network: the popularity of a node can be enhanced by the endorsement it receives from the nodes that are pointing to it (e.g. Page et al. (1998)). From the perspective of shock diffusion, the PageRank centrality of a node captures the linear backward propagation to its in-coming neighbors. Recently, the idea of this algorithm has been also applied to analyze the systemic importance of financial institutions (e.g. Battiston et al. (2012); Battiston et al. (2016)).

As we mentioned in the main text, in the literature on directed production networks, there are two distinct propagation mechanisms, i.e. the upstream propagation via in-coming linkages and the downstream propagation via out-going linkages. Therefore, it is relevant to introduce the another variant of PageRank algorithm that showing the centrality of a node based on the endorsement it gives to other nodes. To do that, we also measure the forward PageRank of every node that captures the propagation to its out-going neighbors.

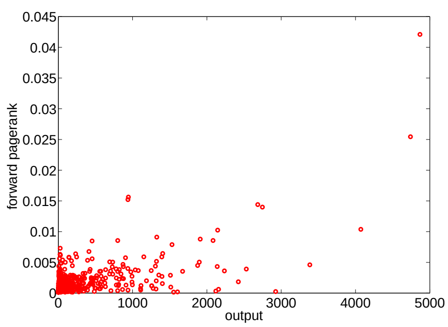
The scatter plots for the relationships between the two different measures of PageRank centrality (in the weighted version) with the outputs are shown in Figures (15), (16).



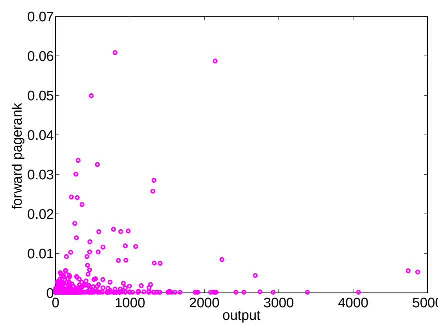
(a) in aggregate network, 2005



(b) in external network, 2005

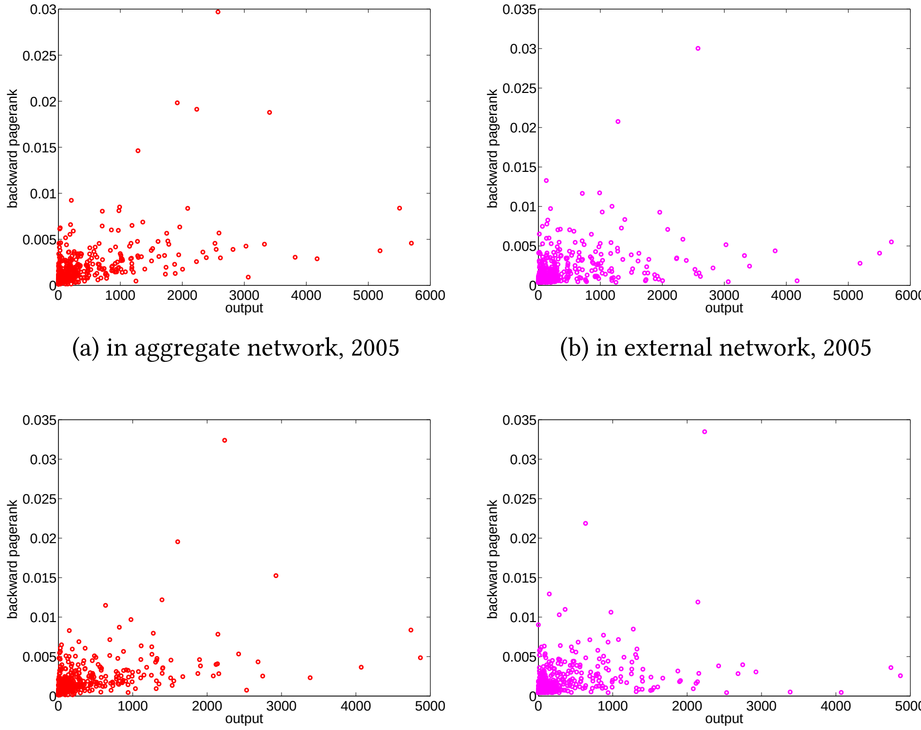


(c) in aggregate network, 2011



(d) in external network, 2011

Figure 15: Forward PageRank centrality in the aggregate and in external networks vs. outputs, in 2005 and 2011.



(a) in aggregate network, 2005 (b) in external network, 2005

(c) in aggregate network, 2011 (d) in external network, 2011

Figure 16: Backward PageRank centrality in the aggregate and in external networks vs. outputs, in 2005 and 2011.

