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SNA metrics in the analysis of international trade measured by added value – the example of the EU trade network

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Abstract

Research background: Dynamic changes in the trade network are evidence of the rapid development of the world economy. There is a need to analyse these transformations in the 21st century. A comprehensive description of the adjustments in the European Union trade network in terms of value added has not yet been carried out in the literature, especially in the context of network analysis.

Purpose of the article: The paper presents the changes in the European Union trade network structure measured by value added and in gross terms in the years 2005 and 2018 using social network analysis (SNA). This study makes it possible to verify whether the proposed new research methodology will find confirmation in the conclusions of the research carried out with the use of other methods.

Methods: For this purpose, the authors proposed applying SNA metrics to trade data, including density, weighted degree centrality, average link strength of vertex, and the PageRank algorithm. The analysis used trade data measured by value added and gross terms from the OECD trade in value added (TiVA) database for 65 economies in 2005 and 2018.

Value added & findings: The literature lacks comprehensive analyses of trade value added data by using SNA metrics. The use of SNA in the study demonstrated different complexities of the EU trade network measured in gross and value added data. This confirmed that gross trade data were overestimated and did not indicate actual connections between economies. Networks based on data on trade in value added are much less developed and only consist of real connections between economies without 'intermediary countries'. Changes in the connections between European countries in 2005 and 2018 reflect the changes occurring in the global economy, resulting in the decreasing share of the United States and Japan in the European Union trade network in favour of China. The results of the conducted research confirm the great effectiveness of the SNA methodology in the analysis of trade links in the context of the networks created by the analysed entities.

Keywords: international trade, EU, value added, social network analysis (SNA), degree centrality

1. Introduction

While observing the processes taking place in today's world economy, it can be seen that international trade is increasingly becoming a network, as there are complex trade relations between the participating countries. This network has specific properties and some dependencies. Various research methods can be used to explore them, i.e. descriptive statistics, indicator analysis, and econometric models. One of those is social network analysis (SNA) based on network science, which allows the researcher to consider data from a new perspective. However, these studies are not widespread (Aller et al., 2015).

SNA contains algorithms and statistics that allow the analysis of information in the relationships between entities that make up the database. It is an interdisciplinary research method widely used in biology, computer science, mathematics, sociology, and physics. However, it is still applied only to a relatively small extent in economics to study enterprise networks, business networks, economic networks, and trade networks. The authors aimed to present the changes in the structure of the European Union (EU) trade network measured by value added and in gross terms in 2005 and 2018 using SNA. Thus, the use of SNA metrics is designed to determine which countries occupy a central position in the examined trade network, with their presence essential to maintain network consistency. The article attempts to compare the changes taking place in the structure of EU trade measured by value added with the structure of EU trade in the traditional (gross) approach.

The remainder of this article is structured as follows. The next section explains the essence of the value added trade. Section 3 briefly reviews the prior research on the role of SNA in investigating international trade. Section 4 describes methodological issues, especially the metrics used in the analysis of the trade network. Section 5 presents the empirical results. Finally, section 6 summarises and presents the concluding remarks.

2. Value added trade

The development of the modern world economy is primarily associated with liberalisation. The liberalisation of trade and capital turnover, as well as the increased freedom in investment, enabled the creation of strong ties between various economies. Trade links in connection with the increasing foreign investments of enterprises are of particular importance. In striving to maximise their profits, enterprises began to search for 'cheaper' production markets in the 1980s. This trend intensified in subsequent years, along with the development of international transport and of technologies that enable the efficient management of distance production. At the same time, the offshoring phenomenon has intensified. Many production stages and services tasks previously performed domestically are now sourced from abroad (Acemoglu et al., 2015).

As a result, there has been a rapid development of trade in the world. Figure 1 presents changes in the volume of world exports since the mid-20th century. A surge in exports occurred in the first decade of the 21st century, rising from USD 6 billion to over USD 16 billion in 2008. However, the economic crisis of 2009 significantly reduced global exports by around 25% in that year. In subsequent years, the value of world exports was characterised by fluctuations. After a rapid increase in 2010, the upward trend continued for the next four years but halted in 2015-2017. After the breakthrough 2018, in which world exports reached almost $ 19.5 trillion, in 2019 a decline was re-recorded. In the context of the COVID-19 pandemic, it is likely that 2020 would not bring an increase in international trade.

However, do the data from Figure 1 show the actual trade turnover? For many years, exports were directly linked to the production of a given country, which had almost 100% of the value added by the exporting country (Johnson, 2014). Along with the progressing globalisation, more and more often in international trade one is dealing with the trade of parts and semi-finished products which cross borders many times and, as a result, are counted several times in trade statistics. Thus, statistics presenting trade in traditional (gross) terms distort trade links between economies.

The differences related to the use of different statistical data affect not only the value of trade, but also the geographical structure of international trade (Figure 2). In the traditional approach to trade, statistics will not record exports from country A to country C. It is only when analysing the export of value added does it turn out that one of the trading partners of country A is country C. Therefore, analysing trade in terms of value added allows to indicate real trade connections between economies without any ‘intermediary countries’.

The division of trade into streams related to domestic and foreign value added has been presented in several approaches. One of the first works regarding tracing value added in global production chains was prepared by Koopman et al. (2010). In the following years, Stehrer et al. (2012) and Koopman et al. (2014) also described the full decomposition of gross exports. Work on the statistical approach to the decomposition of exports was also carried out by the OECD and the WTO; a synthetic division of exports into domestic and foreign value added according to OECD and the WTO is given in Figure 3.

The authors attempted to estimate the trade exchange in terms of exported value added. This approach more accurately reflects the connections between economies. Not only does it show the real amount of country exports, but it also enables the indication of target export markets.

