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ORIGINAL ARTICLE

Network analysis of international export pattern

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Abstract
There is a relationship between the trade flows of the countries and their economic growth potential and development. One way to analyze the trade flows of countries with each other is the use of network analysis techniques. Network analysis uses a visual, mathematical and statistical approach to identify and quantify the structural properties of networks. In this study, the relationship of the first 50 countries in the world in terms of export volume was evaluated with Gephi 0.9.2, one of the social network analysis programs. The effect of the COVID-19 epidemic disease on the commercial flows of the countries is the main purpose of the study. The existence of the effective role of geographic proximity in commercial flows, the commercial partners of the countries, the centrality criteria and the existence of countries that have an active role in the world are clarified with this study.

Keywords Gephi · Social Network analysis · Trade flow · Export · Network

JEL Classification D85 · N70 · C88 · C60

1 Introduction

Countries in the world can be in commercial, political and economic relations with each other. Each sort of interaction brings different values to countries. Relationship levels are critical for a country's growth and improvement in well-being. Trade between countries, together with the increase in productivity, enables the spread of new technological developments with a faster solution, and as a result, it directly affects the amount of economic growth (Bolata 2018). With international commerce, countries' development accelerates, their productivity rises, and their growth accelerates at the same rate. Over time, the change in global production and consumption to different countries, trade relations between countries have begun to increase. As a result of these increasing relations between countries, a large network between countries has been formed (Wei and Liu 2012). Hilgerdt (1943) and Deguchi et al. (2014) stated that trade networks were created following the Second World War. Since then, global trade networks have been and continue to be studied in various fields.

We can observe that more than one approach is used in the study of relations. Traditional techniques of assessing trade connection take into consideration countries' export–import values and the percentage of exports in GDP. These techniques only reflect the characteristics of the countries. The connection between countries can be omitted. At this stage, the Social Network Analysis (SNA) approach allows us to analyze country's based on their position and structure in the network by concentrating on the relationships. Network analysis is a method that may be applied in a variety of fields, has its own methodologies and explanations, and requires specialized software. SNA has been employed extensively recently in the examination of global commerce networks. The representation of trade flow networks displays the relationship between countries in the network as well as the structure or systematic element of the network (Benedictis and Tajoli 2011).

The most crucial aspect that separates SNA from other approaches is that it examines and test ideas using structural or relational information (Wasserman and Faust 1994). Unlike

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traditional research, SNA focuses on interactions between things rather than relationships between variables (dependent/independent).

The structural attributes of nodes, groups, or the complete network may be calculated and mapped using SNA. SNA can produce basic, descriptive statistical data that characterize network interactions between nodes. The main difference between SNA and statistics is that SNA is concerned with the qualities of edges between nodes. SNA tools use several techniques to depict ensembles or clusters, ranks, and locations while also analyzing the studies with an analytical methodology, allowing node statistics and edge filtering. Centrality statistics offer information on the responsibilities of nodes in the network, and the interpretation of each centrality number and its relevance within the network varies. A node with a good value in one centrality measure cannot be expected to rank in the same order in other centrality measures. Similarly, it is not appropriate for the network analysis to clearly state that a node will be in a very good position in a single centrality criterion and that other centrality criteria will be the same.

Basic analytic methods are explored in the literature within the context of displaying social network data or constructing graphs, as well as performing other numerical analyses on the data. Figures (or graphs) are used to visualize data in various areas. When it comes to explaining what is desired, a well-structured graphical depiction outperforms numerous The data have become a sort of commodity to be traded with. The technology needed to exploit information and make a benefit of it already exists and continues to develop. This has major outcomes for personal privacy in the digital sphere. The lack of training in the way we use the network implies that sometimes we do not manage correctly our privacy in the Internet.

The top 50 countries with the biggest export volume in 2019 and 2020 were modeled and analyzed using complicated network analysis criteria in this study. In the year 2020, the COVID-19 pandemic has expanded globally. At this stage, it has been attempted to comprehend how COVID-19 influences the export flows of the nations included in the study. Graphs were built and processed using several techniques in the Gephi application. The positions of the countries in the network have been determined. Degree centrality, closeness centrality, and betweenness centrality criteria were examined among network statistics. Modularity analysis was used to determine the network's communities. The research also sought to introduce the Gephi software and demonstrate its many capabilities.

2 Literature review

Since the Second World War, social network research on the structure of international commerce networks have been conducted. Different network analysis programs and techniques were used in the studies.

Serrano and Boguna (2003) conducted the first empirical study to characterize trade relations between countries as a world trade network. Serrano and Boguna (2003) conducted empirical analysis to define bilateral trade connections as a global trade network. Sui et al. (2021) evaluated the nations engaged in the Belt and Road Initiative over three time periods: value-added trade, real-trade, and value-added trade. They made use of the Gephi network analysis software. Based on 2018 data, Pacini et al. (2021) conducted a social network study of the worldwide plastic scrap trade. They used the Gephi tool to analyze the nations based on the centrality criterion in their study. As a result, they determined that the European Union and North American nations play a significant part in the plastic trash trade, while Latin American, African, and Eurasian countries play a little one. Sikos and Meirmanova (2020) explored the global import and export linkages of wheat commerce in their study. They applied several algorithms and statistical approaches from the Gephi SNA application. The modularity characteristic, as well as degree centrality, proximity centrality, and betweenness centrality criteria, was used to identify important nations in wheat trading. They came to the conclusion that the world's wheat supply trade is characterized by a scale-free nature. In their work, Amador et al. 2018 depicts global value chains. NODEXL, a network analysis tool, was employed for the analysis. As a consequence of network measures, they discovered that China, Germany, the USA, and Japan all play vital and distinct roles in international manufacturing. Germany is both a user and a provider, while the USA primarily serves as a supplier that adds value to other nations.

Wei et al. (2018)** used SNA to evaluate the structure and growth of the Belt and Road Initiative's business relationship networks (Belt and Road Project). The UCINET initiative was utilized. Changes in the placements of the nations in the network, as well as the variability of the modularity, have been noticed throughout time. Xanat et al. (2018) analyzed the international trade of genetically modified products over a 27-year period with UCINET and Netdraw. They have reached the conclusion that each different product has a unique trade model that changes over time, different countries are at the center over time in some products, there are changes in genetically modified adoption even though there are partnerships of countries for certain products. Benedictis and Tajoli (2016) examined Italy's export market share and location in the global trade network in 1965, 1995, and 2011. They used network analytic methodologies to analyze the centrality criteria. Walther (2015) used SNA to investigate informal trading. They spoke about how social relationships between nations affect economic performance, how to utilize network analysis to disperse resources and information, and how network analysis affects commercial policy. Using the SNA approach, Aller et al. (2015) assessed the

environmental effect of the global commerce network. One of the findings of their research is that the presence of multinational corporations in developing nations has a negative impact on environmental quality.

With network analysis, Iapadre and Tajoli (2014) attempted to uncover the commercial flows of emerging nations and regions. They discovered that regionalization fell between 1995 and 2011, that each of the BRIC nations had a particular role in the area, that China acted as a hub in South-East Asia, and that Brazil, India, and Russia were regional racists. Deguchi et al. (2014) used SNA to study global commerce networks from 1992 to 2012. In their research, they demonstrated the shifts in time zones of nations that serve as global centers and authority. They discovered that the years when the USA and China were hubs and authorities varied, and that Europe's authority and hub values had dropped through time. Using the SNA approach, Wei and Liu (2012) disclosed their worldwide business networks from 1962 to 2000. Benedictis and Tajoli (2011)) used network analysis to assess the change in the global commerce network. According to the findings of the study, global trade networks are still not fully integrated, there is variability in the choice of partners (business partners), and there exist regional clusters. Schiavo et al. (2010) used complex network analysis to investigate international trade and financial integration models. They discovered that international trade is more densely integrated than financial networks, and that high-income nations are more interconnected. Fagiolo et al. (2010) used the network technique to analyze trade flows between nations. According to their findings, many nations have weak linkages with one another, but there is also a group of countries with strong ties, affluent countries have more intensive trade links, and these network features remain consistent over time.