Betweenness centrality vs. outputs

In production network, there could be key intermediary sectors that are at the same time active in both supplying and demanding from other sectors. They tend to "lie at the cross roads", to link different groups of sectors in the network (for instance, to link highly connected sectors with peripheral sectors). When considering both upstream as well as downstream propagation, a negative shock to a key intermediary sector can be propagated to different parts of the network.

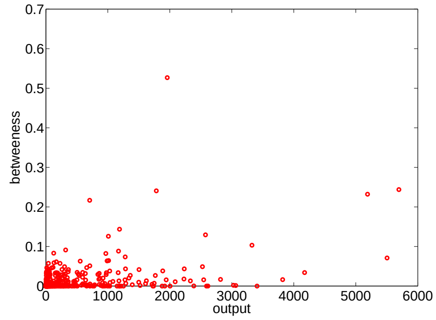
The betweenness centrality is a measure of centrality based on the shortest paths (e.g. see Freeman (1977); Brandes (2001); Borgatti and Everett (2006)). In a network of size n, for every node i, its betweenness centrality, $bt(i)$, is defined as

$$bt(i) = \frac{1}{[(n-1)(n-2)]} \frac{\sum_{j,k} st_{jk}(i)}{\sum_{j,k} st_{jk}} \tag{7}$$

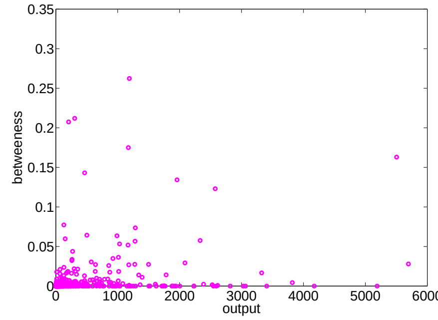
where st_{jk} is the number of the shortest paths going from node j to node k, and $st_{jk}(i)$ is the number of the shortest paths from node j to node k going through node i.[4] A nodes with high value of betweenness centrality will participate in a large number of shortest paths. In this context, the betweenness centrality is potentially a proper method to identify key intermediary sectors in the production network.

The relationship between the betweeness centrality (in the weighted version) and the outputs is illustrated in Figure (17).

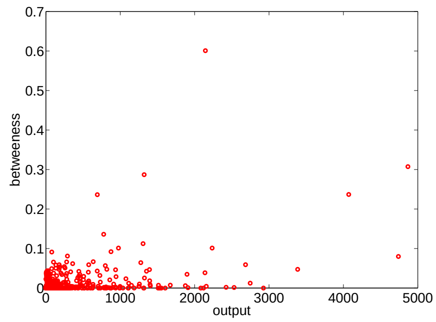
[4] In this equation, the fraction $\frac{1}{[(n-1)(n-2)]}$ is used to normalize betweenness centrality to the range [0,1].



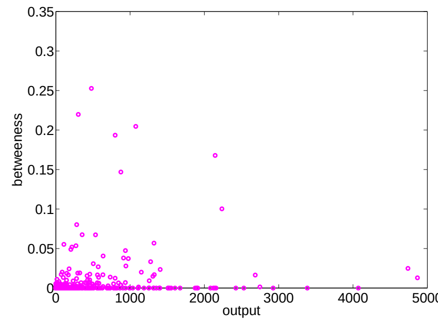
(a) in aggregate network, 2005



(b) in external network, 2005



(c) in aggregate network, 2011

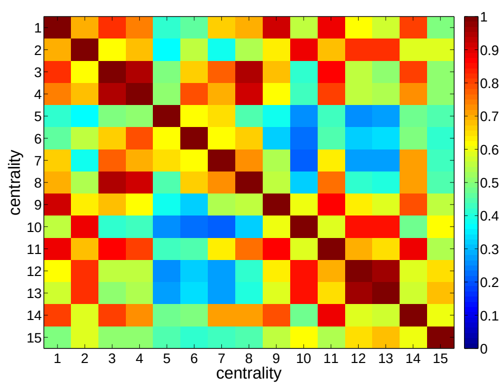


(d) in external network, 2011

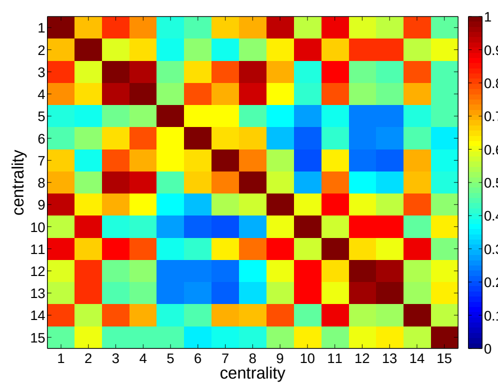
Figure 17: Betweeness centrality in the aggregate and in external networks vs. outputs, in 2005 and 2011.