3. Literature review regarding the use of SNA in research in international trade

Research on the structure of global trade networks and the impact of external factors has not often been discussed in the literature (Aller et al., 2015). Inhomogeneities in international trade flow and connections between economies, as well as the participation of partners in these connections, were noted by Bernard and Jensen (1995) and Bernard et al. (2007). Meanwhile, Serrano, Boguñá & Vespignani (2003) showed that the world trade network is complex, but they did not apply SNA metrics (especially centrality measures) in analysing trade data.

At the beginning of the 21st century, a network approach was used in internationalisation-related analyses (Ellis, 2000; Ellis & Pecotich, 2001; Harris & Wheeler, 2005). The number of scientific studies using network analysis tools to study international financial and trade flows has gradually increased. Interesting research in this field published by Dueñas et al. (2017) highlighted the similarities and differences between the international trade network (ITN) and the international M&A network (IMAN). They noted that the most relevant difference between these networks is the level of relations reciprocity. In contrast to M&A transactions, which are mainly unilateral, trade relations are typically reciprocal, leading to a higher density and full connectivity. However, both the IMAN and the ITN are characterised by highly unbalanced bilateral flows. In the ITN, developed countries have more balanced trade relations than developing countries.

Kim & Shin (2002) and Mahutga (2006) analysed long-term changes in trade networks in the second half of the 20th century, indicating progressive globalisation processes. Using a social network approach, they showed that these changes intensified in the 1990s, as evidenced by the increase in world trade network density. Bhattacharya et al. (2008) and Zhou et al. (2016) pointed to the significant asymmetry of the network and the concentration of trade in several developed countries. Benedictis et al. (2014) examined the centrality and importance of individual countries in the world trade network, while Cingolani et al. (2017) studied the position of individual countries in global value chains (GVC) and pointed out that centrality varies according to the production process stages.

Benedictis & Tajoli (2011) used network analysis tools to graphically and analytically present world trade features. They showed that the trading system is becoming more closely interconnected, and that trade integration at the global level is increasing, but is still far from complete, except in a few areas. At the same time, strong and growing heterogeneity was observed between countries (in the choice of trade partners); countries engage in very different positions on the network. In addition, the analysis revealed that trade policy plays an important role in shaping the trade network and that WTO members are more closely connected than the rest of the world. The structural difference between the extensive and intensive trade margins was also highlighted. An important feature of these results is that they relate to the trading system as a whole, giving a unified picture of the system's features and complexity. Fagiolo (2010) obtained similar results.

An overview of measures that can be used in SNA in research on international trade networks was presented by Kangodan (2018) and Andrade & Rego (2018), who not only summarised but also indicated how minor modifications to measures can help provide a better picture of the international trade network. In addition, social network analysis may also be used to examine international trade in product groups (Lovrića et al., 2018). Product group studies are an interesting example of the application of SNA to international trade. Zhang & Zhou (2023) studied the status of economies in international crop trade networks and assessed the importance of economies using multidimensional node importance metrics. The dynamics in the automotive international trade networks were analysed by Russo et al. (2023). Their study focused on identifying clusters and structure of the international trade of automotive components and changes of parts. The results highlighted the changing role of individual countries (nodes) and their contribution to trade. The SNA methodology was also used in a study of cereal trade and carbon emission networks to quantify the role of countries in the networks (Lin et al., 2023). However, all these studies refer to data on international trade in traditional (gross) terms.

Few attempts were also made to analyse trade networks in terms of added value. Amador and Cabral (2017) using data from 1995-2011 noticed that trade networks were centralised and asymmetric in which several central countries dominated. SNA was also used by Dong (2022) to study trade facilitation on the value-added trade networks. The results indicated that trade facilitation helps to increase the density of the trade network and keep world trade stable. It should be emphasised that the study was conducted for the period 2008-2014 and did not include the analysis of positions in the network of individual countries, but only two communities (European and Asian Pacific).

4. Research methodology – basic concepts and measures of SNA

In SNA, the network is defined by a set of nodes and the connections between them. Thus, two main elements that form a network can be distinguished (Barabasi, 2012):

1) nodes (vertices) – entities included in the system,
2) edges (relations) – relations that reflect interactions between entities in the system.

Networks are often presented in the form of graphs. Graphically, the node is presented as a circle and the edge as a straight line linking two nodes (Sanjeev, 2007).

The subject literature highlights the fact that the SNA metrics can be considered from the perspective of both the whole network and individual entities. The first group includes (Abramek, 2021):

1) density – measures how close the network is to being complete, i.e. a complete network has all possible edges and a density equal to 1,

2) diameter – specifies the longest graph distance between any two nodes in the network,
3) average path length – the average distance between all pairs of nodes in the network,
4) average degree – the average number of all direct connections of the node in the network,
5) average weighted degree – the average sum of the weighted direct connections of the node in the network.

The second group of SNA metrics includes centrality indicators, which are essential to analyse the position of a given entity in the network. Four basic types can be distinguished (Yang et al., 2017):

1) degree centrality – the number of all direct connections of a given node,
2) closeness centrality – the average distance from a given starting node to all other nodes in the network,
3) betweenness centrality – specifies how often a node appears on shortest paths between nodes in the network,
4) prestige centrality, also known as eigenvector centrality (Lee & Sohn, 2016) – measures the connection of a given node to well-connected nodes.

The interpretation of these metrics should be adapted to the type of research network. Owing to the specifics of this study (i.e. weighted directed networks), only the value related to degree centrality and prestige centrality was calculated.

For the trade network, the degree centrality (denoted by $C_d(n_i)$) makes it possible to specify the number of direct trade relations of a given country with other countries in the network. This indicator, proposed by Freeman (1978), is specified in the following equation:

$$C_d(n_i) = \sum_{j=1}^{n} a(n_i, n_j), \tag{1}$$

where n_j – nodes that are directly connected with the node n_i, $a(n_i, n_j) = 1$ if n_i and n_j are connected and 0 otherwise.