Hafner-Burton et al. (2009) investigated whether approaches may be used to model international relations networks and what factors should be taken into account during network analysis. To assess the consequences of globalization, Kastelle, Steen, and Liesch (2006) investigated international trade networks between 1938 and 2003. According to the findings of the study, the international commerce network followed a steady route for a length of time. Kim and Shin (2002) used SNA to conduct a longitudinal analysis of commodities trade across nations and regions in their study. According to the findings of the study, the globe grew increasingly globalized between 1959 and 1996, with intra-regional links being stronger than regional ties (Caldarelli et al. 2012).

Barnett (2001) examined telecommunications networks from the late 1970s to the mid-1990s for the analysis of international relations. As a result of their studies, they found that the international telecommunication network is increasingly dense, more centralized and highly integrated, that the centrality of a nation is linked to that country's GDP. The research has turned out to be compatible with world-systems theory as well. Barnett et al. (1999) studies examined the international money network by examining the global information flows. They analyzed commercial, monetary transactions and telephone conversation networks with the NEGOPY network analysis program. As a result of their research, all three networks show similarity. It shows that the relationship between commerce and telecommunications is stronger than the relationship between money and commerce or money and telecommunications networks. Overall, these results were consistent with past research describing the world system as trade-based. Smith and Timberlake (1995) with the idea that the economic, cultural, political and social relations between global cities reveal the organization of the world system, they examined the relations among 23 world cities. They analyzed the relationship between cities by revealing the passenger networks traveling between cities with network analysis. In their studies, they identified global cities that are central according to network theory and compared them with similar studies in other literature. Smith and White (1992), in their studies, examined the international trade flow relations and measured the world economic structure in three different times. Between 1965 and 1980, the international economy was stable, while the 1970s and 1980s led to a less US-dominated core. As a result, the research supports the world system theory. Snyder and Kick (1979) grouped countries with respect to various international connections with the network analysis method. Their findings confirm that countries with peripheral or semi-peripheral positions have slower economic growth than countries with core positions, thus appearing to lend support to a world-systems explanation of national development.

3 Methodology

The study compared the trade flows of the top 50 nations with the greatest export level for 2019 and 2020. The relations were discovered using Gephi 0.9.2, a network analysis application. Gephi 0.9.2 is an open source network analysis application that may be used to uncover complicated relations. Gephi is more adaptable and has better visualization capabilities than other existing network software packages.

The nations export data were collected from the Trademap (trademap.org) website. The collected data were modified to the network structure and loaded into the Gephi application. The Gephi Program received a total of 8992 data in 2019 and 8933 data in 2020. It has been discovered that certain countries' data contain errors or insufficient information. Such issues have frequently been discovered in developing or small countries. These data are limited in quantity and have been detected and cleaned.

Each nation is a "node" in the graphs, while export flows between countries are defined as "edges." Because each nations export flow is not reciprocal, the connections are weighted and directed. Directional-weighted graphs were constructed by using the export quantities as connection weights. Weighted graphs can provide more precise and through information.

Figure 1 depicts graph of nations based on total export quantities. The geo-based network was spatialized using Geo-Layout, a geographic layout method. Each nations' geographic coordinates (latitude and longitude) were gathered and placed into the Gephi application. Node sizes and colors are also formed according to export sizes (the big and bright pink node has the most export amount). The nations having the greatest export levels are China, the USA, and Germany, in that order. At first, it can be observed that the USA has a strong commercial flow with China, Canada, and Mexico; China has strong links with Hong Kong, Japan, and Korea, and Germany has strong relations with both China and the USA. Since the diagram for 2019 is not different from the diagram shown, it has not been redrawn. This algorithm allows us to see all countries according to the coordinates. This technique, however, does not allow us to obtain precise information. Starting from this algorithm, we can see that Germany, China and the USA carry out a very large part of the export volume of the whole World.

In Fig. 2a and b, the nodes are positioned according to the Fruchterman-Reingold algorithm. The continents are used to categorize countries. Because the network has a large number of nodes and edges, the Fruchterman-Reingold layout is utilized, which distributes the nodes equally across the display and prevents the edges from overlapping. The Fruchterman-Reingold algorithm follows the force distribution law. This method groups and puts the highly linked nodes in the center of the graph, while scattering the less connected nodes about the network. The size of nodes varies depending on the amount of export. The fact that the nodes in the picture are grouped together in the center indicates that the export flow is between Asian and European nations. The low level of economic development of the countries in the African continent is also reflected in the graphs. South Africa is the only country on the African continent with the greatest export level. Chile, Brazil and Argentina from the South American continent are countries with high export levels. Although the export levels of the countries are different between Fig. 2a and b, it is understood that the positions of the countries that are related to each other have not changed. With this algorithm, we can see the countries that have an intense relationship, and we can also distinguish the countries with low export volumes and those with little relationship. Although in large networks, it is not possible to see the one-to-one relationships of the nodes, it is convenient in terms of seeing the whole and positioning the nodes according to the power law distribution.

In big networks, "filtering" is required to improve intelligibility and assure the emergence of active nodes. The Gephi program's filtering feature is utilized in Fig. 3. The average number of degrees was calculated for both graph and the connections below the mean were removed from the graphs. As a result, densely connected nodes evolved. Germany, the USA and China meet a very large part of the export amount in the world. In terms of global commerce, it can

