

Network analysis of the intra-EU trade

Anita Modrzejewska,^a Piotr Biskup^b

Abstract. The research presented in the paper used tools offered by network analysis and the graph theory. The study examined the empirical properties of the intra-EU trade network in the years 1999–2019 and confirmed that the EU trade links were of a disassortative nature. The use of network indicators has proven that the European trade network was characterised by a core-periphery structure. The study shows that Germany was the undisputed leader of the EU trade network over the studied years, although its central position was weakening over the years.

Keywords: network analysis, international trade, European integration, core-periphery structure

JEL: D85, F14, F15

1. Introduction

Network analysis serves to examine the relationships between interacting units, which requires the use of a different set of methods and analytical concepts from those applied in traditional statistics. It is not the attributes of autonomous individuals, but the associations between these attributes that are studied in search of patterns or regularities in the behaviour of the tested objects (Wasserman & Faust, 1994).

Another key feature of the network perspective is its symbiotic relationship between theory (network science) and method (social network analysis – SNA). Since network science is rooted in a wide range of academic disciplines, the research on networks is inter- and multidisciplinary by nature (Jackson, 2008). The fields where SNA is applied include the Internet, the WWW, train routes, airline connections, electronic circuits, semantic structures, biological systems, social interactions, and many others. The economics literature on networks has been thriving for the past 20–25 years. As a result, such economic systems as labour markets, banking sectors or the world economy began to be considered as networked structures. Thus, a network-based approach has been employed in empirical studies of international trade (Fagiolo et al., 2010). In this context, countries represent the nodes and an export/import relation between any two countries plays the role of a trade linkage.

^a Krakow University of Economics, Doctoral school, ul. Rakowicka 27, 31-510 Kraków, Poland, e-mail: amodrzejewska2000@wp.pl, ORCID: <https://orcid.org/0009-0006-4086-7452>.

^b Cracow University of Technology, Faculty of Computer Science and Telecommunications, ul. Warszawska 24, 31-155 Kraków, Poland, e-mail: piotr.biskup@pk.edu.pl, ORCID: <https://orcid.org/0000-0003-3742-8388>.

According to Beaudreau (2004), the EU is an example of a trade network. Generally, the main idea of European integration is based on trade between nations. In this context, determining the specific characteristics of trading partners seems to be of crucial importance. The use of network indicators allows the measurement of the number and intensity of trading relationships, of the clustering level and the centrality of each node. The analysis of the structure of the intra-EU network and the search for some potential trade patterns is based on these indicators. This study, therefore, seeks to answer the following questions: are some countries more connected than others? Do well-connected nodes trade with partners that are also well-connected or rather less-connected? Which countries occupy the most central positions in the intra-EU trade network? Does the network have a core-periphery structure? Additionally, the evolution of the network over time was observed.

Determining such topological properties provides a more detailed insight into the European integration process. It may also uncover the logic behind the propagation of macroeconomic shocks through trade channels in times of financial crises. Moreover, it shows how much stress EU countries place on the intra-EU trade in their development strategy.

The remainder of this paper is organised as follows: Section 2 introduces the main tools of trade network analysis and Section 3 briefly describes the results of the empirical studies on international trade networks. The data and methodology used are discussed in Section 4, while Section 5 presents the findings and Section 6 the conclusions.

2. A statistical analysis of undirected trade networks

A trade network can be described by means of a graph consisting of nodes (countries) connected by a set of links (export/import relations).¹ The ordinary type of graph is binary and undirected, which means that between any two nodes a tie exists or not, and the direction of the link has no meaning. If any two nodes are connected by a link, then they are called ‘partners’ or ‘nearest neighbours’.

A trade network can also take the form of a matrix. To formally characterise binary undirected networks (BUNs), it is sufficient to provide symmetric $N \times N$ binary adjacency matrix A , where N is the number of countries, and whose elements $a_{ij} = a_{ji} = 1$ if there is an edge (trade relation) from vertex i to vertex j , and 0 otherwise. When $i = j$, 0 is also used, i.e. diagonal elements $a_{ii} = 0$.²

¹ Regardless of what flow of goods we take into account in the analysis, we can read the values of exports and imports from the same matrix for a given year, because exports from country i to country j should be equal to imports to country j from country i .

² It is assumed that no country trades with itself.

The notation used below is provided by Fagiolo et al. (2010), unless specified otherwise. The most common nodal statistic of the BUNs is the node degree (ND). It is defined as:

$$d_i = \sum_j a_{ij} = \mathbf{A}_{(i)} \mathbf{1}, \quad (1)$$

where $\mathbf{A}_{(i)}$ is the i -th row of matrix \mathbf{A} and $\mathbf{1}$ is the N -dimensional column vector made of all ones. ND simply stands for the number of links that a given vertex has.

It is worth emphasising that any two nodes with the same ND can assume a different importance in the network, because the connections of their partners are also significant. To measure how many partners of node i are linked with one another, the average nearest-neighbour degree (ANND) may be computed, i.e. the average of the ND of all the partners of node i :

$$annd_i = d_i^{-1} \sum_j a_{ij} d_j = d_i^{-1} \sum_j \sum_h a_{ij} a_{jh} = \frac{\mathbf{A}_{(i)} \mathbf{A} \mathbf{1}}{\mathbf{A}_{(i)} \mathbf{1}}. \quad (2)$$

Another significant BUN statistic is the clustering coefficient (CC). It quantifies the average probability that two neighbours of a vertex are partners themselves. The CC of node i equals:

$$C_i(\mathbf{A}) = \frac{\sum_j \sum_h a_{ij} a_{ih} a_{jh}}{d_i(d_i - 1)} = \frac{(\mathbf{A}^3)_{ii}}{d_i(d_i - 1)}, \quad (3)$$

where $(\mathbf{A}^3)_{ii}$ is the i -th element of the main diagonal of $\mathbf{A}^3 = \mathbf{A} \cdot \mathbf{A} \cdot \mathbf{A}$. Each product $a_{ij} a_{ih} a_{jh}$ is meant to count whether a triangle exists around i or not. Notice that the order of the subscripts is irrelevant, as all entries in \mathbf{A} are symmetric (Fagiolo, 2007).

