Yıldız Social Science Review vol. 6 *no.* 2, *pp.* 99-118
https://doi.org/10.51803/yssr.822506

Covid-19 and Digitalization: Network Analysis on Industrial Robots Trade Among the BRI Countries

Covid-19 ve Dijitalleşme: KYG Ülkeleri Arasındaki Endüstriyel Robot Ticareti Üzerine Ağ Analizi

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Research Article/Araştırma Makalesi
Received/Başvuru: 09.11.2020; Accepted/Kabul: 29.12.2020

ABSTRACT

The pandemic indicates that the use of digital technologies is going to become more important hereafter. In such a world where countries need to take action to shape their future in accordance with this 'new normal', the policies followed by countries in high technological sectors will be determinative on their positions within global value chains in the future. Based on this, international trade of industrial robots among the Belt and Road Initiative members is analyzed via complex network tools in the present study. The empirical results indicated that the international trade network of industrial robots has complex system properties such as power-law distribution, disassortativity, core-periphery structure etc. The results also revealed that developing members of the Initiative may exploit export hubs of the network, namely South Korea, Singapore, Austria and Italy in order to digitalize their economies in the short-term.

Keywords: complex network analysis, Covid-19, international trade, industrial robots, digitalization

ÖZ

Pandemi, yaşamımızın bundan sonraki kısmında dijital teknolojilerin kullanımının daha önemli hale geleceğini göstermektedir. Ülkelerin bu 'yeni normal'e uygun olarak geleceklerini şekillendirmede eyleme geçmeleri gereken böyle bir dünyada, yüksek teknolojili sektörlerde izlenecek politikalar, ülkelerin gelecekte küresel değer zincirindeki pozisyonları üzerinde belirleyici olacaktır. Buna dayanarak bu çalışmada, Kuşak ve Yol Girişimindeki üye ülkeler arasındaki uluslararası endüstriyel robot ticareti kompleks ağ araçları ile incelenmektedir. Ampirik sonuçlar uluslararası endüstriyel robot ticaret ağının güç yasası dağılımı, farklılık eğilimlilik, merkez-çevre yapısı gibi birtakım kompleks ağ özellikleri taşıdığını ortaya koymuştur. Sonuçlar ayrıca, girişimin gelişen ülkelerinin kısa dönemde ekonomilerinin dijital dönüşümünü sağlamada, ağda yer alan Güney Kore, Singapur, Avusturya ve İtalya gibi ihracat merkezlerinden yararlanabileceğini ortaya koymuştur.

Anahtar kelimeler: kompleks ağ analizi, Covid-19, uluslararası ticaret, endüstriyel robotlar, dijitalizasyon

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1. Introduction

It is stated that China's Belt and Road Initiative (BRI), which was announced in 2013 and has started to be implemented in a serious way with significant infrastructure investments reaching a wide geographical coverage every passing day, is a project put forward to strengthen China's economic situation. Because it is believed that demand shrinking in the US, the EU countries and Japan, which are the most important trade partners of China, had effect on the slowing growth rate of China (Bocutoğlu, 2017, p. 267; Karagöl, 2017, p. 3). China also evaluated Transatlantic Trade and Investment Partnership (TTIP), which was signed by the US and the EU, as a reason of decrease in its export (Karagöl, 2017, p. 3). Thus, the initiative, put forward by China, is thought to be a project in order to retain the capital accumulation and to increase the demand for the goods manufactured in the country (Balcı, 2018, p. 2; Bocutoğlu, 2017, p. 267). On the other hand, there is a significant amount of infrastructure investments within the scope of the Initiative. It is a probable outcome of these investments that trade among the BRI countries will be affected positively. So, within the scope of the initiative that involves such big investments and constitutes a new global value chain, what is the case in terms of international trade in the sectors that are vital for digitalization? This question has especially become necessary to answer after the Covid-19 pandemic.

As it is known, the world has encountered the Covid-19 pandemic, originated from China, since the end of 2019. One of the features of the pandemic is that it is contagious not only in terms of health, but also in terms of economy. The reason is the increased inter-connectedness of global economy through global value chains (GVCs) and international movements of capital, people, goods and services (Strange, 2020, p. 2). That’s why the case of re-nationalisation of GVCs is mentioned as insulation of countries from the economic consequences of the pandemic (OECD, 2020, p. 3). However, this idea increases, let alone decreases, the importance of robots which are important components of GVCs. Because it is said that the automation and the use of robots is an urgency against the destructive impact of the pandemic on supply chains through the restrictions of the movement of people. That’s why digitalization of supply chain is accepted as a new strategy (Baker & McKenzie, 2020, p. 16).

Therefore, it is important to examine the initiative, which covers many developing countries from Asia to Africa, Europe and Latin America, for the robot industry that has the potential to shape future of these countries in terms of both short-term and long-term. Short-term impact is related to recovery of the immediate effects of the pandemic and highly important. Long-term impact is crucial in terms of the propitiousness to the ‘new normal’ and its sustainability. In this study, in line with this importance, the international trade among the BRI countries in industrial robots sectors is analyzed for the year 2018 with complex network analysis.

The main objectives to use complex network approach in this study are:

(i) to determine the complex structure properties of the network statistically,

(ii) to calculate complex system measures as high-degree indicators (such as assortativity/disassortativity, core-periphery structure, density, hub and authority centralities, power-law degree distribution etc.),

(iii) to compare and evaluate these high-degree measures with first degree ones within the scope of the dynamics of the network structure,

(iv) to make more realistic evaluations, inferences and policy recommendations related to the pandemic for the countries with reference to the differences between high and first degree results.

With reference to these objectives, the flow of the study is planned as follows: First, the relationship between the pandemic and industrial robots sectors is discussed in the Section 2.

Literature search and methodological information is given in the Section 3 and Section 4 respectively. Empirical results are presented in Section 5 and discussed in the Section 6.

2. The Pandemic and the Use of Industrial Robots

Strange (2020, p. 2) mentions about three features of the pandemic that differentiate it from the previous crises. First one is that it is a global phenomenon that has health effects that are not limited and localized same as virus outbreaks before. Secondly, the pandemic has multidimensional effects: public health and economic activity. Policy responses to recover one dimension have adverse impact on the other. This feature differentiates the pandemic from financial crises experienced so far. Third, the pandemic is contagious in economic sense as much as in health sense due to GVCs. Because global economy is highly inter-connected due to international movements of people, capital, goods and services.

OECD (2020, pp. 2-3) draws attention to the development of GVCs. Accordingly, the expansion of GVCs has stopped since 2011 and, trade tensions and rising protectionism has decreased global import content of production. However, the pandemic has revealed a different debate that GVCs create additional economic vulnerabilities since international trade is disrupted. There are different suggestions by scholars and policy-makers about the future of GVCs. Some suggestions say that there is no need to rethink GVCs while some reveals that contraction of GDP would have been worse with re-nationalized GVCs (OECD, 2020, pp. 2-3). However, digitalization, in any case, either in value chains or in national economy, seems to be inevitable. Del Rio-Chanona et al. (2020) developed an index, called Remote Labour Index (RLI) for each occupation. Index value equals to 1 indicates that the activities associated with an occupation can be overcome at home, while index value equals to 0 indicates that none of the activities related to the occupation can be performed at home. Accordingly, when the occupation list is examined, it is observed that occupations related to service sector have values close to 1, while occupations related to manufacturing have values close to 0. Thus, we can deduce that digitalization is required for manufacturing activities during the pandemic since production activities within this sector are not appropriate for social distancing measures.

Replacement of manpower with machines is not something new. This can be observed in each stage of industrial revolution. Steam engines, that were the symbol of Industry 1.0, replaced labor force and became driving force of industrialization. Electrification was accepted as the beginning of the second industrial revolution. Within this stage of the industrial revolution, the assembly line was first used in the automotive industry. The result was acceleration of the production process and serial production. The third industrial revolution, which began in the 1970s, had some characteristics such as IT and further automation through electronics. This stage of the industrial revolution is characterized by the replacement of labor force by machines in serial production. Finally, Industry 4.0 refers to the technical integration of cyber physical systems into production and logistics, and also the use of the IoT and services in industrial processes. What distinguishes the fourth industrial revolution from the third is the introduction of Artificial Intelligence (AI) in the service sector (Wisskirchen et al., 2017, pp. 11-12).