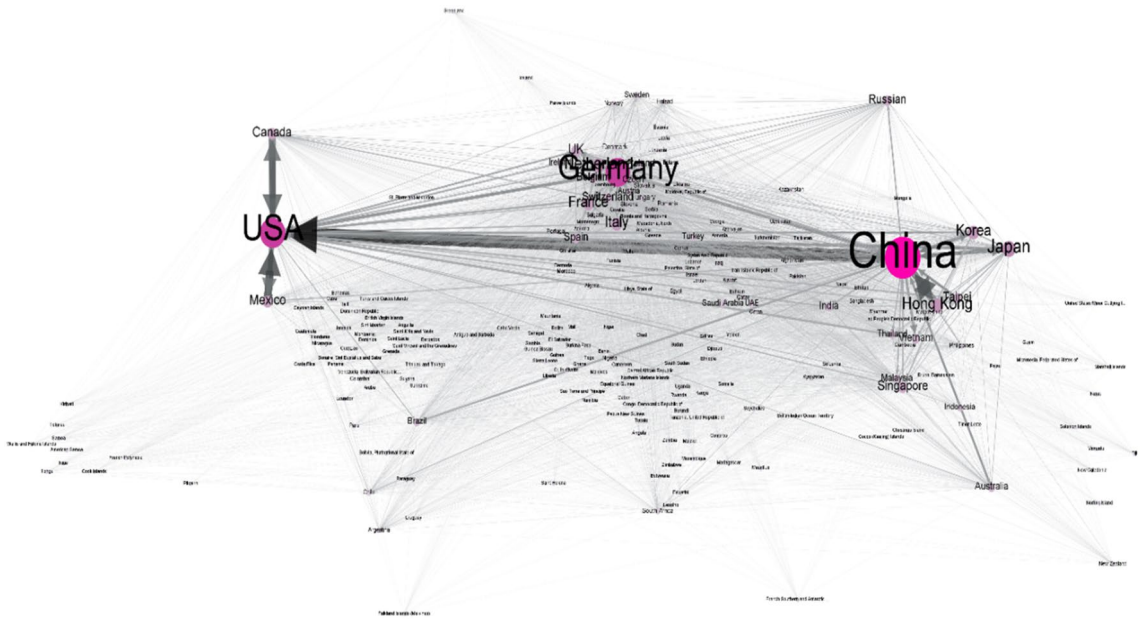

Fig. 1 International export network with geo layout algorithm

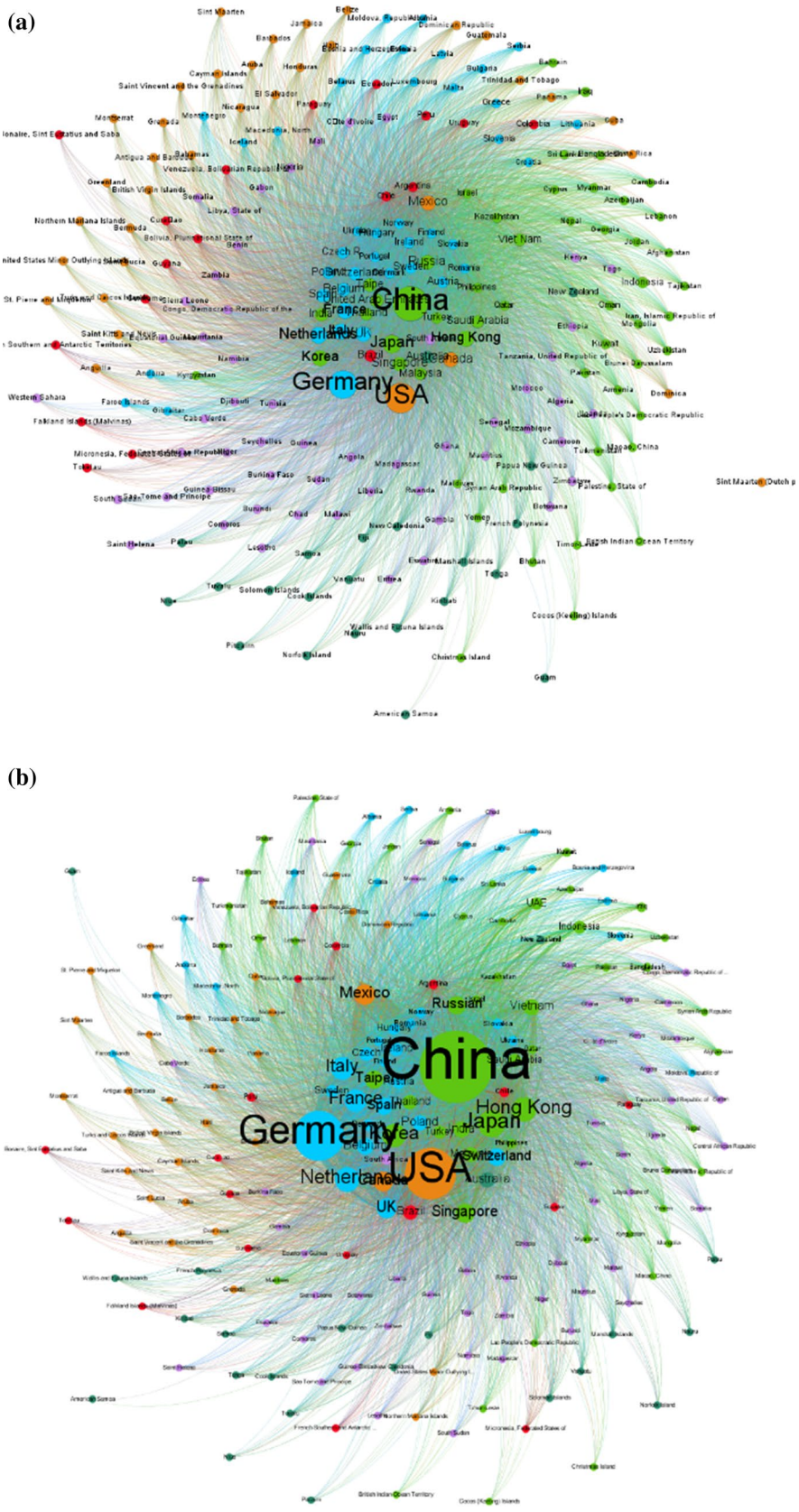

Fig. 2 **a** The Network of the Year 2019 With Fruchterman-Reingold Algorithm. Africa, Asia, Europe, North America, Oceania, South America. **b** The Network of the Year 2020 With Fruchterman-Reingold Algorithm

be seen that Asian and European nations have more intense links with each other. European nations with high GDP and sophisticated economies are positioned to be concentrated in the center for both Fig. 3a and b. Country with few connections are situated along the network's edges, which also reveals the economic status of the countries. When we compare 2019 and 2020, it is seen that although the export flow between countries decreased in 2020, the countries that steer the world economy did not change. The locomotive of Europe is Germany, followed by the Netherlands, France, Italy and England, respectively. It is an active participant in the trade network of North and South American nations such as the USA, Mexico, Canada, Argentina, Chile, and Brazil. The People's Republic of China has the largest export value among Asian countries and all countries in the globe.

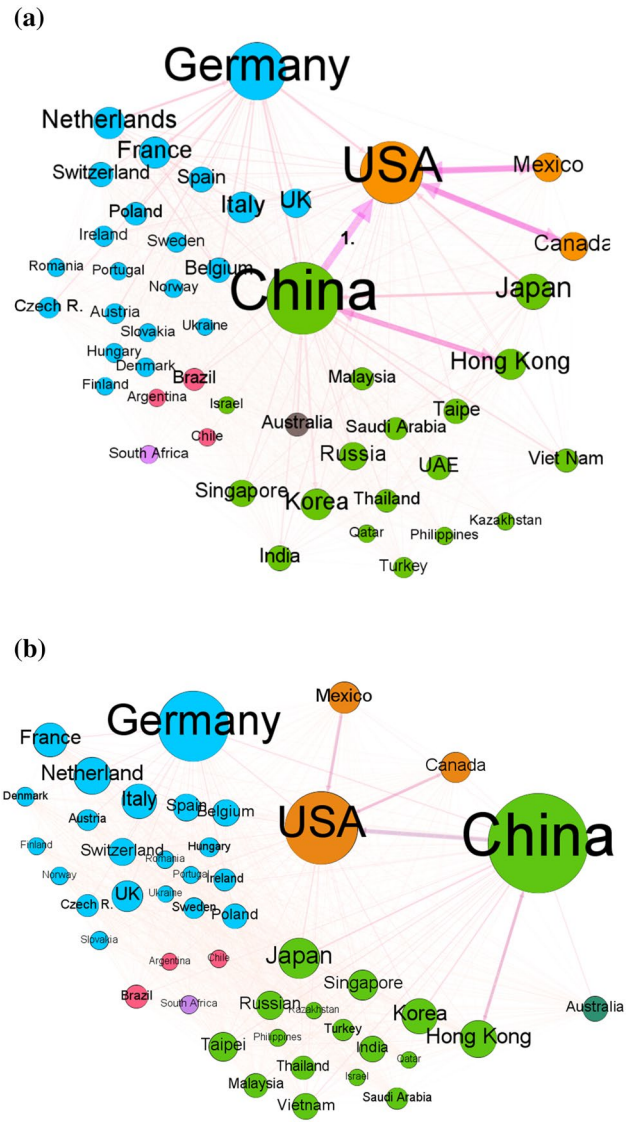

Fig. 3 **a** International Export Flow with Filtered of 2019. **b**International Export Flow with Filtered of 2020

With the emergence of the COVID-19 virus in the People's Republic of China in 2019, it has developed into a pandemic that will engulf the entire planet by 2020. Despite this, China continues to be the country with the highest volume of exports. The deepening of the linkages between nations indicates a high level of commerce movement. As a result, Germany, along with many other nations in Europe and, notably, the USA and China; we can see the intensive commercial flows of the People's Republic of China to Hong Kong and the USA, as well as the USA to Mexico and Canada. Despite the fact that the analysis includes the commercial movements of 53 nations in South and North America, it is clear that the whole continent is exported through six countries. Geographic distance is obviously quite important in all of these movements. It is assumed that trade volumes between neighboring nations are increased as well. The countries' stronger neighborly ties and cheaper logistical costs are two of the most important factors for this.