In the case of BUNs, the stress is put on the mere presence or absence of an interaction between any two nodes. Since trade as an economic relationship can vary in intensity, the weighted undirected network (WUN) perspective is an appropriate approach. A WUN is defined by means of symmetric $N \times N$ ‘weight’ matrix \mathbf{W} , whose generic $w_{ij} = w_{ji} > 0$ entry measures the intensity of a trade relation between two countries, and it is 0 if no edge exists between them (Fagiolo et al., 2010).

The equivalents of ND, ANND and CC in WUN are: the node strength (NS), the average nearest-neighbour strength (ANNS), the weighted average nearest-neighbour degree (WANND) and the weighted clustering coefficient (WCC), respectively. The first statistic, NS, designates the sum of weights associated to the links that a given node has:

$$s_i = \sum_j w_{ij} = \mathbf{W}_{(i)} \mathbf{1}, \quad (4)$$

where $\mathbf{W}_{(i)}$ is the i -th row of matrix \mathbf{W} and $\mathbf{1}$ is the N -dimensional column vector made of all ones. The larger the NS of a country, the more intense trade relations it bears. As can be seen, nodes with the same ND do not necessarily have the same NS.

To assess the strength of node i 's partners, one may compute the ANNS:

$$anns_i = d_i^{-1} \sum_j a_{ij} s_j = d_i^{-1} \sum_j \sum_h a_{ij} w_{jh} = \frac{\mathbf{A}_{(i)} \mathbf{W} \mathbf{1}}{\mathbf{A}_{(i)} \mathbf{1}} \quad (5)$$

or WANND:

$$wannd_i = s_i^{-1} \sum_j w_{ij} d_j = s_i^{-1} \sum_j \sum_h w_{ij} a_{jh} = \frac{\mathbf{W}_{(i)} \mathbf{A} \mathbf{1}}{\mathbf{W}_{(i)} \mathbf{1}}, \quad (6)$$

which determine to what extent the partners of node i themselves are represented by high degree nodes. Similarly to ND and NS, vertices with the same ANND can be characterised by a different level of ANNS or WANND.

As far as the WCC is concerned, it takes into account the weights of all the edges in a triangle and it is defined as:

$$\tilde{c}_i(\mathbf{W}) = \frac{\sum_j \sum_h w_{ij}^{\frac{1}{3}} w_{ih}^{\frac{1}{3}} w_{jh}^{\frac{1}{3}}}{d_i(d_i - 1)} = \frac{\left(\mathbf{W}^{\left[\frac{1}{3}\right]}\right)_{ii}^3}{d_i(d_i - 1)}, \quad (7)$$

where $\mathbf{W}^{\left[\frac{1}{3}\right]} = \left[w_{ij}^{\frac{1}{3}}\right]$, i.e. the matrix obtained from \mathbf{W} by taking the 3-rd root of each entry. The WCC can be considered as the geometric average of the subgraph edge weights based on the concept of subgraph intensity (Onnela et al., 2005). The resulting values are no longer probabilities, but they can be considered as proportional to probabilities.

One of the primary uses of SNA is the identification of the nodes which occupy the most central position in the network. There are many concepts and indicators of the ‘centrality of a node’ (Bloch et al., 2023). In this paper, however, we concentrate only on the index called random-walk betweenness centrality (RWBC) that fits both BUN and WUN analyses (Fagiolo et al., 2010):

$$RWBC_i = \frac{\sum_h \sum_{k \neq h} I_i(h, k)}{N(N-1)}, \quad (8)$$

where the current (i.e. the intensity of the interaction) originating from node h , flowing through node i and reaching node k equals:

$$I_i(h, k) = \frac{1}{2} \sum_j |v_i(h, k) - v_j(h, k)|. \quad (9)$$

Here, $I_h(h, k) = I_k(h, k) = 1$ (Fisher & Vega-Redondo, 2006) and v_i shows the intensity (i.e. the strength) of the flow through node i from source node h to target node k , which was represented by the voltage in the original paper of Newman (2005). RWBC can be applied to networks in international trade (Fisher & Vega-Redondo, 2006). RWBC measures how often a node is traversed by a random walk between two other nodes (Newman, 2005). Vertices with a high RWBC may thus affect the spread of trade flows across the network.

Finally, in order to adopt the undirected approach, the symmetry of matrices \mathbf{A} and \mathbf{W} must be checked. Since trade relationships (exports/imports) are directed by nature, we must assess empirically whether the observed network is sufficiently symmetric or not to justify a BUN/WUN analysis (Fagiolo, 2006). This process is discussed in Section 4.

3. Literature review

The concept of the empirical analysis of the structure of the international trade network and its topological properties, regardless of the social or economic relationships that might underlie them, originates from econophysics. The international trade network (ITN), also called the world trade web (WTW) or the world trade network (WTN), is most often examined. Since the origins of networks go back to complexity economics (Beinhocker, 2006), many researchers focus on the complex nature of the ITN. For instance, Serrano and Boguñá (2003), who studied the WTW using the binary approach, have proven that this network displays the typical properties of complex networks (scale-free degree distribution, the small-world

property and a high CC). Moreover, the WTW follows a disassortative pattern, where well-connected vertices (countries with high NDs) are joined with less-connected vertices (i.e. with low ANNDs). Garlaschelli and Loffredo (2004, 2005), Fagiolo et al. (2010) and Squartini et al. (2011a) reach similar conclusions. Furthermore, they indicate that partners of well-connected nodes are less interconnected than those of poorly connected ones, implying the occurrence of some hierarchy in the network.

