Global Input - Output Analysis: A Network Approach

Semanur Soyyigit*, and Çiğdem Boz†

Abstract

Network analysis, a tool that is used to analyze complex systems, which also appeared in economics, which is defined as a complex - adaptive system. Although the international trade networks and financial networks are most popular areas, this method has been employed for input-output Networks. In today's globalized production chain, international input-output network has a prominent role since it captures input flows among each sector of each country which occurs in the network. So, it can easily be understood why globalized production chain is also called as 'global production network'. Network analysis is a significant tool since it takes international links among sectors of national economies into consideration. Thus, findings of the analysis can be informative about how a potential demand/supply shock in this global input flow may affect this globalized production chain. In this study, global input-output tables will be examined and compared for 1995 and 2011, via network tools. It is aimed to reveal both inter-sectoral connectivity and centralities of sectors and also change of these properties from 1995 to 2011.

Keywords: Economic networks, Global production networks, Input-output networks

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1 Introduction

Network analysis has become a very popular tool to analyze complex systems in a vast number of disciplines. Economics has become one of these disciplines as a result of interaction with other disciplines such as computer sciences, physics, biology, mathematics, psychology etc. Economic fields in which network tools are used largely are international trade and finance. However, global value chain is also a new field which uses network analysis to investigate global production network.

Developments in transportation and communication have weakened the significance of specialization depending on geographic domain. Countries have started trading in not only whole goods but mostly specific parts of these final goods. This disaggregation of production process has revealed the concept of 'global value chains (GVC)' which means the international fragmentation of production. Restructuring of this international fragmentation of the production process of a final good has been accompanied with outsourcing and offshoring. Final good trade among countries is not the only criteria anymore in terms of competition. It is also necessary to take the intermediate good trade into consideration. In this context, import content of export increases and domestic value added per unit export decreases. However, intermediate good import increases the profits in the firm-level. This new structure has changed the traditional relations between international trade and value added and also the relations between production and profit ((Milberg and Winkler, 2013, p. 48), (De Backer and Yamano, 2007, p. 5-6)).

*Department of Economics, Erzincan University semanur.soyyigit@erzincan.edu.tr.
†Department of Economics, Batman University, Istanbul, cigdem.boz@batman.edu.tr

Both financial and real shocks may spread to the whole system via GVC due to internationalization of supply chain (Milberg and Winkler, 2013, p. 55). Thus, GVC becomes more significant concept for today's globalized World. GVC concept was used to explain trade and industrial organization as an international value added chain in 2000's. Recently, it has been called as 'network' rather than 'chain' since economic process depends on complex interactions among global producers (De Backer and Yamano, 2007, p. 5).

Recently, GVC has also become a popular research field analyzed via network tools. There is an interdependent relationship between intermediate good suppliers and demanders. For instance, in the sector-level, each sector provides some intermediate goods to other sectors and also gets intermediate goods in return. From network viewpoint, importance of some sectors became more important relatively based on these bilateral relations. Determination of these sectors is vital since shocks in one sector can spread to the whole. In the literature, there are a great number of studies investigating GVC via network analysis.

Network analysis of this global production chain is managed via utilization of input-output tables. Usage of these tables provides some advantages. First of all, the problems stemming from different data definitions of countries are eliminated and a standard data structure is obtained. Besides, goods are categorized as 'intermediate' and 'final' goods in these tables. And these tables also include not only goods but also services.

In this paper, network approach to global input-output relations has been applied by using global input-output tables for the years 1995 and 2011. Within this scope, literature review of network approach to input-output data has been given in the second section and methodological information has been given in the third section. After description of the data structure in the fourth section, evaluation and interpretation of the results have been presented in the following section.

2 Literature Review

There are some studies about network analysis of input-output tables in the literature. Grazzini and Spelta analyzed the flow of intermediate good in 2011 (Grazzini *et al.*, 2015, p. 21-22) and found that both out-strength and in-strength flows have heavy tail distribution meaning that input-output network is asymmetrical in regard to both input suppliers and input users. The authors also analyzed the evolution of input-output network. They found that the network fragility has increased from 1995 to 2011. The authors also revealed the rise of some new central sectors. According to their findings, China has become highly central in global production. Another finding of this part of the analysis is that the leading Chinese sectors are intermediate manufactured goods producers while the western leading sectors are financial and business services.

Wu (2015) built a supplier network from 2004 to 2014 and calculated the centralities (degree, eigenvector, hub and authority centralities) of each company as a supplier. Then, the author constructed supplier-central stock portfolio based on the top ten company and found that supplier-central portfolios tended to be more volatile than customer-central portfolios.

Blöchl *et al.* (2011) derived two centrality measures that are well-suited for input-output networks that contain nodes with strong self-loops and are completely connected. The findings support the geographical proximity and similar developmental status of the countries in terms of sectoral centrality. According to their results, centrality ranking of sectors in Belgium and Spain looked similar, as Turkey and India had also similar centrality ranking of sectors.