Lee and Sohn (2016) pointed out that in the case of directed networks for a given node, the following can also be calculated:

1) out-degree centrality – its level is determined based on relations pointing away from the given node. In this study, this indicator makes it possible to identify the number of countries in the network to which the country exports goods.
2) in-degree centrality – its level is determined based on relations towards the inside of a given node. In this study, this indicator makes it possible to identify the number of countries from which the country imports goods.

If the edges have assigned weights in the considered network (i.e. a weighted nrk), the weighted degree centrality for a given node can also be calculated. This indicator is equal to the sum of the edge-weights that are connected to the given vertex which can be represented as an equation (De Andrade & Rego, 2018):

$$C_d^w(n_i) = \sum_{j=1}^{n} w(n_i, n_j), \tag{2}$$

where w – weight of the link between n_i and n_j.

In addition, De Andrade and Rego (2018) proposed a new indicator to determine the average weight of a node connection, i.e. the average link strength of vertex n_i, denoted by $LS(i)$. This measure is defined as the ratio of weighted degree centrality $C_d^w(n_i)$ and degree centrality $C_d(n_i)$:

$$LS(i) = \frac{C_d^w(n_i)}{C_d(n_i)}. \tag{3}$$

For the purposes of this study, the value of this indicator informs about the average strength of trade relations between a given country and its trading partners. It shows to what extent trade volume is related to the number of direct trade relations of a given country with other countries in the network.

Based on formula (3), the input average link strength and the output average link strength for a given vertex can also be determined.

Another essential metric that determines the position of a node in the system is the eigenvector centrality, which in the case of a trade network, measures the closeness of a country to other 'central' countries, therefore the central location of a given entity depends on the centrality of the main trading partners (Aller et al., 2015). This indicator was used to identify the most prestigious (i.e. flagship) nodes, and refers to the quality of relations between entities.

The PageRank algorithm, the one variant of the eigenvector centrality, determines the node's relative significance in the network. This measure is used by, among others, Google Search for positioning websites, but it can also be used to evaluate other data describing the network. The PageRank indicates the importance of a given node based on the quality of the nodes connected to it. This algorithm determines the positioning of the node in the network, and it makes it possible to identify nodes that maintain relations with other relevant members of the network (Khokhar, 2015). Furthermore, it is worth emphasising that the Gephi package1 takes into account the weights of particular edges when calculating the PageRank values, which is crucial from the point of view of this article.

In order to meet the objectives of this paper, the two formulated research hypotheses state that:

1) statistics presenting EU trade in traditional (gross) terms distort real connections in trade networks,
2) changes in the EU trade network indicate the increasing role of three regional supply hubs (DEU, USA, and CHN)[2] between major supply chain blocks (Europe, America, and Asia).

Testing these research hypotheses was based on trade data measured by value added and gross terms from the OECD TiVA database for 2005 and 2018. The specificity of preparing a graph showing the linkages between entities required the use of one type of data. For gross trade network analysis, country-specific gross export data were used. This resulted in two problems. Firstly, the study used 'overestimated' data and secondly, presented a 'falsified' geographical structure of trade. For trade network analysis in value-added terms, one can choose several approaches:

(1) if domestic value added in exports (DVA) is used then, on the one hand, one is naturally no longer using overestimated data, but this still does not solve the problem related to the geographical structure of trade;
(2) it is therefore possible to divide domestic value added in exports (DVA in Figure 3 into direct domestic value added (DDVX), indirect domestic value added (IDVA) and domestic value added re-imported in the economy (RE-EX DVA), hence:
(2a) using only the DDVA as a basis for building the network does not solve the problems – both of estimating export volumes and the geographical structure of export;
(2b) using IDVA as a basis for network construction would enable an examination within global value chains (GVCs) – this issue, however, lies outside the objectives of the article;
(3) it is also possible to use a combination of DDVA, IDVA and RE-EX DVA data and analyse domestic value added embodied in foreign final demand.

Therefore, the authors decided to use a combination of DDVX, IDVX and RE-EX DVA data which made it possible, on the one hand, to present information on national value-added exports produced in a given country and, on the other, "not to fall into a geographical trap". The 2021 ICIO and TiVA databases are primarily based on statistics compiled according to the System of National Accounts 2008 (2008 SNA) and contain both trade and service data. The time range of the analysis is related to the limited availability of data. The research includes 65 entities: 64 countries and the rest of the word (ROW).

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[1] In this paper, the Gephi 0.9.2 package was used to visualise trade networks and calculate the value of the SNA indicators.

[2] In the Annex, a list of country abbreviations is provided.

To sum up, SNA allows researchers to explore statistical data from a new perspective. It makes it possible to study the phenomena of a relational nature and perform quantitative analysis. It also allows to visualise data to reveal latent structures or patterns in connections between the examined entities. However, calculating the value of SNA metrics without specialist computer software is extremely difficult. For instance, in the Gephi package, which is usually used in network analysis, for the weighted graph, it was impossible to compute the weighted closeness centrality and the weighted betweenness centrality, which limits the scope of the findings from the study.

5. Results and discussion of the EU trade network study using SNA measures

In employing SNA indicators to study the structure of EU trade, four trade networks were used:

1) the EU trade network in traditional (gross) terms in 2005,
2) the EU trade network in value added terms in 2005,
3) the EU trade network in traditional (gross) terms in 2018,
4) the EU trade network in value added terms in 2018.

The examined EU trade networks consisted of 65 nodes (economies) and, on average, 2 825 edges, i.e. direct relations between them.

Within the metrics that refer to the entire network, only the density, average degree, and average weighted degree were determined (see Table 1). In the case of average degree, both in 2005 and 2018, all the considered networks achieved a level of 43, which means that particular countries had, on average, about 43 trade connections with other economies. These networks also had a similar density, of around 68%, which from the perspective of the directional nature and specificity of trade relations, was sufficient to carry out a detailed network analysis. However, in 2005 and 2018, a characteristic feature of the value added trade network was a lower weighted average degree than in the gross trade networks. The level of this parameter confirmed that trade statistics collected traditionally were overestimated (by approximately 23%, on average, over the considered period) in relation to trade measured in value added (see Banerjee & Zeman, 2020 and Johnson & Noguera, 2017).