A more detailed picture of ITN delivers a weighted perspective of network analysis. The reason for this is that a binary approach does not fully take advantage of the wealth of information about the intensity of trade relations represented by each edge. Thus, it tends to underestimate the role of heterogeneity in trade linkages (Fagiolo et al., 2010). According to Bhattacharya et al. (2007, 2008), the world trade is dominated by only a few top rich countries (i.e. countries with high NSs) which control half of the world's trade volume. However, the size of the rich-club shrinks with time. Fagiolo et al. (2008) show that the average ND is relatively high, while the average NS is low, which means that the majority of the existing connections are relatively weak. The average ND-NS correlation coefficient is 0.5. The correlations of WANND and ANNS with ND and NS are negative, which confirms the disassortative nature of the WTW. Moreover, the WTW displays an increasing, positive and significant correlation between NS and WCC, which means that countries with more intense relationships are more likely to form strongly connected trade triangles. In other words, trade clubs (cliques) exist in the WTW. Serrano et al. (2007) also studied the network of trade imbalances between different pairs of countries (net producers which export more than they import and net consumers for which the opposite is true). They form the backbone of the WTW characterised by a high level of heterogeneity: for each country, the profile of trade fluxes is unevenly distributed across their partners. The properties of the trade fluxes of the WTW determine a ranking of trade partnerships that highlights global interdependencies. A different approach is followed by Fagiolo (2010). The author identifies the main determinants of international trade flows using a standard gravity equation and builds a 'residual' weighted trade network by removing the whole existing structure from the data. The purpose is to check whether this ITN exhibits topological features comparable to those of the original ITN. It appears that the residual ITN has power-law distributions of link weights and node statistics (e.g. NS, WCC and RWBC) in contrast to the original ITN, which is characterised by a log-normal distribution. In other words, the weighted ITN shows signs of complexity. Moreover, the correlations between the node statistics and the correlations between the node statistics and the national GDP *per capita* are calculated. As a result, a considerably divergent picture of the architecture of the world trade is created. While the original

ITN is geographically clustered and organised around a few large-sized hubs, the residual ITN consists of many small-sized but trade-oriented countries that, regardless of their geographical position, either play the role of local hubs or attract large and rich countries in relatively complex trade-interaction patterns. The only known contribution to network analysis of the intra-EU trade is the paper of Modrzejewska and Pajor (2011). They indicate that the European trade network (ETN) also fits into a disassortative pattern of trade relationships: the correlations between ND and ANND and between NS and ANNS are strongly negative. In addition, the values of RWBC confirm the existence of a core-periphery structure at the European level, as is the case at the global level (Fagiolo et al., 2010).

Last but not least, the issue of the directed or undirected nature of the ITN should be mentioned. Researchers develop various strategies in this regard. Some examine either both the directed and undirected trade network (e.g. Squartini et al., 2011a, 2011b), or the directed trade network only (e.g. Garlaschelli & Loffredo, 2004), while others explore the conditions under which one can investigate the trade relationships as an undirected network (e.g. Fagiolo, 2006, Fagiolo et al., 2008, Fagiolo et al., 2010). The last method has been employed in this paper.

4. Data and methodology

The analysis of the intra-EU trade network is based on aggregate bilateral merchandise import data measured in current U.S. dollars, provided by the UN Comtrade Database. The database reported on 28 countries ($N = 28$) from 1999 to 2019 ($T = 21$).³ The GDP and GDP *per capita* data were extracted from the website of the World Bank. They were also provided in current U.S. dollars.

The methodology adopted in the study is similar to that applied by Fagiolo et al. (2010) and Modrzejewska and Pajor (2011). The first step involved building a sequence of weighted adjacency matrices of the weighted directed networks defined for the years 1999–2019, in which rows represented the exporting countries and the columns referred to the importing countries. Secondly, the export and import values were divided by the GDP values of the exporter and the importer, respectively.⁴ Let $\widetilde{W} = [\widetilde{w}_{ij}]$ be a $N \times N$ weight matrix, where $\widetilde{w}_{ij} \in [0,1]$ and $\widetilde{w}_{ii} = 0$ for all i . Thus, weighted matrix $\widetilde{W} = [\widetilde{w}_{ij}]$ was created for each year and flow type (exports and imports). Thirdly, a ‘trade relationship’ was defined by

³ The study covers 28 EU countries, although the actual number of the EU members varied over time. In this analysis only import data were used because of their greater accuracy than those relating to export (Kim & Shin, 2002). However, due to the missing values of the imports, the export data were employed in the following cases: exports from Luxembourg to the Netherlands in 1999 instead of imports to the Netherlands from Luxembourg in 1999.

⁴ Network parameters for exports were obtained by calculating them by rows, and by columns for imports.

setting 1 for all non-zero elements of matrix \widetilde{W} . In this way, adjacency matrix \widetilde{A} was obtained, which enabled a binary analysis. Finally, the symmetry of the empirically-observed weighted network was verified using the method suggested by Fagiolo (2006). For this purpose, symmetry index $\tilde{S}(Q)$ was calculated (Fagiolo et al., 2010):

$$\tilde{S}(Q) = 1 - \frac{\sum_i \sum_j q_{ij} q_{ji}}{\sum_i \sum_j q_{ij}^2}, \tag{10}$$

and

$$Q = \{q_{ij}\} = \widetilde{W} - (1 - \widetilde{W})\mathbf{I}_N, \tag{11}$$

where \mathbf{I}_N was the $N \times N$ identity matrix and $q_{ij} = \widetilde{w}_{ij}$ for all $i \neq j$, while then $q_{ij} = 1$ for all i . The scaled version of $\tilde{S}(Q)$ ranged from 0 (full symmetry) to 1 (full asymmetry):

$$S(Q) = \frac{N+1}{N-1} \tilde{S}(Q). \tag{12}$$

Hence, the values of $S(Q)$ close to 0 justified a BUN/WUN analysis.⁵ Therefore, the statistical properties of symmetrised ETNs would be explored. In the binary case, any entry a_{ij} of the new adjacency matrix A was set to 1 if and only if either $\tilde{a}_{ij} = 1$ or $\tilde{a}_{ji} = 1$ (and 0 otherwise). In the weighted case, the generic entry of the new weight matrix W was replaced by:

$$w_{ij}^t = \frac{1}{2} (\tilde{w}_{ij}^t + \tilde{w}_{ji}^t) = \frac{1}{2} \left(\frac{e_{ij}^t}{GDP_i^t} + \frac{e_{ji}^t}{GDP_j^t} \right), \tag{13}$$

where e_{ij}^t stood for the export value from country i to country j in year t .