Not all economies are at the same level of industrialization. Manchanda et al. (2020, pp. 3-4) classified countries in three development stages which are low-income economies, emerging markets and more advanced markets. Low-income economies are defined as the countries that are narrowly engaged with GVCs in agriculture, textiles, ready-made garments, light engineering, footwear, electronics assembly and leather goods. Thus, these countries are less advanced technologically in manufacturing industry and dependent on labor force. This country classification includes mostly Sub-Saharan countries. Countries involving emerging markets have an evolving industrial structure. Industrial sector is more diversified and competitive within these economies. Technology skills of the labor force within these countries are also improving. Turkey, Brazil, India, Thailand etc. are the countries within this classification. The more advanced economies have sophisticated industrial structure. These countries are characterized by their competitiveness in GVCs and their high levels of technological sophistication. Germany, Japan, the US and China are the countries within this classification. Taking these differences into consideration, we can say that use of industrial robots in production differ from one classification to the other. However, it is a fact that integration and use of industrial robots in the production facilities, especially during the pandemic which will last for unforeseen period, is vital for each economy, but mostly for the countries of which production processes depends on labor force predominantly.

3. Literature Review

The literature on the BRI flourishes every passing day since it is a popular and novel issue. We can separate the studies on the BRI as pre-pandemic and post-pandemic. Pre-pandemic studies analyze some properties of the trade among the BRI countries. However, post-pandemic studies, very few in numbers, make reassessment of the Initiative and reveal possible outcomes of the pandemic on the Initiative. In this part of the study, we will first mention about the pre-pandemic studies, and then post-pandemic studies.

There are two major methods used in the empirical studies on the trade relations among the BRI members: gravity models and network analysis. It is stated that network analysis is more preferable since it has some advantages compared to gravity models which are based on standard econometric method. This means that gravity models fail to notice some features which network analysis can explain. One of the disadvantages of gravity models is to not to capture skewed distribution of trade relations in the network, meaning that these models do not take one of the most prominent properties of the international trade, namely ‘preferential attachment’, into consideration. Another disadvantage of gravity models is to not to represent the effect of the third party in international trade. This causes to fail to evaluate the holistic structure of the trade network (Smith & Gorgoni, 2018, pp. 27-28). That’s why, in this section, studies that analyzed the trade relations among the BRI via network analysis are summarized. Fu et al. (2018) enhanced standard gravity model by using some additional indicators to reflect geographical, cultural, institutional and factor-endowment properties. They also constituted a trade network covering the BRI countries and applied network analysis. They found that China was at the core and the countries at the first-tier were Russia, Kazakhstan, Indonesia, India, Poland and Turkey. The importance of these countries stems from their being important channels to spread to Mongolia-Russia, Central Asia, Southeast Asia, South Asia, Central and Eastern Europe and West Asia. The findings of the Boffa's (2018) study, which analyzed the BRI via network analysis by using input-output tables, revealed that there were two production networks around China and Russia which is related reciprocally. The key sector of the network was ‘Computer, Electronic and Optical Products’. This sector comprised the 15% of the export from the BRI countries. It was also revealed that the only 15% of the added value of this sector was constituted by the BRI countries while 30% of the added value was constituted by advanced countries. This result was interpreted as the potential to use more input from the BRI countries in the future. The study also revealed that not only trade but also vertical specialization would increase as a result of the decrease of trade costs. Boffa finally stated that the BRI was an initiative that was based on ‘win-win’ principle and let the countries specialize in line with the comparative advantages. Song et al. (2018) analyzed both the trade network that consists of the BRI countries and the trade network that covers countries around the world. The main research question of the study was not topological properties of the BRI trade network, but position of the BRI trade network in global trade network and its interaction with the globe. The authors, firstly, detected trade groups clustered around a hub for both the BRI trade network and global trade network with community detection method. Afterwards, they investigated reciprocal trade relations among these groups and made some suggestions for these countries on how to manage these trade relations in order to increase their powers in global trade. In another study, Liu et al. (2018) analyzed trade network for the BRI countries from 2000 to 2016 via network analysis. They built undirected and weighted adjacency matrices and made used of community detection method. The findings revealed that not all trade relations have importance equally and that centralities of trade groups and countries change over time.

Li et al. (2019), which not directly focused on the BRI countries but gave inspiration for our study, analyzed international trade network for industrial robots, which are an important element of AI to shape the future of the countries, via complex network analysis. Although the authors do not focus on the BRI directly, their findings are important. The results revealed that catch-up countries (such as China within this case) would promote industrial robot trade within the scope of such regional collaborations (Li et al., 2019, p. 12).

When it comes to the literature on the post-pandemic research of the BRI (analyzing the impacts of the Covid-19 pandemic on the BRI) is also so emergent and open to improvement. There are a few studies evaluating this impact. However, these studies do not involve an empirical analysis. In one of these studies, Buckley (2020) evaluated immediate, medium-term and long-term impacts of the pandemic on the BRI and concluded that the BRI, like many pre-pandemic institutions, will require radical reassessment in the post-pandemic world. Buckley reveals that China's health diplomacy in supplying medical equipment may strengthen the tie between the countries and China. On the other side, unemployment in China will be a really big problem and the effects of the dislocation caused by the lockdown may be semi-permanent. Increasing social unrest led by increasing unemployment will lead to rethink of the BRI. The countries have started functioning with decreased physical connectivity since the pandemic. Buckley states that, physical globalization recede while digital globalization will continue to grow. In this case, politically motivated and huge trans-continental links may be re-evaluated as 'wasteful'. However, connectivity between resources and transport hubs may remain their value as trade recovers. Thus, there is a trade-off for China between to increase income, employment and wealth at home and to sustain the initiative. Bugaenko (2020) makes an evaluation of the future of the BRI and its impact in Central Asia. Accordingly, Bugaenko claims that the BRI will undergo two stages. In the first stage, the project will be suspended. The reasons are the quarantine-imposed interruptions in transportation and the diversion of China's resources to remediate its own economy. In the second stage, China will pursuit its BRI policies actively. In this stage, there might be a little change in the strategy. Within this stage, inward-oriented economy will activate the interest in resource and geopolitical reasons will impel cooperation with border countries. Bugaenko says that if Central Asian countries create necessary conditions, local production by Chinese firms will develop. As a result of increased cooperation with China, export of Central Asian countries will become China-oriented, both in energy and mining sectors.

The literature search indicates that there is not any study that directly analyzes trade relations among the BRI countries in terms of the industrial robots sectors that have become crucial especially for the post-pandemic era. Therefore, in this study, we focused on these sectors by being inspired by Li et al. (2019).

4. A Brief Explanation of Network Theory

As stated by Reichardt (2009, p. 2), the first step to understand a complex system is the decomposition of the system into its parts. Economics is approached as a complex system by complexity science, contrary to standard approaches. This resulted to use complex system methods in the field of economics. Network analysis is one of them as a method that is proper to decompose the economic system into its parts. Recently, many economic phenomenon has started being analyzed within the scope of network structure.

It is observed that international trade among countries, financial relations among economic agents and global production relations are the main subfields of economics in which network tools are used widely. Network representation of these economic relations enables us to see the parts of the system and the relations among them. That's why the network analysis has drawn attention of policy makers, recently (OECD, 2009, p. 9).