The visualisation of the EU trade relations was prepared in the form of a directed weighted graph, where the edges move from the exporter to importer, and the weights correspond to the volume of trade flows. Figures 4, 5, 6, and 7 present the relation between exports and imports in gross and value added terms, worth over USD 20 billion in 2005 and 2018, respectively. The nodes' size depends on the value of their weighted degree centrality; a relatively high value indicates key vertices in the network. The nodes' colour indicates belonging to the EU (the countries belonging to the EU are marked in pink, and the countries outside the EU are in green).

Based on the data in Table 1 and Figures 4-7, it should be noted that in both 2005 and 2018, the visualised value added trade networks were characterised by a smaller number of nodes and edges, and at the same time by a higher density than in the case of gross trade networks.[3] What is more, in 2005 and 2018, the value added trade network had a lower average weighted degree than the traditional trade network. These parameters confirmed that value added trade networks were much less developed and consisted only of real trade connections between economies without 'intermediary countries' (cf. World Bank, 2017 and WTO, 2019). Therefore, it can be assumed that in value added terms, the trade network better reflects the actual trade of the EU Member States than in the case of traditional trade networks.

Table 2 shows that no matter how trade was measured, in 2005 and 2018, DEU, GBR, FRA, and ITA had the largest trading relationship within the analysed trade networks (compare Fritsch & Matthes, 2020). In turn, in the group of countries outside the EU, the main trading partners for European countries

[3] Note that in 2005, in the visualised value added trade network, there was a relationship that could not be observed in the visualised traditional trade network, i.e. the connection between JPN (as exporter) and GBR (as importer).

were the USA, CHE, RUS, and JPN. Particularly noteworthy was CHN's growing importance in terms of the average link strength of export-import relations with EU countries. In the ranking presented in Table 2, China was promoted from 9th place in 2005 to 4th place in 2018.

On average, in 2005 and 2018 the most significant differences between the average link strength of the vertices that form the traditional trade networks and those included in the value added trade network were for DEU, FRA, ROW, ITA, GBR, CHE (see Figure 8), which indicated the scale of gross trade data overestimation in relation to these countries. Therefore, it can be concluded that their role in real trade relations was smaller than for the gross trade networks (see Kordalska & Olczyk, 2019). In addition, it should be noted that these differences for all the nodes increased in 2018 compared to 2005. The largest increase occurred in DEU, IRL, NLD, USA, FRA, and CHN.

Moreover, when analysing in detail the data presented in Table 3 and Figure 9 concerning the input and output average link strength of a given node, it can be noted that:

1) whilst in 2005 and 2018, the USA was the main net importer from the EU Member States, followed by GBR, CAN, and IND, whereas DEU, IRL, RUS, NLD, NOR, and CHN were the leading net exporters to EU countries (see Figure 9).
2) In 2018, compared to 2005:
   - DEU strengthened its position as an exporter of value added in the EU trade network. This is demonstrated by both the rise in the level of the output average link strength of the node representing the German economy (by about 41%) and the significant increase in the difference between the output and input average link strength for this country in 2018 (see Figure 9). In contrast, in 2018, DEU remained a crucial importer of value added from the USA, CHN, GBR, and FRA (see Figure 7).
   - The USA strengthened its position as an importer of value added from the EU Member States. In 2005, the USA imported value added primarily from four European countries, i.e. DEU, GBR, ITA, and FRA (see Figure 5), while in 2018 it also imported from IRL, NLD and ESP. However, it is worth emphasising that in 2018, the US economy remained a significant exporter of value added for the German and British economies (see Figure 7).
   - CHN strengthened its position as an exporter of value added to the EU Member States (see Table 3). This reflects the fact that in 2018, CHN exported value added mainly to DEU, GBR, FRA, and ITA (see Figure 7).
   - CHN strengthened its position as an importer of value added from the EU Member States (see Table 3).
3) In 2018, JPN ceased to be a significant exporter of value added to the EU Member States and became a net importer.

As the data in Table 4 confirmed, in both 2005 and 2018, DEU, GBR, FRA, and the USA occupied the leading places in the ranking based on the PageRank value. These economies should be classified as the flagship entities in the examined networks since they built many connections with other entities that hold important positions in the network. In addition, it is worth noting that regardless of how EU trade was measured, in 2018 comparing to 2005:

1) the importance of CHN increased (see Tables 2 and 4), which proves CHN's growing role in the global economy;
2) the importance of FRA, GBR, ESP, ITA, and USA in the examined network fell – in 2018 these nodes reached lower PageRank values than in 2005.

Moreover, in terms of value added trade, in 2005 the nodes representing GBP, USA, and ESP, and in 2018, also those representing FRA and CHN, had a greater PageRank value compared to trade measured in gross terms. This further confirms that their role in trade with the EU Member States was relatively greater than for trade calculated according to traditional statistics. In turn, in both 2005 and 2018, in the instance of value added, the trade nodes representing DEU, NDL and BEL had lower PageRank values than trade measured in gross terms, which may indicate their relatively smaller role in the real EU trade flows.

6. Conclusions

This paper presents a new perspective on the analysis of international trade, in particular, trade measured by value added. Its objective was to apply network analysis to study the structure of the international trade network. Previous analyses of the differences in international trade measured in traditional (gross) terms and value added indicated the overestimation of the former, which were in line with the earlier findings of Johnson and Noguera (2012), Stehrer (2012), Koopman et al. (2014), Nagengast and Stehrer (2016), and more recently Felice and Tajoli (2021). The results of the network analysis confirmed that trade statistics collected traditionally are overestimated in relation to trade measured by value added. The European network visualisations of value added trade showed that these networks were much less developed, and consisted only of real trade connections between economies without intermediary countries. Therefore, it should be expected that this trade network better reflects the actual international trade of EU Member States than was in the case of traditional trade networks. Consequently, this analysis confirms the hypothesis about the distortion of trade links in gross statistics.