3.1 Modularity analysis

Community analysis is used to decompose clusters of highly connected nodes into several relatively independent modules (group, cluster, or community). Modularity is designed to measure the density of connections within communities as compared to links between communities (Zhigao et al. 2018). By means of modularity, information can be obtained about the level of regionalization in world trade. In our study, the modularity optimization approach is used by the Gephi software. The determination of community structures gives a clue to us whether there is also regionalization. The Circle Pack Layout method was used to model community structures. This algorithm allows to determine what is wanted to be shown in the graph with hierarchical order. In 2019, four trade communities developed, with five more to follow in 2020. Figure 4a and b shows the locations of these clusters. In this section, Fig. 4a is referred to as 2019, and Fig. 4b as the year 2020. Each color symbolizes a different group. Within the community, each country is closely interconnected, although there are fewer regular linkages across communities. Four trading communities emerged in 2019 and 5 in 2020. It contains Germany (purple color), which has the biggest community in 2019 and is surrounded by 75 nations. Communities will continue to be led by China, Germany, and the USA in 2019 and 2020. The community headed by India, Saudi Arabia, and the United Arab Emirates in 2019 has shifted in 2020. India exited this commercial community and maintained its commercial activities in the cluster led by China (blue color). In addition, South African-led communities organized and developed a new business cluster in 2020. Although the economic structure of developed nations is solid and trade flows have

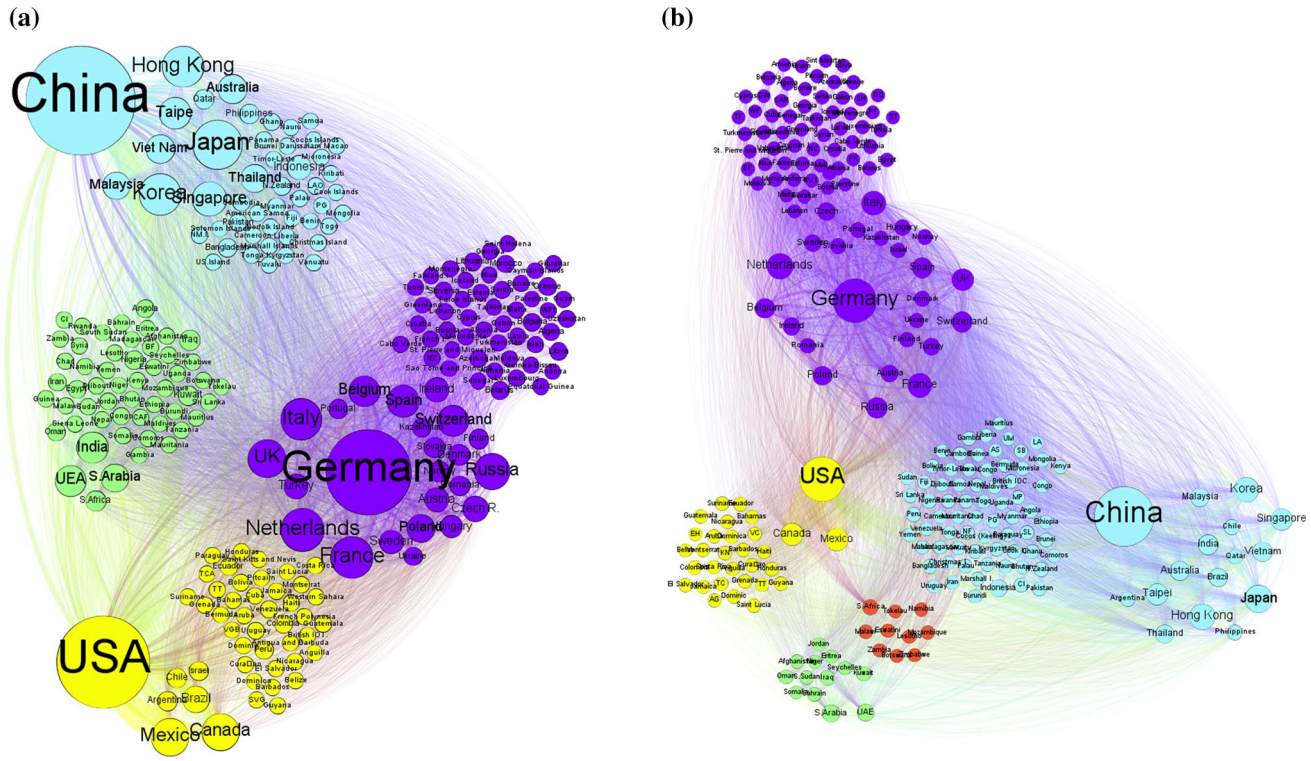

Fig. 4 **a** Modularity analysis of 2019. **b** Modularity analysis of 2020

not changed, we may claim that the Covid pandemic has established new trade avenues for poor countries. Indonesia and the Republic of Congo expanded their exports in 2020 and joined the China-based business community. It is interesting that there are two distinct business groupings in one society, where China is the focal point. In 2020, the number of nations in the trade flow, with China as the core, has risen. The COVID-19 virus emerged in China in 2019 and spread around the world in 2020. We may predict by 2020, China will have gained greater expertise in dealing with the outbreak and will have expanded its business flows in this area. As a result, by 2020, China will have initiated or expanded trade relations with a variety of nations. The number of nations with whom it has formed strong connections has not changed much in 2019 and 2020 under Germany's leadership. According to Wei and Liu (2012)'s analysis, Turkey is placed in the community in which Russia is the center. In 2019 and 2020, it takes place in a Germany-based community. This indicates that Turkey's commerce with European nations is improving, and that Russia is likewise emerging from a central commercial community. Although the number and communities of nations in trade flows focused on the USA, China, and Saudi Arabia have changed in 2020, there is essentially no change in the community structure in which Germany is the center, indicating that the countries with whom Germany deals have not changed. Usually, this is Europe and Russia. Despite the pandemic, the formation of such a picture indicates that Germany's economy is quite robust, and that it has strong relationships with the nations with which it has business dealings. Iapadre and Tajoli (2014) talk about the existence of two opposite situations about regionalization in their study. First is the increase in regionalization in world trade. The second is the decrease in regionalization as a result of the decrease in transportation and communication costs, the increase in the number of commercial partners of the countries and the long-distance trade. Although both ideas require a detailed analysis, the first conclusion that can be drawn according to our study is the existence of regionalization.

3.2 Topological characteristics of the World Trade Network

Table 1 depicts the World Trade method in terms of network analysis. According to the total quantity of exports, there is no notable change in the top 20 nations in 2019 and 2020. For both years, the top five nations with the largest export volume are China, the USA, Germany, Japan, and the Netherlands. Russia will have the greatest shift in export volume in 2020, with a 25% decline. France, England, and India have 17 percent each, while the USA and Canada have 15 percent each. While export volumes declined in several

countries in 2020, the UAE with a 6% rise, Taipei with a 5% increase, China with a 4% increase, and Hong Kong with a 3% increase were among the nations that saw an increase.

One of the most significant network topological aspects is the degree distribution. It is a crucial criteria in large-scale networks for describing and understanding the network's distinctive structure. The degree distribution is a network criteria that specifies how many nodes in a network have particular degree. The force distribution (in this study) is the frequency distribution of the export volume values of the nations in the analyzed network. Figure 5 depicts the distribution of nodes based on export volumes. As a result, the World Trade network is seen to suit the scale-free distribution. Few nations have a large export volume, whereas many countries have a low export volume, based on the distribution of forces. Table 2 shows the export volume distributions of 2019 and 2020. In 2019 and 2020, approximately 12% of the countries included in the study meet 80% of the total export level. In fact, this also confirms a pareto principle. In order not to take up much space, only the export levels of 50 countries are shown. In this situation, the nodes have a heterogeneous structure as opposed to a homogeneous structure.

With this distribution, we can see that the world is still far from being fully connected, but in some subregional components, we can see interconnected nodes. This distribution is in parallel with the Benedictis and Tajoli (2011) study.

Centrality statistics are very useful in comparing the roles of nodes within the network. In this study, degree, closeness, and betweenness centralities were evaluated as centrality statics. Since each centrality criterion has different interpretations in a network, it should not be interpreted through a single centrality value. The measures of centrality that have been used attempt to assess how influential a country is within the international trading system as a whole. Since there are different interpretations of each centrality criterion in a network, it is not necessary to make sense of the nodes over a single centrality value, so different criteria have been evaluated.