Network theory, that is called graph theory in mathematics, was enhanced via the solution method of Königsberg puzzle which was put forward in 18th century. Euler, who is the famous mathematician and physicist of that era, revealed the most important two elements of a network, by defining each land as a node and each bridge as a link (Toroczkai, 2005, p. 96). Based on this, network is basically defined as a set consists of the nodes and the links among these nodes. Mathematical notation of a network is as follows (Estrada, 2015, pp. 95-96):

$$G = (V, E, f)$$

where V is the set of finite nodes, E is the set of links among these nodes and f is the mapping that connects the elements of E and V. Networks are classified as binary or weighted and directed or undirected, depending on the properties of their links (Chow, 2013, p. 3). A weighted network corresponds to a network in which each link has a different weight. Mathematical notation of a weighted network changes as follows:

$$G = (V, W, f)$$

where $W = \{w_1, w_2, \ldots, w_m\}$ indicates the set of weights. Degree and strength are important concepts in binary and weighted networks, respectively. Degree of a node is the number of links that node has. Strength of a node refers to total weight of that node (Chow, 2013, pp. 5-8). Mathematical tool that makes it possible to analyze a network is matrix. This matrix, which is called adjacency matrix, is built for a binary network as follows (Estrada, 2015, pp. 95-96):

$$A_{ij} = \begin{cases} 1 & if \;\; i,j \; \in E \\ 0 & otherwise \end{cases}$$

The factor that has to be taken into consideration to build the adjacency matrix is the direction of the relation for directed networks and the weight of the relation for weighted networks.

Network analysis has two related but distinct methods (Bougheas & Kirman, 2014, p. 9). One of them is the examination of the statistics related to topological properties of the network and the other is the simulations based on these statistical properties.

There are some major properties examined within the scope of topological properties. One of them is connectedness which can be analyzed both in node-level and in network-level. In a directed network, which does not involve self-loops and multilink, connectedness is measured in network-level by a coefficient which is called 'density coefficient'. It is formulized as follows (Newman, 2010, p. 134):

$$\rho = \frac{m}{n(n-1)}$$

where m corresponds to count of links and n corresponds to count of nodes. This coefficient indicates the ratio of count of actual links in the network to the count of maximum possible links. Density coefficient lies between 0 and 1. In other words, this coefficient gives an idea about the realization ratio of the links in the network. The higher the coefficient is, the higher the connectedness.

Another important property of a network is reciprocity that can be related with a lot of important phenomena. Reciprocity indicates the tendency of node pairs to be connected by mutual links pointing in opposite directions (Ruzzenenti, 2010, p. 1716). It is the proportion of mutual connections in a directed graph (Csardi & Nepusz, 2006, p. 331).

Another important topological property is the degree distribution of a network. A great number of studies based on real-world networks have indicated that there are a lot of nodes with weak links and there are a few nodes with strong links. The shape of this distribution in logarithmic scale is a straight line. It means that the distribution follows power-law. Power-law distribution is indicated as $P(k) \propto k^{-\alpha}$ mathematically and means that formation of links in the network is not random. That's an important point, since it implies that network system is managed by some hubs with high degree/strength. These hubs are major determinants on the system behavior even if their number is not much (Newman, 2008, p. 34). In network theory, a network that follows power-law distribution is called scale-free network since the same functional form exists when the variable is rescaled (Boccaletti et al., 2006, p. 188). α has a special importance in network analysis since it means that a higher α leads to a lower probability of nodes with many links. In other words, the higher the α is, the less the super-nodes are (Hein et al., 2006, p. 270).

Power-law distribution has higher peak and haevy-tail. One method to determine whether a distribution has heavy-tail or not is examination of kurtosis and skewness values. If kurtosis value is positive, then the distribution has haevy-tail (Decarlo, 1997, p. 292). Skewness is a measure to determine on which side of the distribution heavy-tail exists. If skewness is positive, then heavy-tail is on the right side, meaning that the distribution is right-skewed. If skewness is negative, then the distribution is left-skewed (Hippel, 2011). However, it is also required to analyze the fitness of a distribution to power-law distribution statistically. One of the tests used on this purpose is Kolmogorov-Smirnov test. If the p-value is lower than 0.05, then the null hypothesis that represents fitness to power-law distribution is rejected (Csardi & Nepusz, 2006, p. 160). Clauset (2011) states that fitness to power-law distribution is an indication of complexity in generating process of structure examined.

Another property of a network is assortativity/disassortativity. Assortativity implies that nodes with high degree/strength have tendency to have links with the nodes with high degree/strength. Oppositely, disassortativity means that nodes with high degree/strength have tendency to have links with the nodes with low degree/strength (Reichardt, 2009, pp. 6-7). A correlation coefficient is used to determine whether assortative or disassortative structure exists in the network (Newman, 2003). This coefficient lies in the range of $-1<r<1$. If it is positive, then there exists assortativity in the network. However, if it is negative, then there exists disassortativity. $r=-1$ corresponds to perfect disassortativity, while $r=1$ corresponds to perfect assortativity. Detection of assortative/disassortative structure is an important part of network analysis since disassortativity indicates existence of core-periphery structure in a network (Fuge et al., 2014; Csermely et al., 2013, p. 99). In a core-periphery structure, nodes in the core are related to each other and also to nodes in the periphery. However, nodes in the periphery are not related to each other (Borgatti & Everett, 1999, pp. 377-378). Borgatti and Everett developed a correlation coefficient that measure fit of a real data network to a network that has ideally core-periphery structure. This correlation coefficient lies between 0 and 1. The closer to 1 the coefficient is, the closer to perfect core-periphery structure the real-data network is (Borgatti & Everett, 1999, p. 393). Existence of core-periphery structure in a network requires the determination of core and periphery nodes of the network. Thus, centrality measure becomes an important tool on this purpose.

There is a great number of centrality measures to determine the importance of nodes in network such as degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, hub and authority centrality etc. In this study, hub and authority centralities developed by Kleinberg (1999) are computed. In a directed network, a hub is a node with high out-going degree/strength and an authority is a node with high in-coming degree/strength. However, Kleinberg stated that it is not sufficient for a node to have high out-going degree/strength to be a 'good' hub; it is also required for this node to be related with 'good' authorities that have high in-coming degree/strength. Similarly, a 'good' authority is a node with in-coming degree/strength from 'good' hubs. Kleinberg stated that, thus, there is a 'mutually reinforcing relationship' between hubs and authorities (Kleinberg, 1999, pp. 7-8). Kleinberg indicated this relationship as follows:

$$x^{<p>} \leftarrow \sum_{q:(q,p)\in E} y^{<q>}$$

$$y^{<p>} \leftarrow \sum_{q:(p,q)\in E} x^{<q>}$$

where $x^{<p>}$ and $y^{<p>}$ are authority weight and hub weight of node p, respectively. Kleinberg developed an algorithm that works with an iterative process in order to compute hub and authority centralities of the nodes in network. Each node in the network is assigned with a hub and an authority centrality value at the end of this iterative process.

Kleinberg, with reference to $G = (V, E)$ in which $V = \{p_1, p_2, \dots, p_n\}$ is node vector, firstly defined y vector which consists of $y^{<p>}$ values and x vector which consists of $x^{<p>}$ values. Then, Kleinberg proved that these vectors converge to y^* and x^* at the end of the iterative process. y^* vector is hub centrality vector and x^* vector is authority centrality vector. With reference to $\boldsymbol{A}$ matrix that is the adjacency matrix of graph G, x^* and y^* vectors are eigenvectors of $\boldsymbol{A^T A}$ and $\boldsymbol{A A^T}$ matrices, respectively (Kleinberg, 1999: pp.9-11). Thus, $\boldsymbol{M_{auth}} = \boldsymbol{A^T A}$ and $\boldsymbol{M_{hub}} = \boldsymbol{A A^T}$ are authority and hub matrices, respectively (Kolaczyk, 2009, pp. 92-93).

In the present study, it is aimed to examine the international trade of the sectors that have importance in today's world of AI with reference to network properties explained above within the scope of the BRI which is a new global value chain formation. The main motivation to select these sub-sectors is their potential to shape the future of the economies. Taking into consideration that the most of the BRI countries are developing countries, it becomes necessary to analyze the trade network in terms of these sectors. The Harmonized System (HS) codes that represent the industrial robots sectors, explanation of these commodity codes and the source of the data are given in Table 1 in detail.