The changes in the connections of European countries between 2005 and 2018 reflect the changes that occurred in the global economy (Fernandes et al., 2022), which resulted, among others, in the growing share of regional supply hubs of Germany, USA and China in the EU trade network, thus confirming the second hypothesis. Similar conclusions can be drawn from the studies by Hanzl-Weiss et al. (2018), Cieślik et al. (2021), and WTO (2019).

Detailed results from the study indicate that:

- regardless of how trade is measured, both in 2005 and 2018, the German, British, French, and American economies held central positions in the EU trade network. These economies should be included in the key entities in the examined networks as they had many connections with other entities that occupied an essential position in the network,
- in both 2005 and 2018, although the role of the German economy was relatively smaller in real EU trade flows than in the case of gross trade, it maintained a central position in the EU trade network as European regional supply hub,
- CHN's role in the EU trade network increased significantly, which indicates the growing importance of the Asian regional supply hub in the global economy.

The conducted research shows that social network analysis allows to draw conclusions that are similar, but at the same time more in-depth, in relation to other research methods. The analysis enables a better understanding of the trade links between European economies, however it is important to highlight some limitations. First of all, it should be remembered that, to some extent, data on trade in value added are estimated. Secondly, the time and spatial range of the data is limited. However, despite these limitations, the use of SNA in combination with data illustrating value added trade allows a deeper understanding of trade relationships between economies.

Further research could be conducted in two directions. Together with the release of new statistical data, the examined period could be extended. One could also try to analyse trade networks in other regions (e.g. Asia), and the world in general. The results of the research can be used to better understand the changes taking place in the global trade network. Firstly, the findings may be useful to those involved in the planning and implementation of foreign trade policy at the level of individual countries, groupings and international organizations. Secondly, the awareness that exporters of goods and services can gain from countries where their products are ultimately used can foster better adaptation to rapidly changing conditions in global value chains.

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Annex

List of country abbreviations:

AUT – Austria
BEL – Belgium
BRA – Brazil
CAN – Canada
CHE – Switzerland
CHN – China (People's Republic of)
CZE – Czechia
DEU – Germany
DNK – Denmark
ESP – Spain
FRA – France
GBR – United Kingdom
HUN – Hungary
IND – Indonesia
IRL – Ireland
ITA – Italy
JPN – Japan
KOR – Korea
LUX – Luxembourg
NLD – Netherlands
NOR – Norway
POL – Poland
ROW – Rest of the World
RUS – Russian Federation
SAU – Saudi Arabia
SWE – Sweden
TUR – Turkey
USA – United States

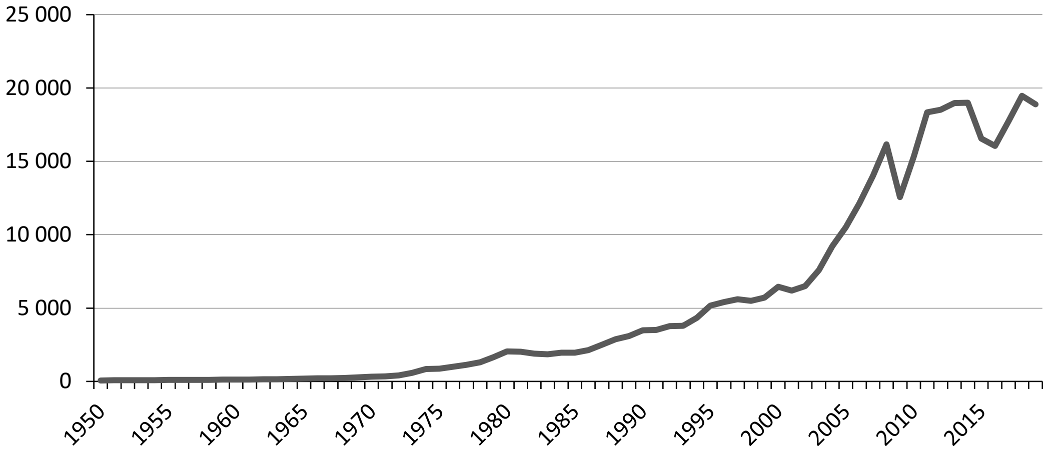

Fig. 1. World exports in 1950-2019 in USD billions

Source: own calculations based on WTO, https://timeseries.wto.org/ (access: 29.06.2020).

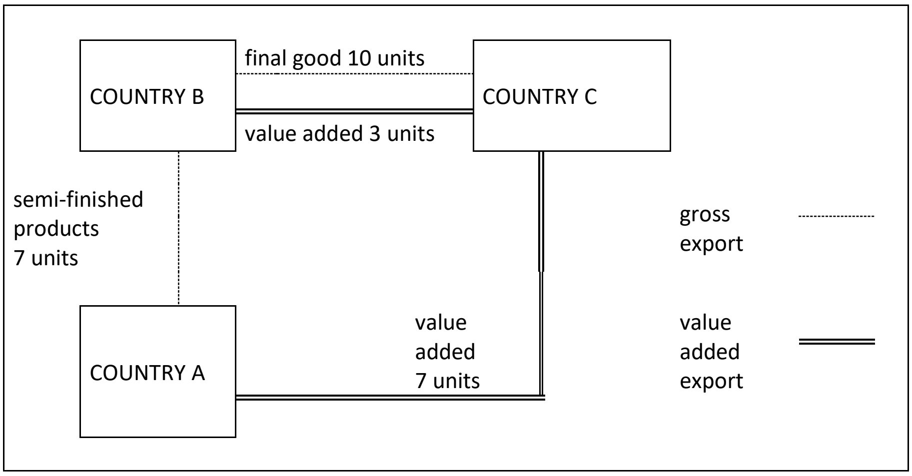

Fig. 2. Comparison of trade measured by gross value and value added

Source: own study.