A degree is the number of neighbors to which a node is linked. Degree centrality is defined by Freeman (1978) as the number of links that connect a node to other nodes. The simplest measure of centrality that measures the importance of nodes in a network is degree centrality. Degree centrality determines if a node is essential. The higher a node's degree, the more important it is in the network. Degree centrality in international trade is the number of countries a country exports to and imports. Therefore, the impact on the international trade network can be determined by degree centrality (Zhigao et al. 2018). Germany, the Netherlands and the UK are the countries with the highest degree in 2019 and 2020. Although China has the largest export volume, degree centrality is low. This suggests that it has a greater volume of trade flows with certain countries.

The number of incoming connection to a node is referred to as the "indegree" in directed (asymmetric) networks, whereas the number of outbound connection from the node is referred to as the "outdegree." While Germany, the Netherlands, and the United Kingdom have the highest outdegree degree, certain nations, such as Austria and the United Arab Emirates, will not be among the top 20 in 2020. Even though Turkey's export volume fell in 2020, its outdegree centrality grew. This indicates that Turkey has begun to establish business with a broader range of countries.

Looking at the indegree centrality, economically weak nations rank first. Because the study only includes the 50 nations with the greatest export levels, the export data of many of the countries with high indegree centrality are missing. Greece and Bulgaria are the most noticeable European continent countries here. When the import and export quantities of both nations are reviewed, it is determined that imports exceed exports, resulting in a current account deficit. As a result of our research, it is suggested that economic issues exist in many of the nations with a high indegree of centrality. Figure 2 shows that Greece and Bulgaria are placed away from the network center, toward the edges of the network which is validating our previous assumption.

Nodes with a high amount of indegree are referred to as "authority," whereas nodes with a high degree of output are referred to as "hubs." When determining authority and hubs, the HITS (Hyper-link Induced Topic Search) method is used. Kleinberg created this method for analyzing the network of web sites, and it is widely used in search engines, data and text mining. The HITS method is used by the Gephi application to do computations. Therefore, it is possible to calculate the authority and hub centrality. Nodes with high centrality of authority have a large number of connections from nodes with high centrality. Similarly, the high centrality of a node means that this node has outbound connections to many high-authority nodes (Newman 2010, p. 179). Table 1 shows the values for the top 20 countries by network metrics. According to Table 1, the nations with the highest hub value in 2019, respectively, whereas Italy, the Netherlands, Germany, and India are the UK, the Netherlands, Germany, and Belgium in 2020. The hub value is proportional to the outdegree. When we look at the outdegrees, we can see that there isn't much of a difference in the ranks. EU nations with a high hub value are also attracting attention. With their trade taxes and policies inside the EU territory, EU nations may gain from free trade. However, because countries outside the EU cannot profit from them, EU countries prefer to trade more with each other. (Deguchi et al. 2014) studies, while China has the world's largest hub value and the third largest authority value, in our study, it is in the 19th place in terms of hub value in 2019 and is not even in the top 20 in 2020. This actually shows that China may switched to a different commercial strategy. It can also show that it has more

Table 1 Network Metrics For The Top 20 Country

Rank	Export rank	Total export	Country	Degree	Rank out-degree	Outde-gree C	Rank indegree	Inde-gree	Rank closeness	Closeness	Rank between-ness C	Between-ness C	Rank hub	Hub	Rank autority	Autority	2020 total export	2019–2020 Export differ-ence (%)
2019																		
1	China	2,498,569,866	Germany	266	Germany	220	Bangla-desh	47	Germany	0.986726	Germany	6,60,39,019	Italy	0.160877	Bangla-desh	0.075162	2.591E+09	4
2	USA	1,645,174,335	Italy	266	Italy	220	Colombia	47	Italy	0.986726	UAE	6,30,61,602	Nether-lands	0.160763	Colombia	0.075162	1.431E+09	−15
3	Germany	1,486,877,250	Nether-lands	266	Nether-lands	220	Egypt	47	Nether-lands	0.986726	Singapore	6,00,70,534	Germany	0.160749	Egypt	0.075162	1.378E+09	−8
4	Japan	705,842,013	UK	264	UK	218	Greece	47	UK	0.97807	France	5,52,79,944	India	0.160402	Greece	0.075162	640,953,137	−10
5	Nether-lands	576,784,455	India	263	India	218	Indonesia	47	India	0.97807	Italy	5,47,29,308	UK	0.160195	Indonesia	0.075162	551,597,804	−5
6	France	555,100,606	Thailand	263	Thailand	217	Morocco	47	Thailand	0.973799	UK	5,14,27,919	Thailand	0.159918	Morocco	0.075162	475,071,675	−17
7	Korea	542,380,692	Spain	262	USA	217	Nigeria	47	USA	0.973799	South Africa	5,08,33,963	Spain	0.159719	Nigeria	0.075162	512,788,606	−6
8	Italy	537,748,429	USA	262	Spain	216	Slovenia	47	Spain	0.969565	Korea	5,04,73,477	USA	0.159641	Slovenia	0.075162	495,976,960	−8
9	Hong Kong	535,711,019	Belgium	259	Singa-pore	214	Sri Lanka	47	Singapore	0.961207	USA	5,03,86,092	France	0.158016	Sri Lanka	0.075162	551,515,756	3
10	UK	468,322,416	France	259	Belgium	213	Bulgaria	47	Belgium	0.957082	India	4,90,70,176	Singapore	0.157878	Bulgaria	0.075162	399,621,519	−17
11	Mexico	460,703,804	Singapore	259	France	213	Lithuania	47	France	0.957082	Thailand	4,88,43,102	Brazil	0.157813	Lithuania	0.075162	418,140,902	−10
12	Belgium	446,876,870	China	253	China	208	Tanzania	47	China	0.936975	Japan	3,56,77,262	UAE	0.155451	Tanzania	0.075162	419,478,288	−7
13	Canada	446,562,311	Brazil	258	Brazil	212	Ghana	47	Brazil	0.952991	Belgium	4,59,79,993	Belgium	0.157545	Ghana	0.075162	389,850,223	−15
14	Russia	422,777,167	Malaysia	257	Malaysia	211	Croatia	47	Malaysia	0.948936	Spain	4,58,73,705	Poland	0.15686	Croatia	0.075162	337,105,352	−25
15	Singa-pore	390,386,234	Canada	256	Canada	211	Uruguay	47	Canada	0.948936	Malaysia	4,43,39,498	Canada	0.156771	Uruguay	0.075162	373,909,153	−4
16	Spain	337,215,114	Korea	256	Korea	210	Malta	47	Korea	0.944915	Canada	4,41,96,055	Malaysia	0.156754	Malta	0.075162	312,080,513	−8
17	Taipei	329,512,433	Poland	256	Poland	210	Panama	47	Poland	0.944915	Australia	4,22,39,147	Taipei	0.15644	Panama	0.075162	346,633,936	5
18	India	323,250,726	Switzer-land	254	Switzer-land	208	Cyprus	47	Switzer-land	0.936975	Brazil	4,19,68,152	Switzer-land	0.156407	Cyprus	0.075162	275,488,745	−17
19	UAE	315,942,728	UAE	254	UAE	208	Peru	47	UAE	0.936975	Poland	4,03,74,917	China	0.156144	Peru	0.075162	335,212,447	6
20	Switzer-land	314,145,207	Australia	253	Australia	208	Azerbai-jan	47	Australia	0.936975	China	3,68,56,053	Japan	0.156125	Azerbai-jan	0.075162	318,985,767	2

Rank	Export rank	Total export	Country	Degree	Rank outde-gree	Outde-gree C	Rank indegree	Indegree	Rank closeness	Close-ness C	Rank Between-ness C	Between-ness	Rank Hub	Hub	Rank autority	Autority
2020																
1	China	2,590,607,686	UK	265	UK	220	Indone-sia	46	UK	0.986726	South Africa	6,63,40,052	UK	0.160288	Indone-sia	0.073929
2	USA	1,431,406,392	Germany	262	Germany	217	UAE	46	Germany	0.973799	Germany	5,31,47,222	Nether-land	0.159774	UAE	0.073929