Chen and Chen (2013) made a network simulation of global embodied energy flows in 2007 based on a multi-region input-output model. The input-output network built by the authors comprised 6384 nodes in global level. The findings of their research show that almost 70 % of the world direct energy input is invested in resource, heavy manufacture and transportation sectors that provide only 30 %

of the embodied energy to satisfy final demand. The authors also show that China is the biggest exporter of embodied energy while the USA is the biggest importer.

In this analysis, we build our input-output table as involving 18 sectors of 40 countries and study the evolution from 1995 to 2011. The methodology used in this analysis is the same with the one used to analyze national input-output tables by using network tools (Soyyigit and Eren, 2016). Before looking at the findings, some technical information about networks and methodology will be given as follows.

3 Methodology

Complex system is basically defined as a large network of relatively simple components with no central control, in which emergent complex behavior is exhibited (Mitchell, 2006). The first step to understand complex systems is decomposition of these systems into their parts (Reichardt, 2008). Network analysis allows one to represent complex systems in terms of their parts and interactions/linkages among these parts. In this context, policymakers have become interested in network analysis to determine the weaknesses of their concerns since these tools are applied to most of the real-world networks (OECD, 2009).

A network is basically represented as $G = (V, E, f)$, where V is a finite set of nodes and E is a set of links among these nodes and, f is a mapping which links elements of E to a pair of elements of V. In a weighted network, each link is given a distinct weight and the definition of network becomes $G = (V, W, f)$, where W represents the set of weights $W = w_1, w_2, ..., w_m$. If two nodes (node i and node j) are linked to each other with the link $e = i, j$ in a network, then these nodes are said to be adjacent. A binary network (which also means unweighted network) is represented with adjacency matrix that is built as follows Estrada (2015):

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

An undirected and binary network is the simplest type of networks while a directed and weighted network is a more complicated one.

One of the extents that are analyzed to get information about the topological properties of a network is connectivity. Connectivity is measured by node degree/node strength (depending on network type) on node-level. Higher node degree/node strength implies stronger impact over the network (Howell, 2012). In network level, connectivity is measured by density which is a ratio of actual count of links to possible maximum count of links. In a directed network without self-loop and multilink, density coefficient is formulized as follows (Newman, 2010):

$$\rho = \frac{m}{n(n-1)} \tag{2}$$

in where m is the count of actual links. Density coefficient lies in the range of $0 \leq \rho \leq 1$.

Degree distribution is another informative property about network topology. It has been indicated in the literature that most real-world networks such as movie network, www, electrical power grid network and citation network follow power-law degree distribution (Barabási and Albert, 1999). These networks that follow power-law distribution are called as scale-free networks in network literature. Scale free networks have some characteristics which distinguish them from random and small-world networks (Mitchell, 2009). First of all, they include small number of hubs which are nodes with high-degree. They also include heterogeneity of connectivity since node degrees/strengths are over a very large range. Another property of scale-free networks is self-similarity which means that even one rescales and reshapes the distribution by focusing on a smaller part of the curve, the shape obtained will look like the previous. Finally, scale-free networks have small-world property which requires small average path length and high degree of clustering.

It is known that power-law distribution belongs to the class of fat-tailed distribution which has higher peak and fat tails compared to Poisson distribution. Power-law distribution is represented as follows (Hein *et al.*, 2006):

$$P(k) \approx k^{\gamma} \tag{3}$$

$P(k)$ shows probability of occurrence of nodes with degree k in network in the Equation (3). γ has a characteristic importance for this distribution. It means that a lower value of γ leads to a higher probability of nodes with many links. In other words, a network with a lower value of γ has a higher quantity of super-nodes which have many links compared to a network with a higher value of γ. It can also be interpreted as such that higher exponent level implies less heterogeneity of connectedness (León and Berndsen, 2014).

One way to determine fat-tailed distribution is to analyze kurtosis value. If kurtosis has positive value, th(DeCarlo, 1997)(Decarlo, 1997: 292). It is also stated that most of the real world networks display right-skewed distribution and these distributions approximate power-law distribution (León *et al.*, 2016). Skewness measure gives information about distributional asymmetry and is used to determine which side of a distribution has a fat-tail. If skewness measure has positive value, then fat-tail is on the right and distribution is right-skewed and vice versa (Von Hippel, 2011).

Another significant topological property of a network is centrality. However, it is more convenient to examine assortativity/disassortativity in order to perceive the importance of centrality. Assortativity means that the nodes with high degree/strength tend to have links with the nodes which have high degree/strength. However, the nodes with high degree/strength tend to have relations with the nodes with low degree/strength in disassortative case (Reichardt, 2008). There are two ways to determine assortative/disassortative structure in a network. One of them is to plot degree and ANND statistics on the same graph and to see the relationship between them. ANND is a statistic shows how connected neighbours of node i are with one another (Fagiolo, 2010: 484). It is measured as the average degree of neighbours of i. It can be formulized as follows (Barrat *et al.*, 2004):

$$< k_{nn,i} \geq \frac{1}{k_i} \sum_j k_j \tag{4}$$

ANND for the nodes which have degree k is calculated with the formula below:

$$< k_{nn}(k) \geq \frac{1}{N_k} \sum_j k_{nn,i} \tag{5}$$

It is possible to decide whether there is a disassortative structure in a network. If the relation between the degree and the ANND is positive, then it is thought there is an assortative structure in the network. On the contrary, if the relation between the degree and the ANND is negative, then there is a disassortative structure in the network. These relations can be seen in Figure (1).