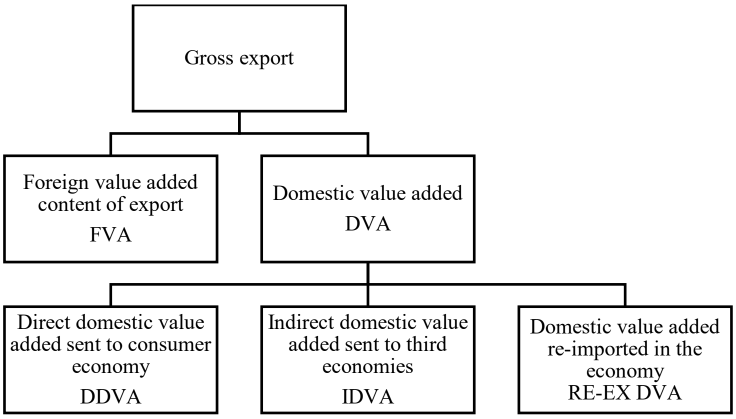

Fig. 3. Division of exports into domestic and foreign value added

Source: own study based on OECD (2016) explanatory notes.

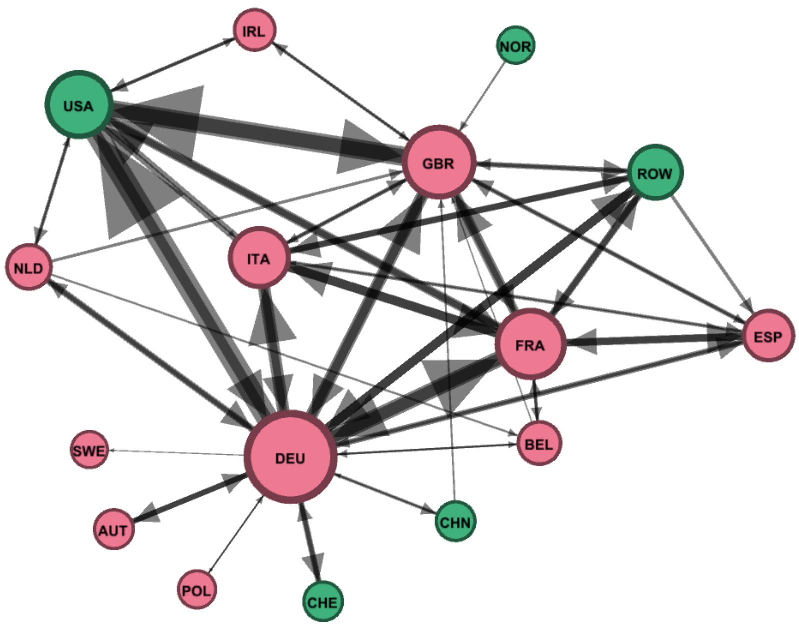

Fig. 4. Visualisation of the EU gross trade network in 2005 (worth over USD 20 billion)

Source: own study in Gephi.

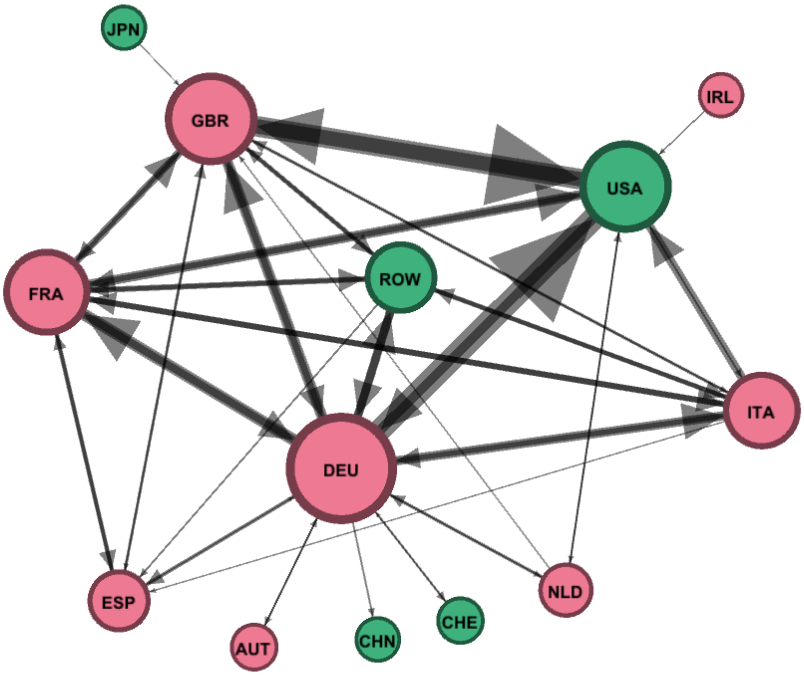

Fig. 5. Visualisation of the EU value added trade network in 2005 (worth over USD 20 billion)

Source: own study in Gephi.