Table 1. Definition and the Source of the Data

HS Codes	Explanation of the Data	Source of the Data
HS Code 842489	Mechanical appliances; for projecting, dispersing or spraying liquids or powders.	United Nations Comtrade
HS Code 842890	Lifting, handling, loading or unloading machinery	United Nations Comtrade
HS Code 847950	Machinery and mechanical appliances; industrial robots.	United Nations Comtrade
HS Code 848640	Machines and apparatus of a kind used solely or principally for the manufacture or the repair	United Nations Comtrade
HS Code 851521, HS Code 851531, HS Code 851580	Welding machines and apparatus	United Nations Comtrade

Directed and weighted adjacency matrices, which are built by using export values for each sector exists in Table 1 for the year 2018, are used in the analysis. We choose the year 2018, because it is the latest year to reach the data for all BRI countries. All data have been obtained from the United Nations Comtrade. We followed Li et al. (2019) within the process of the selection of the sectors. In their study examining global industrial robot trade, Li et al. (2019) defined these sectors mentioned as important sectors in today's AI era. The present study consists of 143 countries which are currently attended the BRI. The list of the countries can be found in Appendix A.

5. Empirical Results

First of all, some descriptive statistics for each sub-sector is given in Table 2. Accordingly, *industrial robots* and *machines and apparatus* sub-sectors have the weakest trade connections among the BRI countries while *mechanical appliances* sub-sector is the sector with the highest count of links. Assortativity correlation coefficient is observed to be negative for each sub-sector, meaning that countries with high trade volumes tend to have relations with the countries with low trade volumes. Depending on the values of assortativity correlation coefficient which is closer to 0 rather than -1, it can be said that disassortativity is weak.

Table 2. Descriptive Network Statistics

Sectors	Nodes	Edges	Assortativity	Transitivity	Reciprocity	Density
Industrial robots	143	512	-0.16	0.31	0.24	0.03
Lifting machinery	143	1286	-0.1	0.34	0.23	0.06
Machines and apparatus	143	231	-0.11	0.17	0.14	0.01
Mechanical appliances	143	1406	-0.07	0.34	0.19	0.07
Welding machines	143	1297	-0.12	0.3	0.21	0.06

Source: Authors' calculation.

Reciprocity values indicate the share of mutual links in the network. *Machines and apparatus* sector has the lowest while *industrial robots* sector has the highest reciprocity value. Ruzzenenti et al. (2010) stated that this measure refers to economic interdependence of countries in the international trade network (Ruzzenenti et al., 2010, p. 1716). It can be observed that *industrial robots* sector has the highest interdependence while *machines and apparatus* sector has the lowest. When it comes to density coefficient, *mechanical appliances* sector has the highest value. *Lifting machines* and *welding machines* follow *mechanical appliances* sector. *Industrial robots* and *machines and apparatus* sectors have the lowest density.

Taken all these results together, it can be stated that there exists a few core countries and periphery countries as a result of disassortative structure. Polarization is more apparent in the *industrial robots* and *machines and apparatus* sectors of which density coefficients are the lowest. In Table 3, 'core-periphery fit' measure, that was developed by Borgatti and Everett (1999) to investigate core-periphery structure, is given.

Table 3. Core-Periphery Fit Correlation

Sectors	Cores	Periphery	Core/Periphery Fit
Industrial robots	CHN, KOR	Other countries	0.68
Lifting machinery	CHN, KOR	Other countries	0.7
Machines and apparatus	CHN, SGP	Other countries	0.81
Mechanical appliances	CHN, ITA, KOR	Other countries	0.68
Welding machines	CHN, KOR	Other countries	0.72

Source: Authors' calculation.

This measure, lies between 0 and 1, indicates to what extent the real-data network fits the network that has ideal core-periphery structure. The closer to 1 the coefficient is, the closer to ideal core-periphery structure the network structure is. Depending on Table 3, it can be said that the networks for each sub-sector fit to core-periphery structure significantly. According to the computations; core countries are China and South Korea in *industrial robots*, *lifting machines* and *welding machines* sub-sectors. The cores are China and Singapore in *machines and apparatus* sub-sector, while the cores are China, Italy and South Korea in *mechanical appliances* sub-sector.

Centrality measure enables us to analyze how central the countries are in the network. However, degree/strength distribution is another major property to investigate.

Table 4. Fitness to Power-Law Distribution

Sectors	Skewness	Kurtosis	α	p-value	KS statistics
Industrial robots	5.41	32	1.34	0.21	0.18
Lifting machinery	6.74	51.14	1.74	0.84	0.14
Machines and apparatus	8.3	71.9	1.35	0.66	0.3
Mechanical appliances	8.26	76.38	1.82	0.97	0.11
Welding machines	6.53	47.19	1.69	0.99	0.11

Source: Authors' calculation.

Positive skewness and kurtosis values for each sub-sector imply respectively that the distribution is right-skewed and that the distribution has heavy-tail. There exist also Kolmogorov-Smirnov test results in Table 4. The null hypothesis, implies the fitness to power-law distribution, cannot be rejected since the p-values are higher than 0.05, meaning that degree distribution for each sub-sector fits power-law. This result is also a proof of that the connectedness in the networks is heterogeneous. In another word, there is a few important hub countries and there are a lot of countries with low trade values in the networks. α can give some information about this heterogeneity. Depending on the explanation in methodology section, it can be said that *industrial robots sector* has the highest probability of having super-nodes while *mechanical apparatus sector* has the lowest probability. After detecting heterogeneity of connectedness, it is important to determine these hub countries. Table 5 represents the country rankings in terms of hub and authority centralities.

In Table 5, hub and authority centralities correspond to export and import centrality, respectively. Thus, hub centrality of a country refers to export impact of this country on the network. Similarly, authority centrality of a country refers to import impact of this country on the network. Country rankings are also given in table in terms of export and import to compare centrality measures. This comparison is important to reveal how differ centralities (as high degree indicators) from import/export shares (first degree indicators). The reason why centrality measures are stated as high degree indicators is that these measures take into consideration both the strength of a node and the strength of the nodes to which that investigated node has link. This is the mutually reinforcing relationship between countries, stated by Kleinberg (1999).

Firstly, it is observed that South Korea ranks first in terms of hub centrality although Italy ranks first in terms of export share in *industrial robots* network. South Korea is more important country in *industrial robot* network as a supplier than Italy although its export share is lower that Italy. The reason is that South Korea has connection with more important importers than Italy has. China, which ranks second in terms of export share, ranks fourth in terms of hub centrality. South Korea, which ranks third in terms of export share, ranks first in terms of hub centrality. Visualization of industrial robots network based on hub centralities is presented in Figure B.1 in Appendix B. When it comes to import, China ranks first in terms of both authority centrality and import share, meaning that China is the most important importer of the network since it has relations also with important exporters (hubs). Poland ranks second in pursuit of China in terms of authority centrality although it ranks fourth in terms of import share. This means that Poland has trade connections with more important exporter countries than Thailand and Vietnam have, although it has lower import share than Thailand and Vietnam have.

When it comes to *lifting machines* sub-sector; China ranks first with 26.7% export share and South Korea ranks second with 22.4% export share. However, South Korea ranks first in terms of hub centrality which is a high degree indicator. In other words, South Korea is more important supplier than China in *lifting machines* network, although China has the highest share in the export among the BRI countries. Besides, Singapore, which cannot take place among first-five countries in terms of export share, ranks third in pursuit of South Korea and China in terms of hub centrality. Visualization of lifting machines network based on hub centralities is presented in Figure B.2 in Appendix B. In terms of import, China ranks first for both indicators, namely authority centrality and import share. Russia, which ranks second with 9% import share in pursuit of China, does not take place among the first-five countries in terms of authority centrality. Czechia, which does not take place among first-five countries in terms of import share, ranks third in terms of authority centrality, meaning that Czechia has trade connection with important exporters in *lifting machines* sub-sector.