By analogy, import values were calculated. $(imp)_{ij}^t$ was inserted instead to describe the import value to country i from country j .

All calculations presented below were done in *R* and Excel.

⁵ The threshold of the index may be arbitrarily decided by the researcher (Fagiolo, 2006). In our case it was very small and ranged from 0.000996 to 0.001799 in exports and from 0.001284 to 0.002268 in imports, respectively.

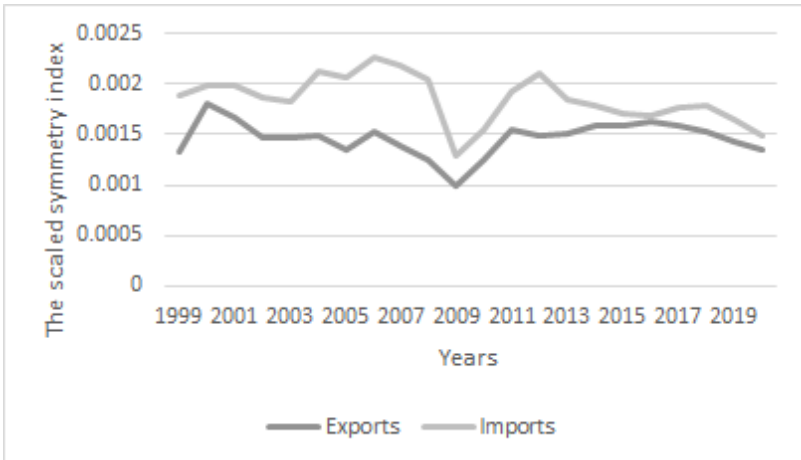
5. Findings

It should be noted that at the outset, the BUN analysis was deliberately omitted in this study, as all pairs of EU countries traded with each other during all the reported years. As a result, ND, ANND and CC took the maximum values of 27 for each country. Thus, the focus was on a WUN analysis instead.

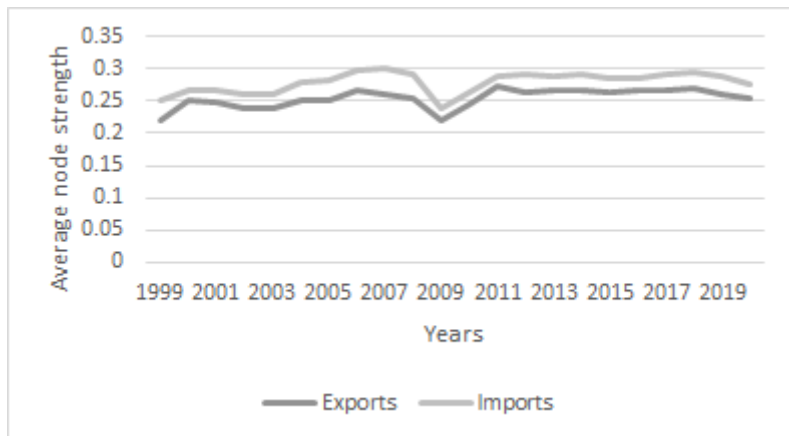
To begin with, the symmetry of matrix \widetilde{W} was checked. As Figure 1 shows, the scaled symmetry index was close to 0 for both exports and imports. This justified a WUN approach. The obtained results indicated that the value of exports from country i to country j equalled approximately the value of exports from country j to country i , and the same applied to imports.

The distribution of NS among countries (in both exports and imports) was right-skewed with the majority of nodes characterised by weak trade relationships (see Table 1 and Table 2). The average NS oscillated between 0.2 and 0.3 (see Figure 2). The most intense trade relations were observed in Germany throughout all the studied years. Its average NS was 0.96 in exports and 1.07 in imports. At the opposite pole were Greece (the minimum value of 0.08 in exports was reported in 2006 and 0.12 in imports in 2010), Luxembourg (0.12 in imports in 2016) and Cyprus (minimum values were noted during all the remaining years in both exports and imports). These findings were consistent with the economic performance of the EU member states. Germany was the undisputed leader in the intra-EU trade. Cyprus, Greece and Luxembourg are small countries rather known for being service providers.

Figure 1. Scaled symmetry index $S(Q)$ for WUN



Source: authors' calculation.

Figure 2. Average NS for WUN

Source: authors' calculation.

The average ANNS took similar values as the average NS (see Figure 3), whereas the WANND was much the same as the ANND and equalled 27 for all nodes in each year. There was a strong negative correlation between NS and ANNS ($r = -1$), which confirmed that the ETN was of a disassortative nature. This means that the probability of a connection between a high-strength and a low-strength node was greater than expected if the network were completely random. In other words, countries that were more closely connected (i.e. the hubs) tended to form trade relationships with more weakly connected countries. This suggests a core-periphery structure of the ETN, at least in terms of link intensity.

Table 1. Node strength of the EU countries in exports in selected years

Country	Years		
	1999	2004	2019
AT – Austria	0.199761	0.252976	0.247008
BE – Belgium	0.368554	0.453586	0.382216
BG – Bulgaria	0.102833	0.168899	0.190895
CZ – Czech Republic	0.233559	0.284407	0.392694
CY – Cyprus	0.033932	0.037207	0.048584
DE – Germany	0.900965	0.927677	0.998063
DK – Denmark	0.149741	0.162462	0.155792
EE – Estonia	0.224115	0.246399	0.194926
EL – Greece	0.062589	0.070991	0.087775
ES – Spain	0.181030	0.204553	0.223817
FI – Finland	0.178373	0.184311	0.157425
FR – France	0.369956	0.408882	0.365435
HR – Croatia	0.084321	0.088367	0.131615
HU – Hungary	0.255647	0.270027	0.382684
IE – Ireland	0.255070	0.235992	0.135715
IT – Italy	0.346196	0.408287	0.361977

Table 1. Node strength of the EU countries in exports in selected years (cont.)