Table 1 (continued)

Rank	Export rank	Total export	Country	Degree	Rank outdegree	Outdegree C	Rank indegree	Indegree	Rank closeness	Closeness C	Rank Betweenness C	Betweenness	Rank Hub	Hub	Rank autority	Autority
3	Germany	1,377,863,429	Netherland	262	Netherland	217	Kuwait	46	Netherland	0.973799	UK	5,15,35,353	Germany	0.159415	Kuwait	0.073929
4	Japan	640,953,137	Belgium	261	Belgium	216	Slovenia	46	Belgium	0.969565	Canada	4,45,49,468	Belgium	0.159248	Slovenia	0.073929
5	Netherland	551,597,804	USA	260	USA	215	New Zealand	46	USA	0.965368	USA	4,44,24,318	Spain	0.159016	New Zealand	0.073929
6	Hong Kong	551,515,756	Korea	260	Korea	215	Greece	46	Korea	0.965368	Malaysia	4,35,32,921	Korea	0.158975	Greece	0.073929
7	Korea	512,788,606	Spain	259	Spain	214	Nigeria	46	Spain	0.961207	France	4,29,25,113	Thailand	0.158543	Nigeria	0.073929
8	Italy	495,976,960	Denmark	259	Denmark	214	Lithuania	46	Denmark	0.961207	Netherland	4,04,23,376	Denmark	0.158503	Lithuania	0.073929
9	France	475,071,675	Singapore	258	Singapore	213	Bulgaria	46	Singapore	0.957082	Belgium	3,91,26,185	USA	0.15801	Bulgaria	0.073929
10	Belgium	419,478,288	India	258	India	213	Colombia	46	India	0.957082	Brazil	3,83,55,229	India	0.157997	Colombia	0.073929
11	Mexico	418,140,902	Malaysia	258	Malaysia	213	Morocco	46	Malaysia	0.957082	Turkey	3,82,89,524	Turkey	0.157782	Morocco	0.073929
12	UK	399,621,519	Thailand	258	Thailand	213	Egypt	46	Thailand	0.957082	Korea	3,76,12,265	Brazil	0.157558	Egypt	0.073929
13	Canada	389,850,223	Brazil	258	Brazil	213	Belarus	46	Brazil	0.957082	Denmark	3,72,25,324	Taipei	0.157456	Belarus	0.073929
14	Singapore	373,909,153	Turkey	258	Turkey	213	Pakistan	46	Turkey	0.957082	India	3,70,76,764	Sweden	0.157433	Pakistan	0.073929
15	Taipei	346,633,936	Sweden	257	Sweden	212	Ecuador	46	Sweden	0.952991	Sweden	3,68,19,131	Poland	0.157332	Ecuador	0.073929
16	Russia	337,105,352	France	256	France	211	Cambodia	46	France	0.948936	Spain	3,22,18,248	France	0.157147	Cambodia	0.073929
17	UAE	335,212,447	Canada	256	Canada	211	Croatia	46	Canada	0.948936	Poland	3,18,85,719	Malaysia	0.156994	Croatia	0.073929
18	Switzerland	318,985,767	Taipei	256	Taipei	211	Estonia	46	Taipei	0.948936	Switzerland	3,17,94,094	Italy	0.156941	Estonia	0.073929
19	Spain	312,080,513	Poland	256	Poland	211	Latvia	46	Poland	0.948936	Austria	3,14,99,429	Singapore	0.156694	Latvia	0.073929
20	Vietnam	281,441,457	Italy	255	Italy	210	Azerbaijan	46	Italy	0.944915	Thailand	3,13,78,248	Austria	0.15609	Azerbaijan	0.073929

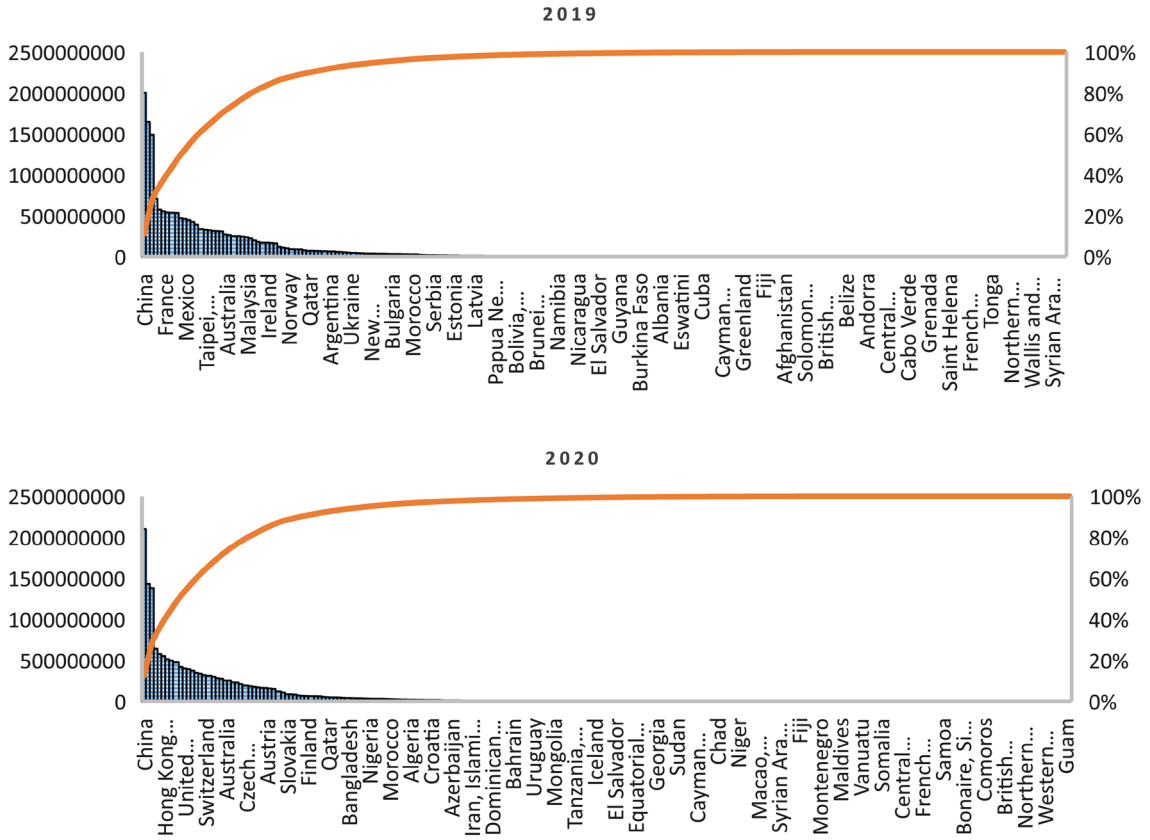

Fig. 5 Distribution of Trade World Network

commercial partnerships with certain countries. It shows that it has moved away from being the factory of the world in the year 2000 and has turned into a more world market.

Closeness centrality is an indicator of the distance of a node from other nodes (in terms of topological distance) and measures how easily a node can be reached by other nodes. It also means that an actor with high affinity has access to many other nodes and is therefore relatively independent of the control of others (Kilduff and Tsai 2003). The closeness centrality of a nation in the trade network relates to how much it is impacted by other countries and how much it is affected by other countries. As a result, after ranking first in 2019, Germany fell to second in 2020.

In betweenness centrality, the location of the node in the network is more essential than the number of nodes linked. Freeman (1977) defined it as the number of shortest paths between two nodes. If one actor is connected to other players in the network by a communication channel, that actor is the center. Actors having a high betweenness centrality may be able to influence how other actors communicate with one another. A more valuable network measure is betweenness centrality in trade network, which indicates how important a country is in terms of connecting other countries. Countries having a high betweenness centrality operate as a commercial bridge with other countries in the trade network. Betweenness centrality therefore quantifies the extent to which a certain node operates as an intermediate or gatekeeper in the network.