Spearman's rank correlation between centrality measures

Since different measures may capture different aspects of network centrality or shock diffusion, in Figure (18) we show Spearman's rank correlation between outputs, degrees, strengths, PageRanks, betweenness in the aggregate and external networks. We can see that not all of them have a high correlation coefficient.



(a) in 2005



(b) in 2011

Figure 18: Spearman's rank correlation between centrality measures in 2005 and 2011. The list of 15 centrality measures is provided in Table 2.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
k^{in}	k^{out}	s^{in}	s^{out}	bt	pr^f	pr^b	output	k^{in}	k^{out}	s^{in}	s^{out}	bt	pr^f	pr^b

Table 2: List of centrality measures in the aggregate network (gray cells), and in the external network (the rest cells) shown in Figure (18). The two notations pr^f and pr^b respectively stand for the forward and backward PageRanks.

Core-periphery structure in the inter-country linkages

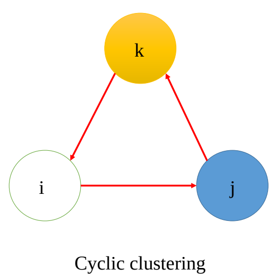
Briefly, a network with the core-periphery structure is can be partitioned into non-overlapping subgroups of core and periphery members (e.g. Borgatti and Everett, 2000). To detect this structure, using the so-called Kernighan-Lin algorithm for graph partitioning we optimize the following core-structure objective function for the weighted version

$$Q_C = \frac{1}{v_C}\Big(\sum_{i,j\in C_c}(w_{ij} - \gamma_c \bar{w}) - \sum_{i,j\in C_p}(w_{ij} - \gamma_c \bar{w})\Big) \tag{8}$$

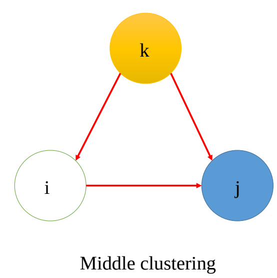
where C_c is the set of all nodes in the core, C_p is the set of all nodes in the periphery, w_{ij} is the weight between nodes i and j, $\bar{w}$ is the weight average, γ_c is a resolution parameter controlling the size of the core, and v_C is a normalization constant.

Maximizing the weight of within core-group edges and minimizing the weight of within periphery-group edges, the measure based on Q_C synthesizes the formulations of core-periphery (Borgatti and Everett (2000)) and community (Newman and Girvan (2004)) structures.

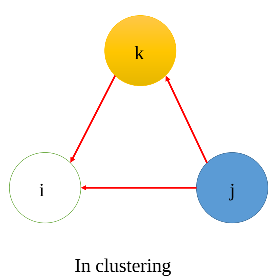
Clustering coefficients



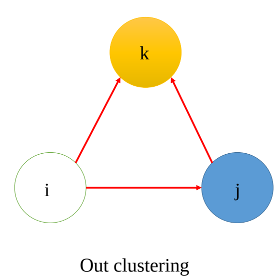
(a) cycle



(b) middleman



(c) inward



(d) outward

Figure 19: Different types of clustering in a network.

A clustering coefficient measures the tendency of two neighbors of a particular node to also be connected to each other. As visualized in Figure (19), in the directed version of a network, four types of clustering behaviors, i.e. cycle, middleman, inward, and outward capture different direct as well as in-direct interactions among three nodes. Let denote a_{ij} and w_{ij} respectively as the elements of the adjacency matrix, $\mathcal{A}^e$, and the weighted matrix, $\mathcal{W}^e$.

In the weighted version, clustering coefficients can be formulated in several ways, depending on how we take into account the roles of the strengths and weights of the nodes in each triangle (see, for example, Barrat et al. (2004); Onnela et al. (2005); Zhang and Horvath (2005); Holme et al. (2007)). For a detailed comparison between different methods of calculating the local weighted clustering coefficients, we refer readers to Saramaki et al. (2007). Following Onnela et al. (2005), we define the (local) inter-country weighted clustering coefficients in the directed version for each node i as

$$C_{w,i}^{in} = \frac{\sum_{j\neq i}\sum_{k\neq i,j} w_{jk}^{\frac{1}{3}} w_{ji}^{\frac{1}{3}} w_{ki}^{\frac{1}{3}}}{(\sum_{j\neq i} a_{ji})^2 - (\sum_{j\neq i} a_{ji}^2)}, \tag{9}$$