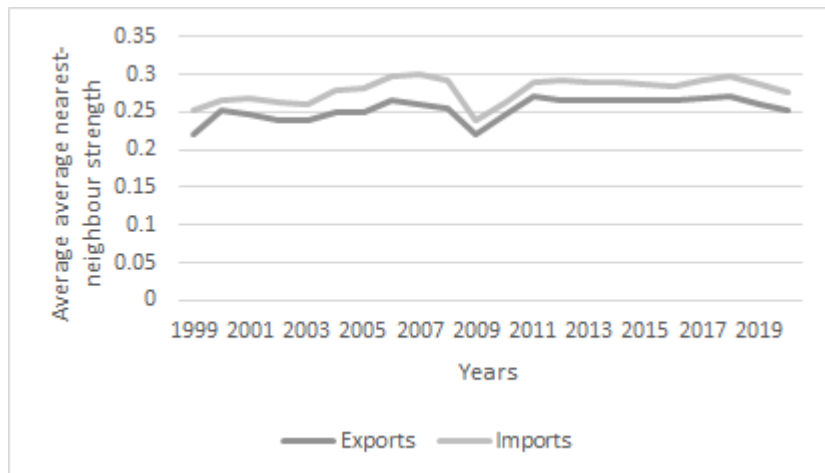
Country	Years		
	1999	2004	2019
LT – Lithuania	0.136734	0.173424	0.235332
LU – Luxembourg	0.131838	0.195042	0.099752
LV – Latvia	0.161128	0.189266	0.197908
MT – Malta	0.114869	0.118795	0.072969
NL – Netherlands	0.327050	0.344058	0.412007
PL – Poland	0.137458	0.207207	0.309558
PT – Portugal	0.106953	0.111030	0.129315
RO – Romania	0.110583	0.156554	0.208952
SE – Sweden	0.220259	0.247660	0.226578
SI – Slovenia	0.177527	0.190962	0.280955
SK – Slovakia	0.182494	0.247167	0.374168
UK – United Kingdom	0.396681	0.408636	0.305586

Source: authors' calculations.

Table 2. Node strength of the EU countries in imports in selected years

Country	Years		
	1999	2004	2019
AT – Austria	0.241303	0.278698	0.278546
BE – Belgium	0.429089	0.500840	0.404789
BG – Bulgaria	0.117564	0.169863	0.198306
CZ – Czech Republic	0.246599	0.303680	0.374606
CY – Cyprus	0.096285	0.113336	0.120678
DE – Germany	0.978395	1.116478	1.055845
DK – Denmark	0.163265	0.167818	0.156561
EE – Estonia	0.255140	0.223365	0.222480
EL – Greece	0.111615	0.120272	0.147078
ES – Spain	0.206490	0.237096	0.261334
FI – Finland	0.218330	0.180263	0.152572
FR – France	0.448696	0.458344	0.358984
HR – Croatia	0.130989	0.154939	0.211148
HU – Hungary	0.253992	0.284634	0.383435
IE – Ireland	0.177845	0.155241	0.129759
IT – Italy	0.439204	0.498765	0.438123
LT – Lithuania	0.172332	0.218377	0.302098
LU – Luxembourg	0.202884	0.228084	0.134828
LV – Latvia	0.168195	0.204835	0.240402
MT – Malta	0.227787	0.257335	0.174235
NL – Netherlands	0.320785	0.370702	0.437496
PL – Poland	0.170463	0.237179	0.367274
PT – Portugal	0.142948	0.140405	0.168788
RO – Romania	0.112606	0.173661	0.214797
SE – Sweden	0.226000	0.231957	0.218522
SI – Slovenia	0.206125	0.224799	0.274649
SK – Slovakia	0.168258	0.222992	0.328852
UK – United Kingdom	0.389917	0.333187	0.285058

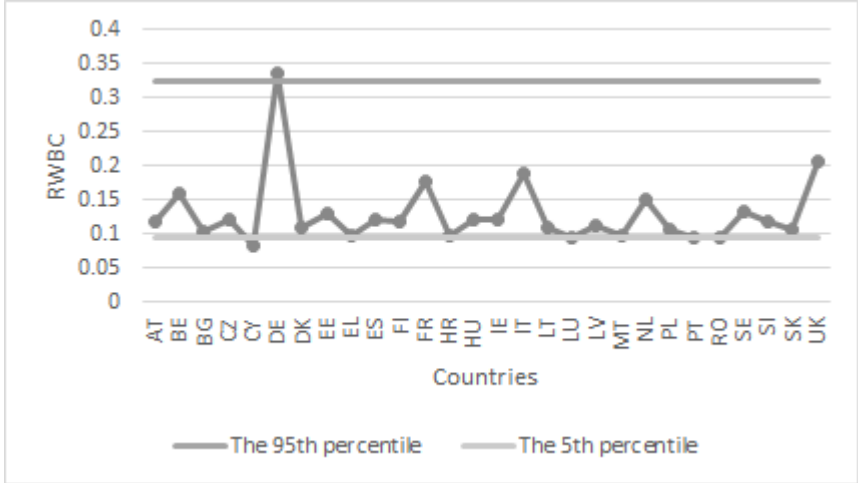
Source: authors' calculations.

Figure 3. Average ANNS for WUN

Source: authors' calculation.