Table 5. Hub and Authority Centralities

Industrial robots							
Rank	Hub centrality	Rank	Export share (%)	Rank	Authority centrality	Rank	Import share (%)
S. Korea	0.82	Italy	22.55	China	0.95	China	21.38
Italy	0.49	China	21.14	Poland	0.18	Thailand	12.07
Austria	0.26	S. Korea	15.49	Vietnam	0.11	Vietnam	6.54
China	0.11	Austria	13.9	Czechia	0.11	Poland	6.43
Singapore	0.08	Singapore	12.55	Thailand	0.1	S. Korea	6.34
Lifting Machinery							
Rank	Hub centrality	Rank	Export share (%)	Rank	Authority centrality	Rank	Import share (%)
S. Korea	0.98	China	26.73	China	0.94	China	15.43
China	0.12	S. Korea	22.36	Vietnam	0.24	Russia	8.99
Singapore	0.1	Italy	11.81	Czechia	0.11	Vietnam	7.25
Italy	0.07	Luxembourg	4.89	Hungary	0.1	Italy	5.38
Austria	0.07	Austria	4.49	Thailand	0.08	Thailand	4.89
Machines and apparatus							
Rank	Hub centrality	Rank	Export share (%)	Rank	Authority centrality	Rank	Import share (%)
S. Korea	0.74	Singapore	50.15	China	0.95	China	59.61
Singapore	0.67	S. Korea	38.33	S. Korea	0.3	S. Korea	20.23
Malaysia	0.04	China	6.2	Malaysia	0.06	Singapore	5.83
Thailand	0.01	Malaysia	4.24	Vietnam	0.04	Malaysia	4.34
China	0.01	Thailand	0.5	Phillipines	0.02	Vietnam	2.98
Mechanical appliances							
Rank	Hub centrality	Rank	Export share (%)	Rank	Authority centrality	Rank	Import share (%)
China	0.81	China	38.34	Russia	0.47	Russia	10.1
Italy	0.5	Italy	21.32	Vietnam	0.41	China	7.41
S. Korea	0.24	S. Korea	10.55	Poland	0.32	Vietnam	6.78
Poland	0.11	Czechia	3.86	Austria	0.27	Poland	6.28
Czechia	0.08	Austria	3.41	Italy	0.24	Austria	4.82
Welding machines							
Rank	Hub centrality	Rank	Export share (%)	Rank	Authority centrality	Rank	Import share (%)
S. Korea	0.97	China	27.44	China	0.74	China	14.47
China	0.18	S. Korea	24.97	Hungary	0.55	Hungary	9.01
Italy	0.14	Italy	13.4	Vietnam	0.33	Vietnam	8.45
Austria	0.11	Austria	10.8	Russia	0.1	Russia	7.96
Poland	0.02	Poland	3.4	Indonesia	0.06	Poland	5.84

Source: Authors' calculation.

In terms of export share of *machines and apparatus* sub-sector, Singapore ranks first with 50.2% and South Korea ranks second with 38.3%. However, South Korea has more impact than Singapore has in terms of hub centrality. This result indicates that South Korea is more important exporter than Singapore is due to its trade connections with important importer countries of the network. Visualization of machines and apparatus network based on hub centralities can be seen in Figure B.3 in Appendix B.

When *mechanical appliances* sub-sector is evaluated in terms of export, it is observed that there is not a significant distinction between first and high degree indicators. China, Italy and South Korea ranks first-three countries respectively for both of the indicators namely hub centrality and export share. Czechia, which ranks fourth with 3.9% export share, is replaced by Poland in terms of hub centrality and thus Czechia ranks fifth. Network visualization of mechanical appliances network based on hub centralities can be seen in Figure B.4 in Appendix B. In terms of import, Russia ranks first according to both high degree and first degree indicators. However, China which ranks second with 7.41% import share does not take place among first-five country ranking. In other words, Vietnam, Poland, Austria and Italy have trade connections with more important exporters in comparison with China in *mechanical appliances* trade network.

A similar evaluation also exists in *welding machines* network. China ranks second in pursuit of South Korea in terms of hub centrality, although it is the biggest exporter in terms of export share. This result also indicates that South Korea has more impact on the *welding machines* trade network as an exporter country than China has. Network visualization of welding machines network based on hub centralities is presented in Figure B.5 in Appendix B.

6. Conclusion

In the present study, we analyzed international trade of robot industries which has importance in today's AI era. This subject has recently become more crucial to examine especially in terms of post-pandemic world. Because, the world is believed to be a different place from the pre-pandemic term. Physical globalization is said to be replaced by digital globalization. Digitalization in national economies has become primary goal of the countries to recover the immediate impacts of the pandemic stem from lockdowns, quarantines and social distancing measures. All routines from consumption to production has started changing. Thus, use of industrial robots has gained importance for all economies.

When empirical results are evaluated generally, it can be concluded that there is heterogeneous connectedness and disassortative structure for each sub-sector. In other words, there is a few countries with high export volumes while there is a great number of countries with low export volumes. Besides, the countries with high export volumes tend to have trade connections with the countries with low export volumes, meaning that core-periphery structure exists. When the centralities are evaluated, it is observed that China, as the country that suggested the BRI, is an important importer rather than being an exporter in terms of the sectors in question. Because China ranks first in industrial robots, lifting machines, machines and apparatus and welding machines sectors in terms of authority centrality which is a high-degree indicator. In other words, China is the biggest importer of the network in mentioned sectors. When the results are evaluated in terms of export, hub centrality of South Korea is remarkable. South Korea ranks first in industrial robots, lifting machines, machines and apparatus and welding machines sub-sectors overwhelmingly. Singapore is another important exporter in pursuit of South Korea. Additionally, Italy and Austria are important exporters in industrial robots, lifting machines and welding machines sectors. Depending on these, it can be concluded that South Korea is the leader country as a supplier of high-tech robots to the BRI trade network. The mentioned European countries are also important actors that supplies high-tech robots to the BRI countries. Briefly, South Korea and Singapore are the hubs in Asia while Italy and Austria are the hubs in Europe. Thus, physical transportation connections within the BRI may help the BRI members to obtain industrial robots from these hubs and transform their production facilities. However, this will bring some other obligations for these countries. Digitalization of economies is crucial for the post-pandemic era and it seems it is going to be crucial for a long time. BRI may ease the digitalization for the developing members of the BRI. However, these member countries should also transform their labor market properly. Labor force that is replaced by machines should be trained to comply with this new formation. In addition, education and training of labor force should also be planned hereafter in the long-run.

Finally, we presented two graphs in Appendix C for the countries mentioned above in order to indicate the importance of R&D. Share of R&D expenditure in GDP and R&D researcher per million are presented in Figure 6 and Figure 7, respectively. When remembering that China, which is called as the factory of the world, does not have power within these industrial robots sectors as an exporter, it becomes more meaningful that China also has a weak performance in both of the indicators in Appendix C. South Korea has the best performance in both indicators in Appendix C. Similarly, Austria and Singapore have also good performances. We can relate this performance of the countries with their hub centralities. That is to say, the countries, which invest in R&D, also have good performance in the export of industrial robots.

Thus, it can be concluded that the BRI countries, which are mostly developing countries and also enthusiastic to take place in such a new global value chain formation, should follow some policies. In the short-term, they need to transform their economies as proper to the 'new normal' to recover the immediate impacts of the pandemic, meaning that digitalization, accompanied with right labor market policies, should be applied. In the long-term, these countries should give more importance to research and development. Research and development will be the most crucial factor for the sustainability of the new normal.