$$C_{w,i}^{out} = \frac{\sum_{j\neq i}\sum_{k\neq i,j} w_{ik}^{\frac{1}{3}} w_{ij}^{\frac{1}{3}} w_{jk}^{\frac{1}{3}}}{(\sum_{j\neq i} a_{ij})^2 - (\sum_{j\neq i} a_{ij}^2)}, \tag{10}$$

$$C_{w,i}^{cyc} = \frac{\sum_{j\neq i}\sum_{k\neq i,j} w_{ij}^{\frac{1}{3}} w_{jk}^{\frac{1}{3}} w_{ki}^{\frac{1}{3}}}{(\sum_{j\neq i} a_{ij}\sum_{j\neq i} a_{ji}) - (\sum_{j\neq i} a_{ij}a_{ji})}, \tag{11}$$

$$C_{w,i}^{mid} = \frac{\sum_{j\neq i}\sum_{k\neq i,j} w_{ik}^{\frac{1}{3}} w_{jk}^{\frac{1}{3}} w_{ji}^{\frac{1}{3}}}{(\sum_{j\neq i} a_{ij}\sum_{j\neq i} a_{ji}) - (\sum_{j\neq i} a_{ij}a_{ji})}. \tag{12}$$

where here three indices i, j, k are associated with sectors in three different countries.

Inter-country connectivity and intensity

Based on the external network (represented by $\mathcal{W}^e$ and $\mathcal{A}^e$), we measure the averages of connectivity and intensity between every two countries. Without loss of generality, we consider the external linkages between two countries α and β, represented by a weighted matrix

$$\mathcal{W}_{\alpha,\beta}^e = \left[\begin{array}{c|c} O & W_{\alpha,\beta} \\ \hline W_{\beta,\alpha} & O \end{array}\right], \tag{13}$$

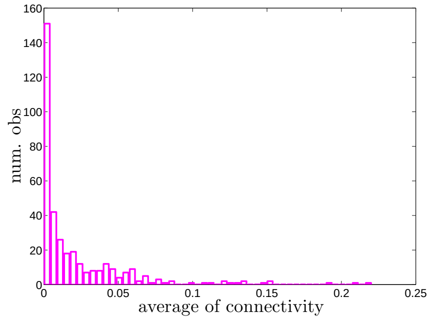
and an adjacency matrix

$$\mathcal{A}_{\alpha,\beta}^e = \left[\begin{array}{c|c} O & A_{\alpha,\beta} \\ \hline A_{\beta,\alpha} & O \end{array}\right] \tag{14}$$

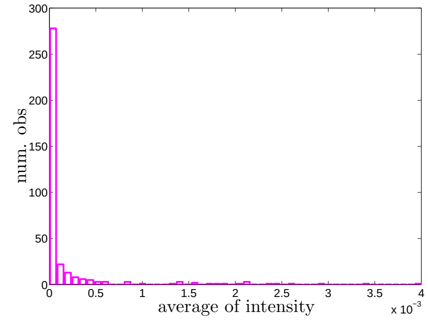
The average of intensity from country α to country β is defined as the average of the normalized elements of $W_{\alpha,\beta}$.[5] In contrast, the average of connectivity from country α to country β is the average of the elements of $A_{\alpha,\beta}$.

Besides the color coded matrices shown in the main text, Figure (20) provides additional results on the distributions of the averages of connectivity and intensity.

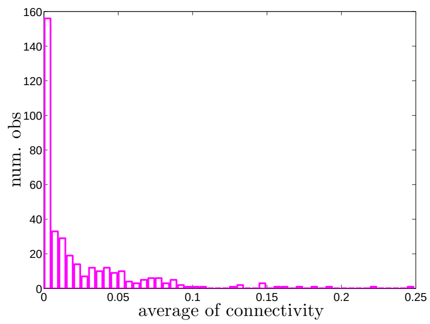
[5]Here all elements of $W_{\alpha,\beta}$ are normalized by w^{max}, which is defined as the maximum value of all elements of $\mathcal{W}^e$.



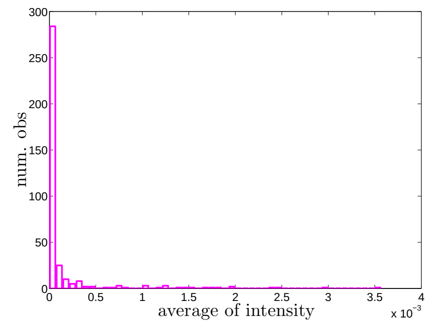
(a) average of connectivity, 2005



(b) average of intensity, 2005



(c) average of connectivity, 2011



(d) average of intensity, 2011

Figure 20: Distributions of the averages of connectivity and intensity, in 2005 and 2011. The average of connectivity between each pair of countries is based on the external (directed) links. The average of intensity between each pair of countries is based on the external (directed) weights.