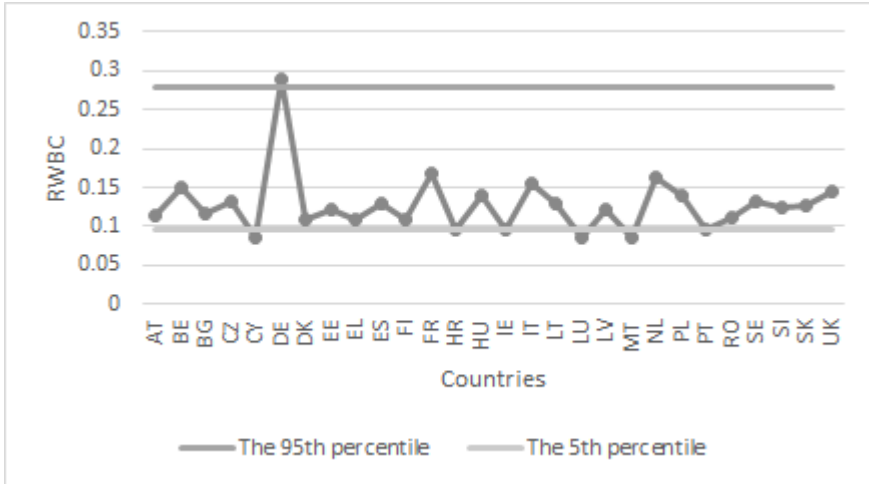
The next feature explored was the level of clustering. This raised the question of whether countries holding more intense trade relationships showed a tendency to trade with pairs of countries that themselves exchanged goods with each other. The answer was no. The average WCC ranged from 0.005 to 0.007 in exports and from 0.006 to 0.007 in imports. As regards the correlation between WCC and NS, a strong positive relationship was proven (the average of $r = 0.97$ in both exports and imports). Therefore, countries with a high NS were typically involved in highly-interconnected triples (Fagiolo et al., 2010). This pattern of nodes' behaviour could imply the occurrence of the 'rich club phenomenon'. However, the NS-GDP *per capita* and the WCC-GDP *per capita* correlations did not support this interpretation. The correlation between NS and GDP *per capita* was decreasing over time from 0.34 in 1999 to -0.02 in 2019 in exports and from 0.35 in 1999 to -0.05 in 2019 in imports. The correlation between WCC and GDP *per capita* took similar values varying from 0.39 in 1999 to -0.017 in 2019 in exports and from 0.35 in 1999 to -0.066 in 2019 in imports, respectively.

Figure 4. RWBC for WUN in exports in 1999

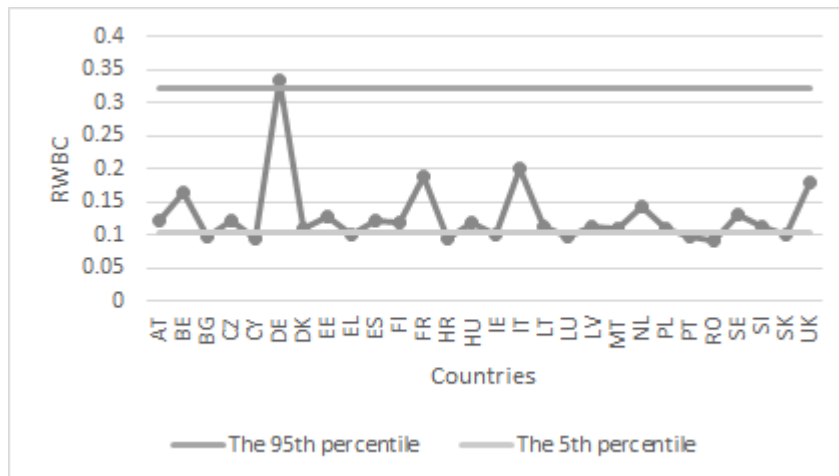


Source: authors' calculation.

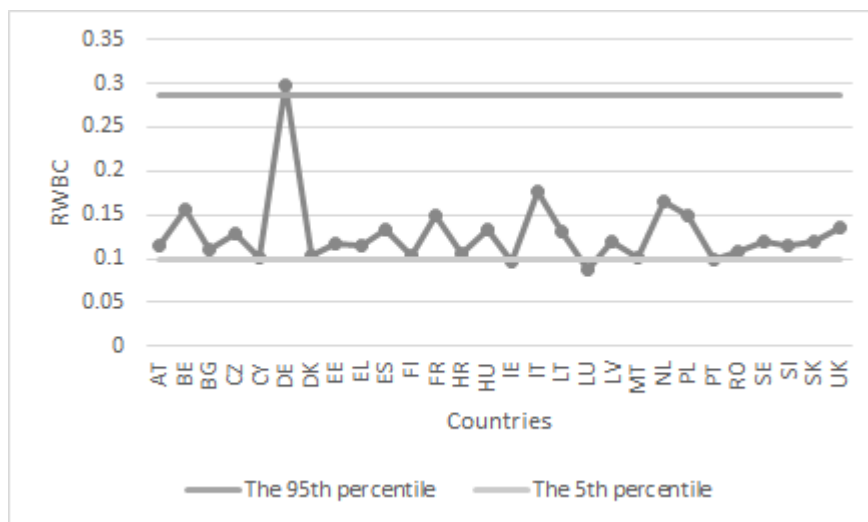
Figure 5. RWBC for WUN in exports in 2019



Source: authors' calculation.

Figure 6. RWBC for WUN in imports in 1999

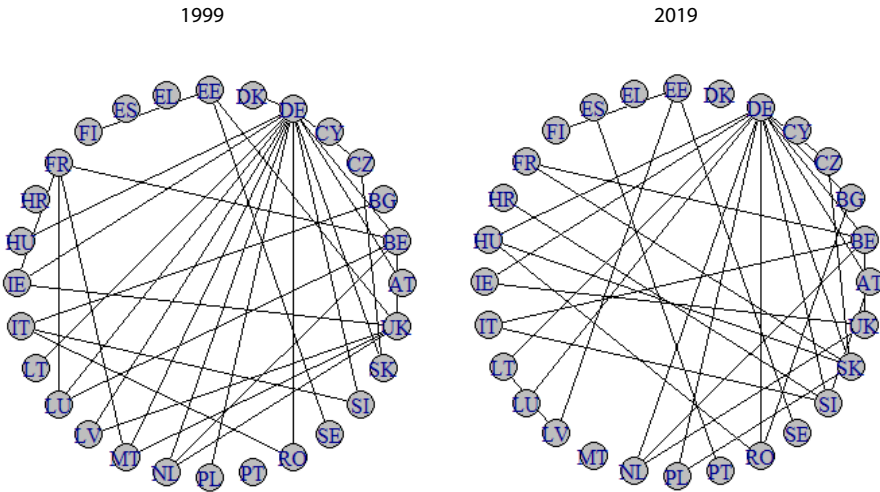
Source: authors' calculation.