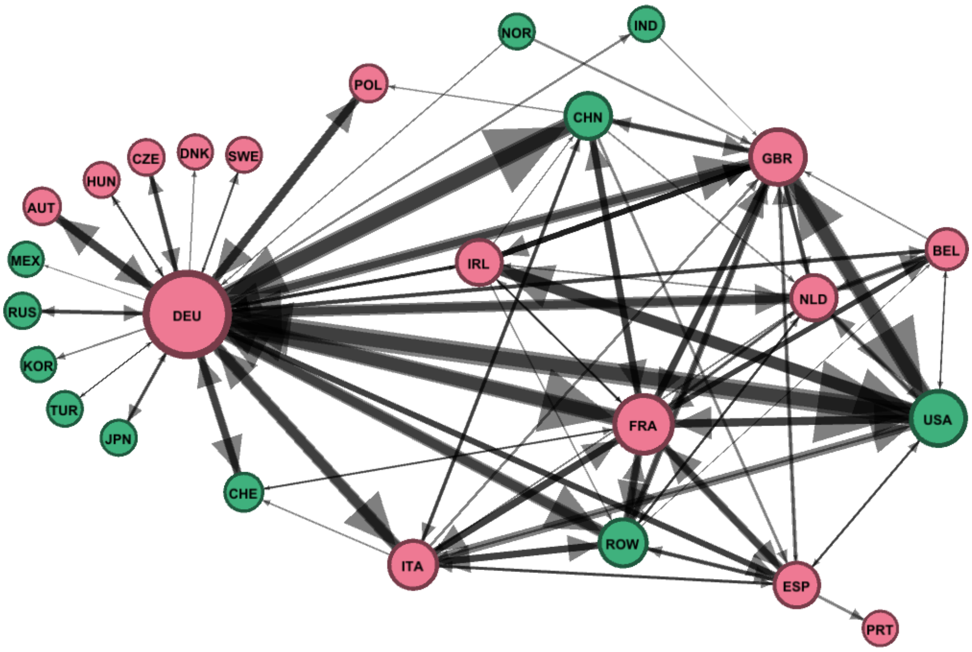

Fig. 6. Visualisation of the EU gross trade network in 2018 (worth over USD 20 billion)

Source: own study in Gephi.

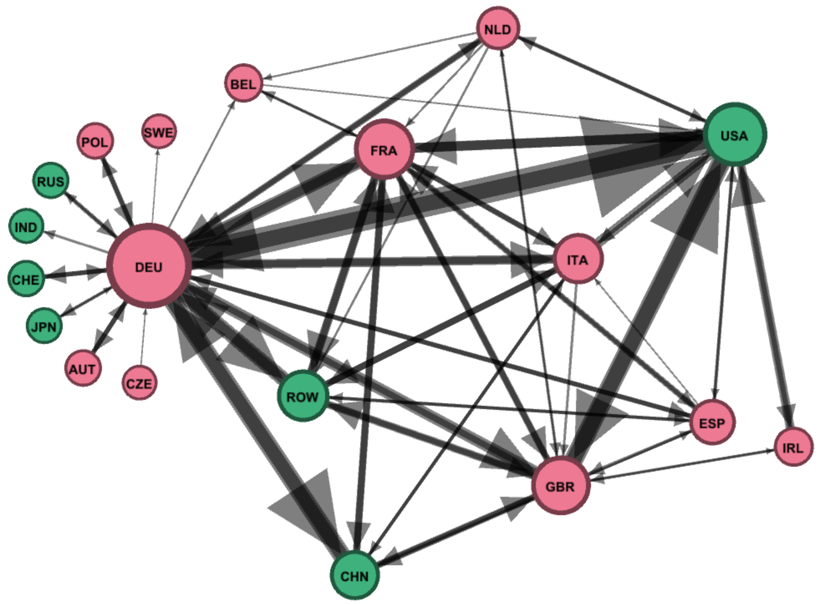

Fig. 7. Visualisation of the EU value added trade network in 2018 (worth over USD 20 billion)

Source: own study in Gephi.

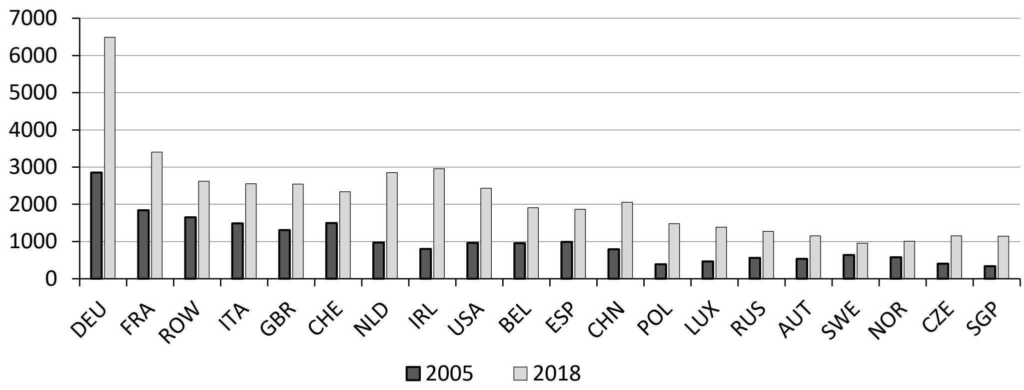

Fig. 8. The difference in the average link strength of weighted degree centrality between the nodes that form the gross trade network and the nodes that are part of the value added trade network in 2005 and 2018 (in USD million)

Source: own calculations.

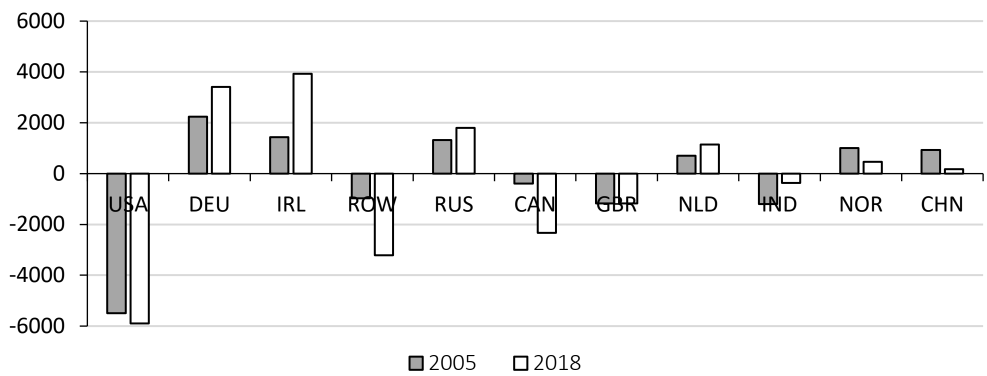

Fig. 9. The countries with the highest average net export* value to EU Member States in value added terms in 2005 and 2018 (in USD million)

*Net export calculated as the difference between output and input average link strength of nodes forming part of EU trade networks measured in value added.