References

Baker & McKenzie International. (2020). *Beyond Covid-19: Supply chain resilience holds key to recover*. https://www.bakermckenzie.com/-/media/files/insight/publications/2020/04/covid19-global-economy.pdf

Balcı, Z. (2018, January). *Çin'in yeni 'İpek Yolu' projesi* [China's new 'Silk Road' project] (Research No. 52). İHH İnsani ve Sosyal Araştırmalar Merkezi. https://insamer.com/rsm/files/CININIPEKYOLUPROJESI.pdf

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., & Hwang, D. U. (2006). Complex networks: Structure and dynamics. *Physics Reports*, *424*(4-5), 175-308. https://doi.org/cjpbxz

Bocutoğlu, E. (2017). *Çin'in "Bir Kuşak-Bir Yol" projesinin ekonomik ve jeopolitik sonuçları üzerine düşünceler* [Considerations on the Economic and Geopolitical Consequences of China's "One Belt-One Road" Project]. In S. Sarı, J. Primbaev, A. H. Gencer, A. Turdalieva, & B. Tufaner (Eds.), *Proceedings of the International Conference on Eurasian Economies* (pp. 265-270). http://avekon.org/papers/1995.pdf

Boffa, M. (2018). *Trade linkages between the belt and road economies* (Working Paper No. 8423). World Bank. http://hdl.handle.net/10986/29768

Borgatti, S. P., & Everett, M. G. (1999). Models of core/periphery structures. *Social Networks*, *21*(4), 375-395. https://doi.org/10.1016/S0378-8733(99)00019-2

Bougheas, S., & Kirman, A. (2014). *Complex financial networks and systemic risk: A review* (Working Paper No. 14/04). Center for Finance, Credit and Macroeconomics. https://www.nottingham.ac.uk/cfcm/documents/papers/cfcm-2014-04.pdf

Buckley, P. J. (2020). China's belt and road Initiative and the COVID-19 crisis. *Journal of International Business Policy*, *3*(3), 311-314. https://doi.org/gg7vc7

Bugaenko, A. (2020, May 13). Impact of the COVID-19 pandemic on the belt and road initiative in Central Asia. Central Asian Bureau for Analytical Reporting. https://cabar.asia/en/impact-of-the-covid-19-pandemic-on-the-belt-and-road-initiative-in-central-asia/

Chow, W. (2013, July 5). *An anatomy of the world trade network*. Hong Kong Economy. https://www.hkeconomy.gov.hk/en/pdf/An%20Anatomy%20of%20the%20World%20Trade%20Network%20(July%202013).pdf

Clauset A. (2011, September 1). *Lecture 3: Inference, models and simulation for complex systems* [Lecture Notes]. Santa Fe Institute. http://tuvalu.santafe.edu/~aaronc/courses/7000/csci7000-001_2011_L3.pdf

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, *Complex Systems*, 1695. https://cran.r-project.org/web/packages/igraph/index.html

Csermely, P., London A., Wu, L.Y., & Uzzi, B. (2013). Structure and dynamics of core/periphery networks. *Journal of Complex Networks*, *1*(2), 93-123. https://doi.org/10.1093/comnet/cnt016

Decarlo, L.T. (1997). On the meaning and the use of kurtosis. *Psychological Methods, 2*(3), 292-307.

Del Rio-Chanona, R.M., Mealy, P., Pichler, A., Lafond, F., & Farmer, J.D. (2020, April 17). Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective. *Covid Economics*, *6*, 65-103.

Estrada, E. (2015). Introduction to complex networks: Structure and dynamics. In J. Banasiak & M. Mokhtar-Kharroubi (Eds.), *Evolutionary equations with applications in natural sciences* (pp. 93-131). Springer International Publishing.

Fu, X. M., Chen, H.X., & Xue, Z.K. (2018). Construction of the belt and road trade cooperation network from the multi-distances perspective. *Sustainability, 10*(5), 1439. https://doi.org/10.3390/su10051439

Fuge, M., Tee, K., Agogino, A., & Maton, N. (2014). Analysis of collaborative design networks: A case study of openideo. *Journal of Computing and Information Science in Engineering, 14*(2), p. 021009. https://doi.org/10.1115/1.4026510

Hein, O., Schwind, M., & König, W. (2006). Scale-free networks – the impact of fat tailed degree distribution on diffusion and communication processes. *Wirtschaftsinformatik, 48*(4), 267-275. https://doi.org/10.1007/s11576-006-0058-2

Hippel, P. (2011). Skewness. In M. Lovric (Ed.), *International Encyclopedia of Statistical Science*. Springer. https://doi.org/10.1007/978-3-642-04898-2_525

Karagöl, E. T. (2017, May). *Modern İpek Yolu projesi* [Modern Silk Road project] (Rapor No. 174). Siyaset, Ekonomi ve Toplum Araştırmaları Vakfı Perspektif. http://www.setav.org/assets/uploads/2017/05/174_Perspektif.pdf

Kleinberg, J. M. (1999). Authoritative sources in a hyperlinked environment. *Journal of the ACM (JACM), 46*(5), 604-632. https://doi.org/10.1145/324133.324140

Kolaczyk, E. D. (2009). *Statistical analysis of network data: Methods and models*. Springer. https://doi.org/10.1007/978-0-387-88146-1

Li, Y., Peng, Y., Luo, J., Cheng, Y., & Veglianti, E. (2019). Spatial-temporal variation characteristics and evolution of the global industrial robot trade: A complex network analysis. *PLoS ONE, 14*(9), Article e0222785. https://doi.org/ghr3b6

Liu, Z., Tao, W., Sonn, Jung W., & Chen, W. (2018). The structure and evolution of trade relations between countries along the belt and road. *Journal of Geographical Sciences, 28*(9), 1233-1248. https://doi.org/10.1007/s11442-018-1522-9

Machanda, S., Kaleem, H., & Schlorke, S. (2020). *AI investments allow emerging markets to develop and expand sophisticated manufacturing capabilities* (Issue Brief No. 87). International Finance Corporation. http://hdl.handle.net/10986/34851

Newman, M. E. J. (2003). Mixing patterns in networks. *Pyhsical Review E, 67*(2), Article 026126. https://doi.org/10.1103/PhysRevE.67.026126

Newman, M. E. J. (2008). The physics of networks. *Physics Today*, *61*(11), 33-38. https://doi.org/10.1063/1.3027989

Newman, M. E. J. (2010). *Networks: An introduction*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199206650.001.0001

OECD. (2009). *Applications of complexity science for public policy- new tools for finding unanticipated consequences and unrealized opportunities*. http://www.oecd.org/science/inno/43891980.pdf

OECD. (2020, June 3). *COVID-19 and global value chains: Policy options to build more resilient production networks* [Policy Response]. http://www.oecd.org/coronavirus/policy-responses/covid-19-and-global-value-chains-policy-options-to-build-more-resilient-production-networks-04934ef4/

Reichardt, J. (2009). *Introduction to complex networks*. Springer-Verlag. https://doi.org/10.1007/978-3-540-87833-9

Ruzzenenti, F., Garlaschelli, D., & Basosi, R. (2010). Complex networks and symmetry II: Reciprocity and evolution of world trade. *Symmetry, 2*(3), 1710-1744. https://doi.org/10.3390/sym2031710

Smith, M., & Gorgoni, S. (2018). Network analysis and the study of international trade and investment. In S. Gorgoni, A. Amighini, & M. Smith (Eds.), *Networks of international trade and investment* (pp. 25-48). Vernon Press. https://vernonpress.com/index.php/file/6079/5064e8114cb473f8eed60063843ec28e/1528872547.pdf

Song, Z., Che, S., & Yang, Y. (2018). The trade network of the belt and road initiative and its topological relationship to the global trade network. *Journal of Geographical Sciences, 28*(9), 1249-1262. https://doi.org/10.1007/s11442-018-1523-8

Strange, R. (2020). The 2020 Covid-19 pandemic and global value chains. *Journal of Industrial and Business Economics*, *47*(3), 455-465. https://doi.org/10.1007/s40812-020-00162-x

Toroczkai, Z. (2005). Complex networks: The challenge of interaction topology. *Los Alamos Science*, *29*, 94-109. https://permalink.lanl.gov/object/tr?what=info:lanl-repo/lareport/LA-UR-04-7345