Figure 7. RWBC for WUN in imports in 2019

Source: authors' calculation.

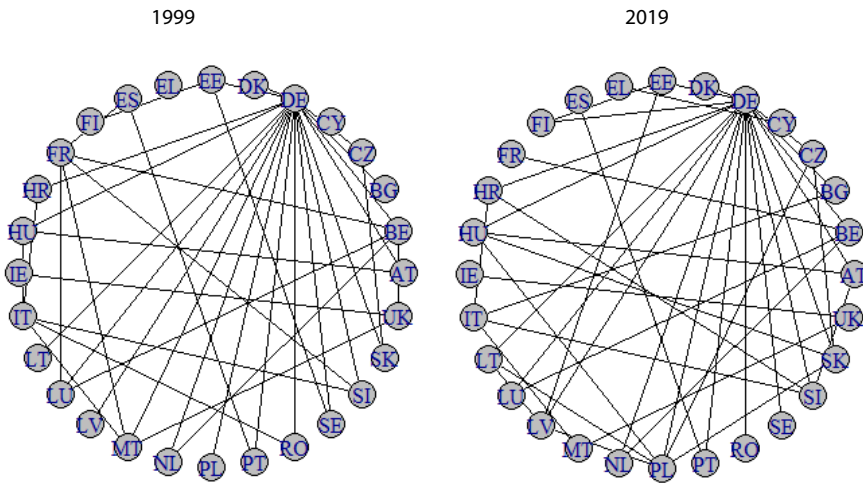
As Figures 4, 5, 6 and 7 show, the core-periphery structure of the ETN was confirmed. The RWBC index measures the likelihood of a given country to appear in a randomly selected trade chain within the network. This likelihood is determined by the number and intensity of trade relationships (Fagiolo et al., 2010). Germany occupied the most central position in the intra-EU network in both exports and imports during all the studied years. It means that this country was the most influential in the network due to a high number of direct and intense trade connections. To identify the core, a method proposed by Fagiolo et al. (2010) and Modrzejewska and Pajor (2011) was applied, i.e. a threshold at the 95th percentile of RWBC was imposed. Germany was the only country located in the core, i.e. within the top 5% of the EU countries. Nevertheless, it should be emphasised that the RWBC index for Germany was shrinking over time. It amounted to 0.34 in 1999 and 0.29 in 2019 in exports, and 0.33 in 1999 and 0.30 in 2019 in imports. In other words, dissimilarities among the EU countries decreased between 1999 and 2019. This was also proven in Modrzejewska and Pajor (2011). The nodes below the threshold of the 5th percentile of RWBC are considered the periphery. The following countries belonged to this area in various years: Croatia, Cyprus, Greece, Ireland, Luxembourg, Malta, Portugal and Romania in exports, and Bulgaria, Croatia, Cyprus, Denmark, Greece, Ireland, Luxembourg, Malta, Portugal, Romania and Slovakia in imports. The remaining countries were situated in an intermediate periphery. Some of them (e.g. the Czech Republic, Hungary, Lithuania, Latvia, the Netherlands, Poland and Slovenia in exports, and Hungary, Lithuania, the Netherlands, Poland and Spain in imports) improved their positions in the EU trade network over the years, whereas France, Italy and the United Kingdom suffered a sharp decline of RWBC in both exports and imports. Finally, the correlation between RWBC and GDP *per capita* was calculated. It revealed a similar pattern to that observed in the case of the correlation between NS and GDP *per capita*, and WCC and GDP *per capita*.

Figure 8. ETN in exports



Source: authors' calculation.

Figure 9. ETN in imports



Source: authors' calculation.

Figures 8 and 9 presenting intra-EU trade networks clearly illustrate the differences in the intensity of trade flows among EU countries. Only the flows above 4% of GDP are marked. Between 1999 and 2019, the structure of intra-EU trade did not change considerably. Some connections decreased in intensity, e.g. France maintained intense trade relations in exports with Belgium, Ireland, Luxembourg

and Malta in 1999, while in 2019 with Belgium and Slovakia. In the case of imports, France had strong trade relationships with Belgium, Luxembourg, Malta and Slovenia in 1999, while in 2019, only with Belgium.

6. Conclusions

In this paper, the statistical properties of the intra-EU trade network were examined. For this purpose, data concerning import connections between all pairs of 28 EU countries from 1999 to 2019 were analysed. The ETN was conceptualised as a weighted network where countries are represented by nodes and export/import flows divided by GDP of a given country by links. Since the ETN is a symmetric network (i.e. all trade relationships appear to be reciprocated with similar intensities), the application of the WUN approach was justified. Despite a high density of the network (all pairs of countries exchanged goods with each other during all the years reported), the average NS did not exceed 0.3. The only country whose average NS oscillated around 1 was Germany. The strong negative correlation between NS and ANNS confirmed a disassortative nature of the intra-EU network, i.e. countries holding more intense trade relationships tended to exchange goods with those less-connected (having less intense trade relations). This suggests a core-periphery structure of the ETN, which was also proven by the results of the RWBC index. Germany again turned out to be the most influential country in the EU trade network. However, its central position in the ETN weakened over the years. A similar situation occurred for France, Italy and the United Kingdom. Their RWBC values decreased between 1999 and 2019. The only exception among the EU's strongest economies was the Netherlands, whose position strengthened in both exports and imports within those years. The countries situated in the periphery of the EU trade network were either small economies (e.g. Cyprus, Malta) or those specialising in trade in services (e.g. Ireland, Luxembourg). The remaining EU member states were located in the semi-periphery of the ETN, where most of the countries of Central and Eastern Europe belonged to. In general, they improved their positions in the EU trade network over the years. As Figure 8 and 9 suggest, the structure of the ETN did not change significantly. Between 1999 and 2019 the intensity of some trade connections decreased (e.g. France-Luxembourg in exports), and some increased (e.g. Estonia-Latvia in imports). Furthermore, very few countries with a high NS were involved in highly-interconnected trade triples. The average WCC was rather poor. Finally, the relationships between network properties and country income (GDP *per capita*) were studied. The 'rich club phenomenon' present in the WTW was not confirmed at the European level.