While Germany, Europe's locomotive, had the greatest value in 2019, it was surpassed by South Africa in 2020, with Germany taking second position. We can observe that European nations' centrality values are in the top 20 for both years. This might imply that European nations have diverse economic partners, as well as that there is a lot of commerce going on between them. The fact that Turkey is ranked among the top 20 nations in 2020 suggests that, in addition to its trade volume, it exports to other countries and serves as a bridge. A more significant organization measure is betweenness centrality, which demonstrates how significant a nation is as far as connecting different nations. High betweenness centralities for the USA, Turkey, and Germany demonstrate those nations are significant extensions between territorial business sectors.

The graphs of the betweenness centralities in Fig. 6 are drawn with the Openord algorithm. This layout is very useful to detect clusters. OpenOrd is basically

Table 2 Export Distribution of Countries

No	Country	Export Volume of 2019	%	Cumulative %
1	China	2,00,05,69,866	11.07	11.07
2	USA	1,64,51,74,335	9.10	20.17
3	Germany	1,48,68,77,250	8.23	28.40
4	Japan	70,58,42,013	3.91	32.31
5	Netherlands	57,67,84,455	3.19	35.50
6	France	55,51,00,606	3.07	38.57
7	Korea, Republic of	54,23,80,692	3.00	41.57
8	Italy	53,77,48,429	2.98	44.55
9	Hong Kong, China	53,57,11,019	2.96	47.51
10	United Kingdom	46,83,22,416	2.59	50.10
11	Mexico	46,07,03,804	2.55	52.65
12	Canada	44,65,62,311	2.47	55.12
13	Russian Federation	42,27,77,167	2.34	57.46
14	Singapore	39,03,86,234	2.16	59.62
15	Spain	33,72,15,114	1.87	61.49
16	Taipei, Chinese	32,95,12,433	1.82	63.31
17	India	32,32,50,726	1.79	65.10
18	United Arab Emirates	31,59,42,728	1.75	66.85
19	Switzerland	31,41,45,207	1.74	68.59
20	Belgium	31,10,15,394	1.72	70.31
21	Australia	27,25,79,608	1.51	71.82
22	Vietnam	26,46,10,323	1.46	73.28
23	Poland	25,18,64,773	1.39	74.68
24	Saudi Arabia	25,18,00,458	1.39	76.07
25	Thailand	24,53,80,465	1.36	77.43
26	Malaysia	23,81,61,125	1.32	78.75
27	Brazil	22,39,98,669	1.24	79.98
28	Czech Republic	19,94,69,710	1.10	81.09
29	Turkey	18,08,70,841	1.00	82.09
30	Austria	17,15,32,055	0.95	83.04
31	Ireland	17,07,43,383	0.94	83.98
32	Indonesia	16,76,82,996	0.93	84.91
33	Sweden	16,05,67,911	0.89	85.80
34	Hungary	12,21,80,658	0.68	86.48
35	Denmark	10,99,91,555	0.61	87.08
36	Norway	10,27,93,716	0.57	87.65
37	Iraq	9,12,29,448	0.50	88.16
38	South Africa	9,04,19,473	0.50	88.66
39	Slovakia	8,99,09,085	0.50	89.16
40	Romania	7,72,98,748	0.43	89.58
41	Qatar	7,29,34,956	0.40	89.99
42	Finland	7,28,39,176	0.40	90.39
43	Philippines	7,03,34,023	0.39	90.78
44	Chile	6,91,45,962	0.38	91.16
45	Portugal	6,70,64,074	0.37	91.53
46	Argentina	6,51,15,327	0.36	91.89
47	Kuwait	6,44,82,097	0.36	92.25
48	Israel	5,84,48,249	0.32	92.57
49	Kazakhstan	5,77,22,942	0.32	92.89
50	Nigeria	5,36,24,701	0.30	93.19

Table 2 (continued)

No	Country	Export Volume of 2019	%	Cumulative %
	Total	18,07,14,13,258	#######	
No	Country	Export Volume of 2020	%	Cumulative %
1	China	2,59,06,07,686	######	14.87
2	USA	1,43,14,06,392	8.21	23.08
3	Germany	1,37,78,63,429	7.91	30.99
4	Japan	64,09,53,137	3.68	34.66
5	Netherland	55,15,97,804	3.17	37.83
6	Hong Kong, China	55,15,15,756	3.16	40.99
7	Korea, Republic of	51,27,88,606	2.94	43.94
8	Italy	49,59,76,960	2.85	46.78
9	France	47,50,71,675	2.73	49.51
10	Belgium	41,94,78,288	2.41	51.92
11	Mexico	41,81,40,902	2.40	54.32
12	United Kingdom	39,96,21,519	2.29	56.61
13	Canada	38,98,50,223	2.24	58.85
14	Singapore	37,39,09,153	2.15	60.99
15	Taipei, Chinese	34,66,33,936	1.99	62.98
16	Russian Federation	33,71,05,352	1.93	64.91
17	United Arab Emirates	33,52,12,447	1.92	66.84
18	Switzerland	31,89,85,767	1.83	68.67
19	Spain	31,20,80,513	1.79	70.46
20	Vietnam	28,14,41,457	1.62	72.07
21	India	27,54,88,745	1.58	73.66
22	Australia	25,45,31,426	1.46	75.12
23	Poland	25,41,69,032	1.46	76.57
24	Malaysia	23,35,53,703	1.34	77.91
25	Thailand	22,92,77,734	1.32	79.23
26	Brazil	20,91,80,242	1.20	80.43
27	Czech Republic	19,23,04,896	1.10	81.53
28	Ireland	18,41,30,806	1.06	82.59
29	Saudi Arabia	17,65,07,506	1.01	83.60
30	Turkey	16,96,57,940	0.97	84.58
31	Indonesia	16,33,06,490	0.94	85.51
32	Austria	16,21,45,129	0.93	86.45
33	Sweden	15,56,07,847	0.89	87.34
34	Hungary	11,93,91,066	0.69	88.02
35	Denmark	10,72,24,300	0.62	88.64
36	Slovakia	8,63,32,984	0.50	89.13
37	South Africa	8,56,86,133	0.49	89.63
38	Norway	8,24,29,462	0.47	90.10
39	Romania	7,10,46,399	0.41	90.51
40	Chile	6,75,57,693	0.39	90.89
41	Finland	6,55,99,590	0.38	91.27
42	Philippines	6,38,79,430	0.37	91.64
43	Iraq	6,32,72,535	0.36	92.00
44	Portugal	6,15,29,077	0.35	92.35
45	Argentina	5,48,21,594	0.31	92.67
46	Qatar	5,15,04,158	0.30	92.96
47	Israel	4,97,61,375	0.29	93.25

Table 2 (continued)

No	Country	Export Volume of 2020	%	Cumulative %
48	Ukraine	4,93,88,093	0.28	93.53
49	Kazakhstan	4,69,49,697	0.27	93.80
50	Kuwait	4,27,97,655	0.25	94.05
	Total Export	17,42,66,77,088	######	