Wisskirchen, G., Biacabe, B.T, Bormann, U., Muntz, A., Niehaus, G., Soler, G. J., & von Brauchitsch, B. (2017, April 4). *Artificial intelligence and robotics and their impact on the workplace* [Report]. IBA Global Employment Institute. https://www.ibanet.org/Article/NewDetail.aspx?ArticleUid=012a3473-007f-4519-827c-7da56d7e3509

World Bank. (2020). Research and development expenditure. Retrieved January 2, 2020, from, https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS

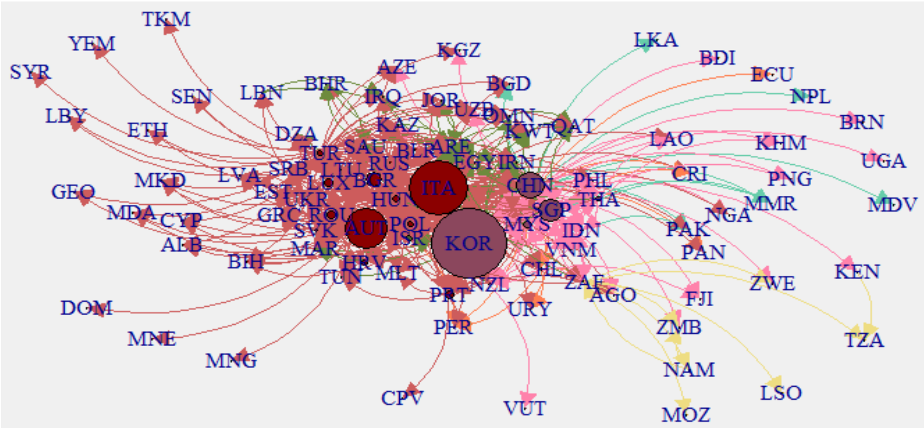
Appendices

Appendix A. The BRI Countries (with 3-digit country codes)

Afghanistan (AFG), Angola (AGO), Albania (ALB), United Arab Emirates (ARE), Armenia (ARM), Antigua and Barbuda (ATG), Austria (AUT), Azerbaijan (AZE), Burundi (BDI), Benin (BEN), Bangladesh (BGD), Bulgaria (BGR), Bahrain (BHR), Bosnia-Herzegovina (BIH), Belarus (BLR), Bolivia (BOL), Barbados (BRB), Brunei Darussalam (BRN), Bhutan (BTN), Chile (CHL), China (CHN), Cote d'Ivoire (CIV), Cameroon (CMR), Congo (COG), Cook Islands (COK), Comoros (COM), Cabo Verde (CPV), Croatia (HRV), Cuba (CUB), Cyprus (CYP), Czechia (CZE), Djibouti (DJI), Dominica (DMA), Dominican Republic (DOM), Algeria (DZA), Ecuador (ECU), Egypt (EGY), Estonia (EST), Ethiopia (ETH), Fiji (FJI), FS Micronesia (FSM), Gabon (GAB), Georgia (GEO), Ghana (GHA), Guinea (GIN), Gambia (GMB), Equatorial Guinea (GNQ), Greece (GRC), Grenada (GRD), Guyana (GUY), Costa Rica (CRI), Hungary (HUN), Indonesia (IDN), Iran (IRN), Iraq (IRQ), Israel (ISR), Italy (ITA), Jamaica (JAM), Jordan (JOR), Kazakhstan (KAZ), Kenya (KEN), Kyrgyzistan (KGZ), Cambodia (KHM), South Korea (KOR), Kuwait (KWT), Laos (LAO), Lebanon (LBN), Liberia (LBR), Libya (LBY), Sri Lanka (LKA), Lesotho (LSO), Lithuania (LTU), Latvia (LVA), Luxembourg (LUX), Morocco (MAR), Moldova (MDA), Madagascar (MDG), Maldives (MDV), Macedonia (MKD), Mali (MLI), Malta (MLT), Myanmar (MMR), Montenegro (MNE), Mongolia (MNG), Mozambique (MOZ), Mauritania (MRT), Malaysia (MYS), Namibia (NAM), Niger (NER), Nigeria (NGA), Niue (NIU), Nepal (NPL), New Zealand (NZL), Oman (OMN), Pakistan (PAK), Panama (PAN), Peru (PER), Philippines (PHL), Papua New Guinea (PNG), Poland (POL), Portugal (PRT), Palestine (PSE), Qatar (QAT), Romania (ROU), Russia (RUS), Rwanda (RWA), Suudi Arabia (SAU), Sudan (SDN), Senegal (SEN), Singapore (SGP), Solomon Islands (SLB), Sierra Leone (SLE), El Salvador (SLV), Somali (SOM), Serbia (SRB), South Sudan (SSD), Suriname (SUR), Slovakia (SVK), Seychelles (SYC), Syria (SYR), Chad (TCD), Togo (TGO), Thailand (THA), Tajikistan (TJK), Turkmenistan (TKM), Timor Leste (TLS), Tonga (TON), Trinidad and Tobago (TTO), Tunus (TUN), Turkey (TUR), Tanzania (TZA), Uganda (UGA), Ukraine (UKR), Uruguay (URY), Uzbekistan (UZB), Venezuella (VEN), Vietnam (VNM), Vanuatu (VUT), Samoa (WSM), Yemen (YEM), South Africa (ZAF), Zambia (ZMB), Zimbabwe (ZWE)

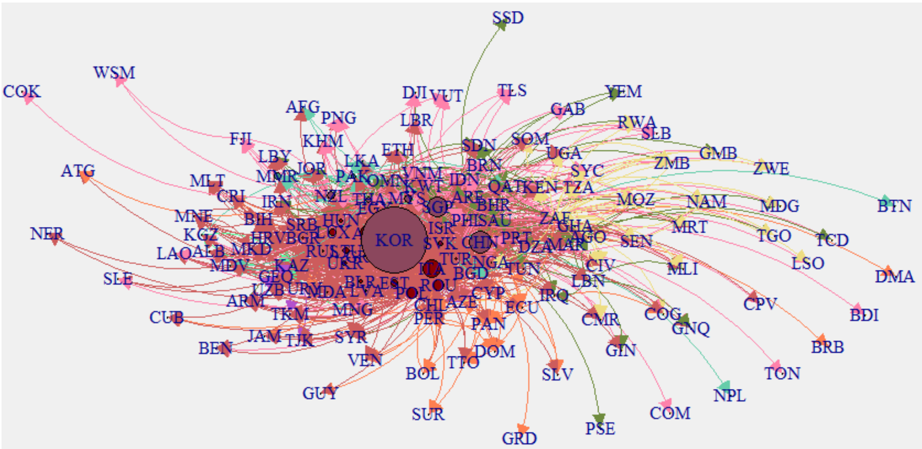
Appendix B. Network Visualizations According to Hub Centralities

Figure B.1. Industrial Robots



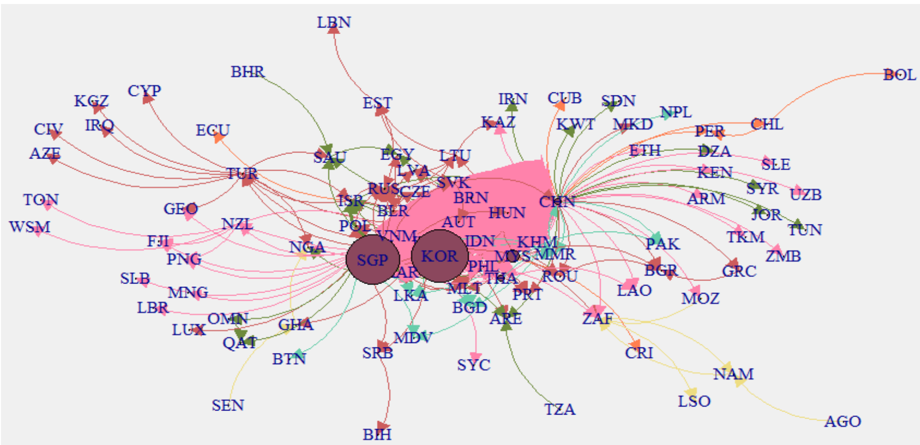
Source: Authors' draw (The data have been obtained from the UN Comtrade)