As mentioned before, this work represents a preliminary step towards the understanding of the topological properties of the ETN and its dynamics. It provides an opportunity for many possible extensions. For instance, one may consider exploring the commodity-specific trade flows in search of specialisation patterns of countries belonging to the EU trade network. Furthermore, one can examine whether the topological properties of the ETN have some policy implications for the logic of European integration.

References

- Beaudreau, B. C. (2004). *World Trade. A Network Approach*. iUniverse.
- Beinhocker, E. D. (2006). *The Origin of Wealth. Evolution, Complexity, and the Radical Remaking of Economics*. Harvard Business School Press.
- Bhattacharya, K., Mukherjee, G., & Manna, S. S. (2007). The international trade network. In A. Chatterjee & B. K. Chakrabarti (Eds.), *Econophysics of Markets and Business Networks: Proceedings of the Econophys-Kolkata III* (pp. 139–147). Springer.
- Bhattacharya, K., Mukherjee, G., Saramäki, J., Kaski, K., & Manna, S. S. (2008). The international trade network: weighted network analysis and modelling. *Journal of Statistical Mechanics: Theory and Experiment*, (2), 1–5. <https://doi.org/10.1088/1742-5468/2008/02/P02002>.
- Bloch, F., Jackson, M. O., & Tebaldi, P. (2023). Centrality measures in networks. *Social Choice and Welfare*, 61(2), 413–453. <https://doi.org/10.1007/s00355-023-01456-4>.
- Fagiolo, G. (2006, December 1). Directed or Undirected? A New Index to Check for Directionality of Relations in Socio-Economic Networks. *Economics Bulletin*, 3(34), 1–12. <https://doi.org/10.48550/arXiv.physics/0612017>.
- Fagiolo, G. (2007). Clustering in complex directed networks. *Physical Review E*, 76(2), 1–16. <https://doi.org/10.1103/PhysRevE.76.026107>.
- Fagiolo, G. (2010). The international-trade network: gravity equations and topological properties. *Journal of Economic Interaction and Coordination*, 5(1), 1–25. <https://doi.org/10.1007/s11403-010-0061-y>.
- Fagiolo, G., Reyes, J., & Schiavo, S. (2008). On the topological properties of the world trade web: A weighted network analysis. *Physica A: Statistical Mechanics and its Applications*, 387(15), 3868–3873. <https://doi.org/10.1016/j.physa.2008.01.050>.
- Fagiolo, G., Reyes, J., & Schiavo, S. (2010). The evolution of the world trade web: a weighted network analysis. *Journal of Evolutionary Economics*, 20(4), 479–514. <https://doi.org/10.1007/s00191-009-0160-x>.
- Fisher, E., & Vega-Redondo, F. (2006). *The linchpins of a modern economy*. 2007 AEA Annual Meeting, Chicago. https://www.aeaweb.org/annual_mtg_papers/2007/0107_0800_1502.pdf.
- Garlaschelli, D., & Loffredo, M. I. (2004). Fitness-dependent topological properties of the world trade web. *Physical Review Letters*, 93(18), 1–4. <https://doi.org/10.1103/PhysRevLett.93.188701>.
- Garlaschelli, D., & Loffredo, M. I. (2005). Structure and evolution of the world trade network. *Physica A: Statistical Mechanics and its Applications*, 355(1), 138–144. <https://doi.org/10.1016/j.physa.2005.02.075>.

- Jackson, M. O. (2008). *Social and Economic Networks*. Princeton University Press. <https://web.stanford.edu/~jacksonm/netbook.pdf>.
- Kim, S., & Shin, E. H. (2002). A Longitudinal Analysis of Globalization and Regionalization in International Trade: A Social Network Approach. *Social Forces*, 81(2), 445–468. <https://doi.org/10.1353/sof.2003.0014>.
- Modrzejewska, A., & Pajor, A. (2011). Analiza sieciowa struktury obrotów handlowych w UE. In: S. Partycki (Ed.), *Społeczeństwo sieci. Gospodarka sieciowa w Europie Środkowo-Wschodniej* (vol. 1; pp. 643–656). Wydawnictwo KUL.
- Newman, M. E. (2005). A measure of betweenness centrality based on random walks. *Social Networks*, 27(1), 39–54. <https://doi.org/10.1016/j.socnet.2004.11.009>.
- Onnela, J., Saramaki, J., Kertész, J., & Kaski, K. (2005). Intensity and coherence of motifs in weighted complex networks. *Physical Review E*, 71(6), 1–5. <https://doi.org/10.1103/PhysRevE.71.065103>.
- Serrano, M. Á., & Boguñá, M. (2003). Topology of the world trade web. *Physical Review E*, 68(1), 1–5. <https://doi.org/10.1103/PhysRevE.68.015101>.
- Serrano, M. Á., Boguñá, M., & Vespignani, A. (2007). Patterns of dominant flows in the world trade web. *Journal of Economic Interaction and Coordination*, 2(2), 111–124. <https://doi.org/10.1007/s11403-007-0026-y>.
- Squartini, T., Fagiolo, G., & Garlaschelli, D. (2011a). Randomizing world trade. I. A binary network analysis. *Physical Review E*, 84(4), 1–17. <https://doi.org/10.1103/PhysRevE.84.046117>.
- Squartini, T., Fagiolo, G., & Garlaschelli, D. (2011b). Randomizing world trade. II. A weighted network analysis. *Physical Review E*, 84(4), 1–16. <https://doi.org/10.1103/PhysRevE.84.046118>.
- Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511815478>.