Source: own calculations.

Table 1. The main parameters of the examined EU trade networks in 2005 and 2018

	2005		2018	
	the EU gross trade network	the EU value added trade network	the EU gross trade network	the EU value added trade network
the entire EU trade networks				
number of nodes	65	65	65	65
number of edges	2816	2828	2826	2828
average degree	43.32	43.51	43.48	43.51
average weighted degree	89793	70195	159700	115056
network density (%)	67.7	68	67.9	68
the visualised EU trade networks worth over USD 20 billion (Figs. 1-4)				
number of nodes	16	13	26	19
number of edges	63	48	114	76
average degree	3.938	3.692	4.385	4
average weighted degree	153481	132265	203546	173977
network density (%)	26.3	30.8	17.5	22.2

Source: own calculations.

Table 2. The level of total average link strength of nodes that are part of EU trade networks in gross and value added terms (in USD million)

place in the ranking	2005				2018			
	country symbol	the EU trade network in gross terms	country symbol	the EU trade network in terms of value added	country symbol	the EU trade network in gross terms	country symbol	the EU trade network in terms of value added
1.	USA	13721	USA	12758	DEU	22731	USA	19212
2.	DEU	12346	DEU	9496	USA	21646	DEU	16245
3.	ROW	10066	ROW	8415	ROW	16298	ROW	13674
4.	GBR	8783	GBR	7472	CHN	14145	CHN	12088
5.	FRA	8382	FRA	6540	FRA	13071	GBR	9678
6.	ITA	6910	ITA	5421	GBR	12222	FRA	9670
7.	ESP	4573	ESP	3584	ITA	9809	ITA	7261
8.	CHE	4354	JPN	3317	NLD	7656	ESP	5241
9.	CHN	3793	CHN	2999	ESP	7108	RUS	4987
10.	NLD	3775	CHE	2857	CHE	6576	NLD	4802
11.	RUS	3399	RUS	2843	RUS	6258	CHE	4237
12.	JPN	3321	NLD	2803	IRL	6049	JPN	3994
13.	BEL	2937	BEL	1983	BEL	5179	BEL	3268
14.	NOR	2505	NOR	1928	JPN	4517	IND	3126
15.	SWE	2312	SWE	1673	POL	4486	IRL	3096
16.	IRL	2057	TUR	1646	IND	3598	POL	3003
17.	TUR	1999	CAN	1443	NOR	3588	NOR	2578
18.	AUT	1934	AUT	1397	AUT	3526	SWE	2499
19.	CAN	1595	IRL	1253	SWE	3454	TUR	2408
20.	POL	1532	KOR	1199	TUR	3305	AUT	2371

Source: own calculations.

Table 3. The level of the input and output average link strength of nodes that are part of EU value added trade networks in 2005 and 2018 (in USD million)

place in the ranking	input average link strength of node				output average link strength of node			
	2005		2018		2005		2018	
	country symbol	indicator value	country symbol	indicator value	country symbol	indicator value	country symbol	indicator value
1.	USA	15505	USA	22159	DEU	10616	DEU	17948
2.	ROW	8899	ROW	15278	USA	10012	USA	16266
3.	DEU	8376	DEU	14543	ROW	7931	CHN	12173
4.	GBR	8056	CHN	12003	GBR	6889	ROW	12070
5.	FRA	6561	GBR	10268	FRA	6519	FRA	9271
6.	ITA	5454	FRA	10070	ITA	5389	GBR	9089
7.	ESP	4031	ITA	6944	RUS	3503	ITA	7577
8.	JPN	3142	ESP	4984	JPN	3492	RUS	5885
9.	CHE	2843	JPN	4409	CHN	3466	ESP	5498
10.	CHN	2532	CHE	4289	NLD	3152	NLD	5372
11.	NLD	2454	NLD	4233	ESP	3137	CHE	4185
12.	RUS	2183	RUS	4090	CHE	2870	IRL	3925
13.	BEL	1868	BEL	3426	NOR	2429	JPN	3578
14.	TUR	1704	IND	3308	BEL	2097	POL	3130
15.	CAN	1639	POL	2876	SWE	1884	BEL	3110
16.	SWE	1461	SWE	2455	TUR	1588	IND	2943
17.	NOR	1428	NOR	2345	AUT	1484	NOR	2810
18.	AUT	1310	CAN	2338	IRL	1439	SWE	2542
19.	IND	1204	TUR	2318	KOR	1351	TUR	2498
20.	POL	1174	AUT	2281	CAN	1248	AUT	2461

Source: own calculations.

Table 4. The level of PageRanks algorithm for the main nodes in the EU trade networks in gross and value added terms

rank*	2005				2018			
	country symbol	the EU trade network in terms of value added	the EU trade network in gross terms	difference between (2) and (3)	country symbol	the EU trade network in terms of value added	the EU trade network in gross terms	difference between (6) and (7)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1.	DEU	0.108	0.113	-0.004	DEU	0.115	0.118	-0.003
2.	GBR	0.103	0.094	0.009	GBR	0.081	0.072	0.009
3.	FRA	0.083	0.082	0.000	FRA	0.079	0.076	0.003
4.	USA	0.077	0.064	0.013	USA	0.066	0.051	0.014
5.	ITA	0.069	0.068	0.000	ITA	0.055	0.054	0.001
6.	ESP	0.052	0.051	0.001	ROW	0.048	0.042	0.006
7.	ROW	0.047	0.044	0.003	ESP	0.042	0.043	-0.001
8.	NLD	0.032	0.035	-0.003	CHN	0.037	0.031	0.006
9.	BEL	0.025	0.028	-0.004	NLD	0.035	0.042	-0.007
10.	SWE	0.020	0.021	-0.002	BEL	0.028	0.03	-0.003

**The ranking is prepared in terms of the PageRanks algorithm value calculated for EU trade networks measured in value added*.

Source: own calculations.