Figure B.2. Lifting Machinery



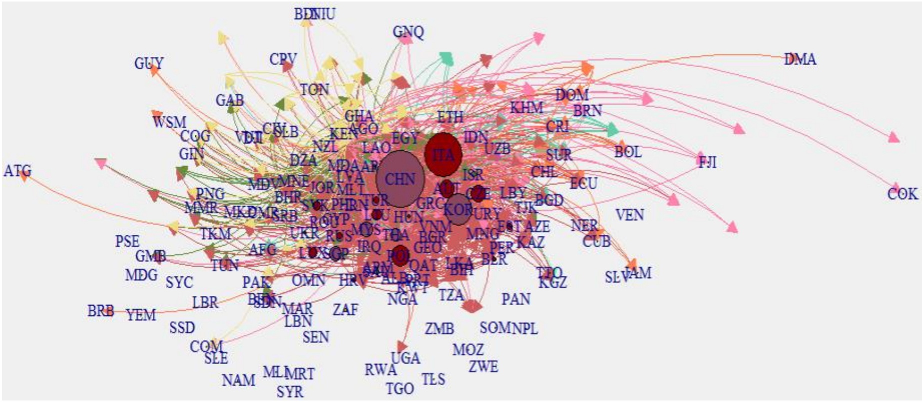
Source: Authors' draw (The data have been obtained from the UN Comtrade)

Figure B.3. Machines and Apparatus



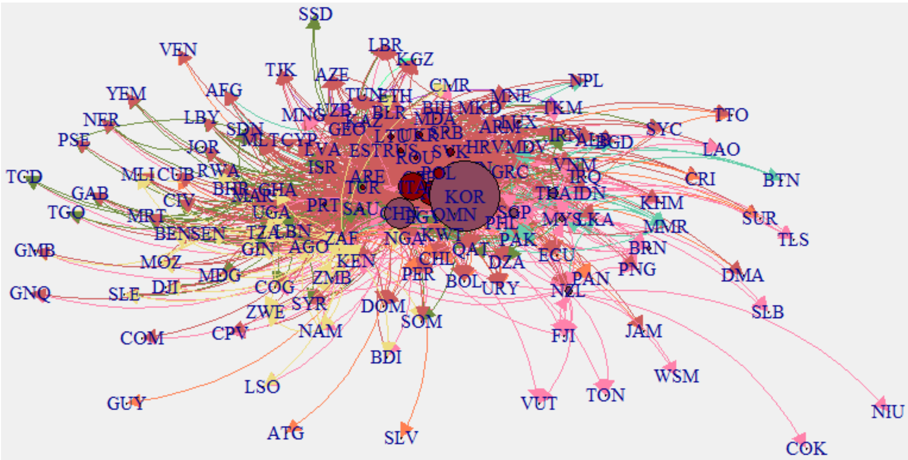
Source: Authors' draw (The data have been obtained from the UN Comtrade)

Figure B.4. Mechanical Appliances



Source: Authors' draw (The data have been obtained from the UN Comtrade)

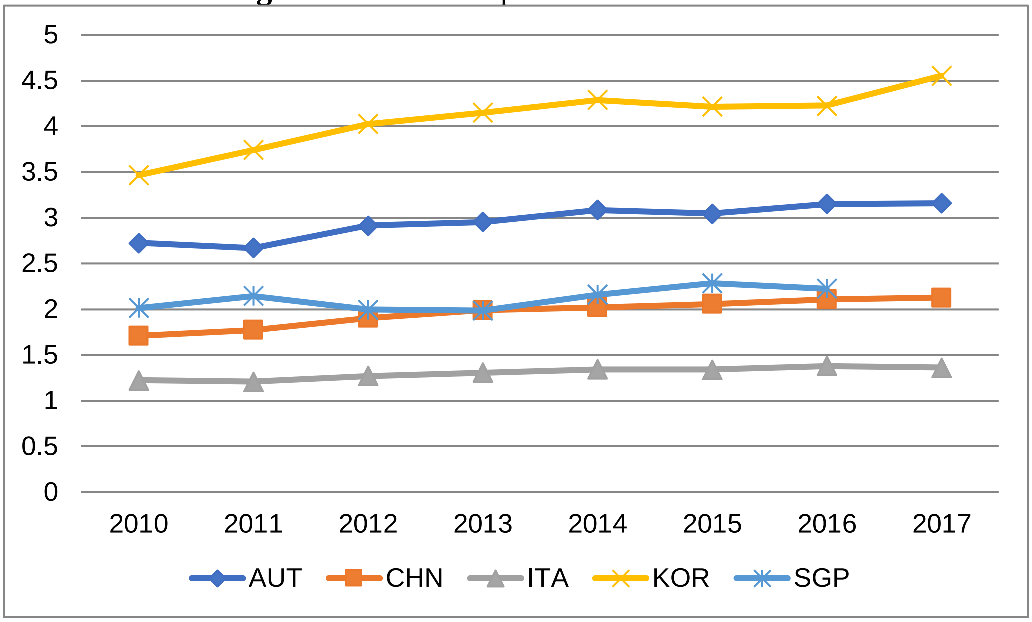
Figure B.5. Welding Machines



Source: Authors' draw (The data have been obtained from the UN Comtrade)

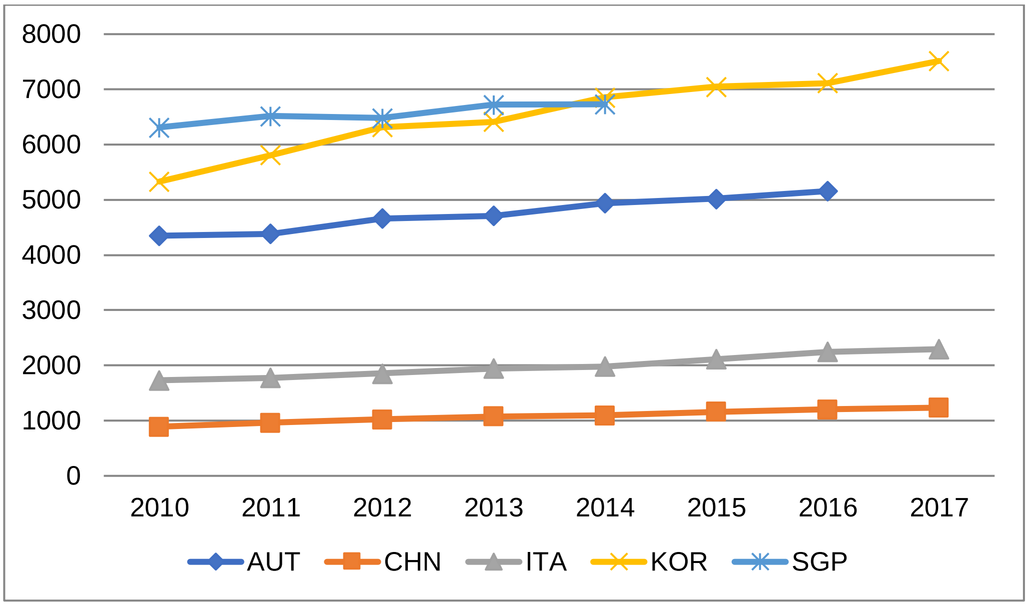
Appendix C. R&D Indicators

Figure B.6. R&D Expenditure Share in GDP



Source: World Bank (2020)
Note: 2017 data for Singapore was not available.

Figure B.7. R&D Researchers per Million



Source: World Bank (2020)
Note: 2017 data for Austria and the data from 2015 to 2017 for Singapore were not available.