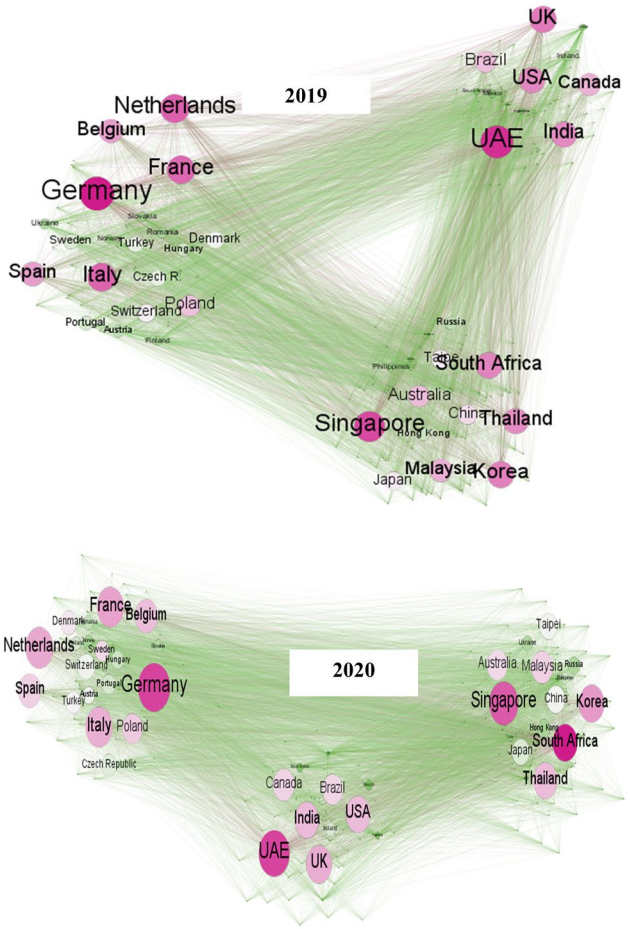

Fig. 6 Betweenness Centrality of International Export Trade

Fruchterman-Reingold with an extra parameter (edge cut) that controls the greatest length of an edge during the optimization process (https://towardsdatascience.com). This layout is more suitable for large networks. The Openord algorithm has divided the graphs into three clusters. In 2019, the countries with high betweenness centrality in each cluster were Germany, UAE and Singapore, while in 2020, it was Germany, UAE and South Africa. Those countries are important bridges between regional markets.

If we evaluate the betweenness centrality over Table 1; while Germany, the locomotive of Europe, had the highest value in 2019, it was replaced by South Africa in 2020. We see that the centrality values of European countries are in the top 20 for both years. This may be an indication that European countries have trading partners in different regions. In the centrality of betweenness, Turkey's being among the top 20 countries in 2020 can mean that it exports to different countries and acts as a bridge.

4 Conclusion

The export relationship of the first 50 countries in the world according to their export level was analyzed with the SNA program Gephi. The aim of this study is to identify the countries that have an important role in the world by analyzing the trade relations between countries. In the study, degree, closeness and betweenness centralities from network statistics were evaluated. In order to detect the existence of commercial clusters in the world, a modularity analysis was performed.

It turns out that countries with high export levels often have specific trading partners. In this study, it has been concluded that commercial partnerships have not changed despite the worldwide crises such as the economic contraction of the countries or the pandemic that may affect all countries. According to Kim and Shin (2002) although this situation seems like a stable stance, increasing interconnectedness not only makes the world harmonious, but also makes it more unstable.

The USA was the largest authority in the global trade network after the second half of the 1990s, until China made a huge leap forward after 2000. China has significantly changed the world trade network, especially since 2001, by significantly increasing its trade volume and the number of trading partners (Deguchi et al. 2014). This rise has continued to the present day. Accordingly, it is understood from the size of the nodes that China has the largest export volume for both years. When we look at the whole picture, we can see that the countries that provide the economic order in the world are China, the USA and Germany. However, the downside of being important is that there are many countries that could be affected if they disappear from the network or in the face of any problems that may arise.

China's continued growth in a year that was traumatic for the global economy in every sense is a significant development that should be considered. It experienced the effects of

the pandemic before all other countries, took its precautions before anyone else, and was in a leading position in economic normalization thanks to its successful practices for pandemic control. China continues to grow and will continue to grow. However, beyond the numerical size, in the changing conditions of the post-pandemic period, it cannot be predicted in which position China will be in the global economy. The world economy is in a state of structural transformation. It existed before this pandemic, but with the pandemic, it gained momentum and a vital priority. How intrusive should the visible hand of the state be against the excesses of free markets? How could efficiency in economies be increased, especially with the use of new technologies? How could sustainable growth be achieved with greater care for the individual and the environment? While all these were discussed, the trade wars between the USA and China, which broke out, added a new question to the questions: How could the fragilities brought about by globalization, caused by the economic dependence of all countries on each other, and the use of the powerful economic instruments as a weapon against others be prevented? We see that China is taking steps in this direction. The fact that the country is experiencing the effects of the pandemic with relatively little damage to public health despite a huge population is not due to the fact that the country is governed by an authoritarian regime, as is widely expressed in the public, but mainly due to the strong state capacity. However, China's 14th Five-Year Plan, which went into effect this year, formalized the "double roaming" concept previously articulated by President Xi Jinping. Accordingly, while China continues its external economic activities such as exports, imports and foreign investments, it will also keep the internal circulation strong against the dependencies that may occur there and will focus on domestic investments and consumption. China is no longer a country with a low cost advantage. It aims to regain its international competitive advantage, which it lost here, by increasing the added value, with technology. For example, at a time when supply chains will be redesigned after the pandemic, China will no longer be able to maintain its position at low cost, this will only be possible by climbing up the value-added chain. The breakthrough in technology in recent years is an important advantage, but for its sustainability, first of all, structural reforms must be brought to a certain point.

When we look at the export flows of the countries in the same region with each other, it is the European countries that have the most intense relations with each other. Countries in the African continent have the least interaction. Although Germany has the highest number of trade relations with the countries in the studies, it is the third country in terms of export level and China is the country with the highest export amount. In this context, it has been concluded that the level of relationship as well as the level of export has an impact on the economic development of the countries.

As a result of the network analysis in the study, it was observed that the trade network exhibited a scale-free network and the network structure was heterogeneous. It cannot be expected that the world trade network will be fully connected due to the differences in the development level, economies, political structures, logistics network structures and resources of the countries. In order to strengthen this claim, we think that the effects of these factors on countries should be investigated by expanding our work in the following years. Considering that many of the real-world networks are scale-free, our result is not surprising, but it is surprising that there has not been a huge change in relationships and network type, even with the COVID-19 epidemic that has affected the whole world. Zhigao et al. (2018) stated in his study, even in global economic crises, commercial relations may not be equally important for a country. Since we evaluated one year after the epidemic, it was observed that the trade partners of the countries did not change. In the coming years, it may be necessary to analyze the change of business partnerships and the effects of the pandemic over a longer period of time. Benedictis and Tajoli (2011) emphasized in their study that the world is far from being fully interconnected. It also shows that networks are "solid yet fragile" (Albert et al. 2000) although the power law has undeniable advantages in many cases. So it is resistant to random failure but vulnerable to targeted attacks. We live the best example of this in the current time period. Russia–Ukraine war caused many problems, as well as the products imported from Russia, especially gas–aluminum, iron–steel, etc. The embargoes imposed have also affected the economy all over the world. Russia is the country that feeds Europe in certain products. Such an embargo was of great interest to the whole of Europe and the USA. This is a very good example of the drawbacks of the power law.

We can see the importance of geographic proximity, especially from the trade relations of European countries with each other. In addition, it is revealed in the study that countries with lower export levels also export to countries close to them.

By using modularity feature in Gephi SNA program, commercial networks are divided into communities. It is divided into four communities in 2019 and five communities in 2020. It has emerged that the leading countries in the clusters are the USA, Germany, China, Saudi Arabia and UAE. Within the clusters, the geodetic distances of the countries from each other are striking. In the European continent, we can see that countries with high economic development or close to each other export with each other. It has been observed that intra-community connections are more intense than inter-community connections. Our findings show parallelism with the studies of Kim and Shin (2002) they have done.

In this study, the Gephi program was also tried to be introduced. Gephi is a very flexible, user-friendly program that also allows network statistics calculations. It has superiority over other network analysis programs in terms of having different algorithms and better reflecting the visuality of networks.

When we look at the effect of COVID-19 on export flows in our study, almost every country except the Republic of China experienced a decrease in export levels in 2020. Despite this, export partnerships have not chanprimaryged. Although there are variations according to the centrality characteristics, it may require longer-term analysis to clearly state that these effects are due to the pandemic. We will be able to see the economic impact of COVID-19 and the existence of economic partnerships better in the coming years.

Author contributions Written all the paper together.

Declarations

Conflict of interest The authors declare no competing interests.

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