Calculation of assortativity correlation coefficient is another way to determine assortative/disassortative structure in the network. Newman defines assortativity coefficient by adjusting standard Pearson correlation coefficient as follows (Newman, 2010):

$$r = \frac{\sum_{ij} ij(e_{ij} - a_i b_j)}{\sigma_a \sigma_b} \tag{6}$$

where $a_i = \sum_j e_{ij}$ and $b_j = \sum_i e_{ij}$ are fraction of edges start and end at node i and node j, respectively. And σ_a and σ_b are the standard deviations of the distributions of a_i and b_j . This

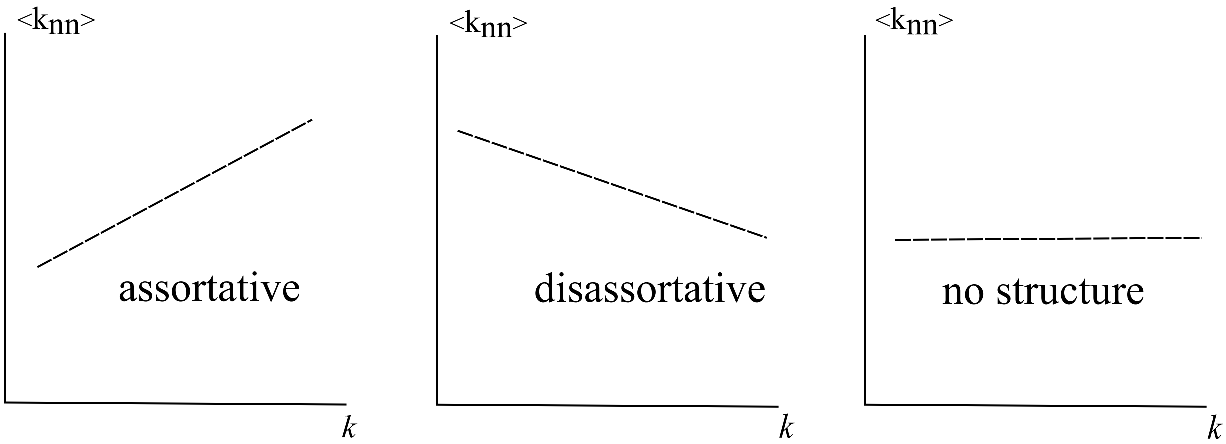

Figure 1: Assortativity - Disassortativity

SOURCE: G. Caldarelli, "Lectures in complex networks", 2008, International Workshop & Conference on Network Science, http://www.ifr.ac.uk/netsci08/Download/Invited/ws1_Caldarelli.pdf

assortativity measure lies in the interval [-1,1]. If $r = 1$, then there is perfect assortativity between i and j. If $r = -1$, then there is perfect disassortativity between the nodes.

Disassortativity is one of the reasons of core-periphery structure in a network (Fuge *et al.*, 2014). Centrality measure enables one to determine the nodes in the core and the periphery. There are a lot of centrality measures such as degree centrality, betweenness centrality, closeness centrality, eigenvector centrality etc. to measure the importance of the nodes in a network.

HITS algorithm was developed by Kleinberg (1999) to calculate hub and authority centralities of web pages which are results of a specific query on the Internet. It based his analysis on a directed network in his original study. As is known, there are two types of links in directed networks: in-links and out-links. In this context, hubs are nodes with myriad out-links and authorities are nodes with myriad in-links. Kleinberg (1999) aimed to calculate two different centrality measures for these distinct type of nodes.

Kleinberg (1999) remarked that these authoritative pages which are related to initial query should not only have large in-links. It is also necessary to be an overlap in the sets of pages which point to these authoritative pages. Similarly, hub pages should have links to multiple relevant authoritative pages. These two different classes of nodes exhibit *mutually reinforcing relationship* means that a good hub is a node that points to many good authorities and a good authority is a node that is pointed to by many good hubs. Kleinberg (1999) used an algorithm, HITS algorithm that uses an iterative process that maintains and updates two weights for each page. In this context, each web page has two non-negative weights: an authority weight $x^{<p>}$ and a hub weight $y^{<p>}$. And there are two operations ($\mathcal{I}$ and $\mathcal{O}$) that update these weights. $\mathcal{I}$ updates the x weights and $\mathcal{O}$ updates the y weights during the iterations. Kleinberg (1999) also expressed this mutually reinforcing relationship between hubs and authorities with equations as follows:

$$\begin{aligned} x^{<p>} &\leftarrow \sum_{q:(q,p)\in E} y^{<p>} \\ y^{<p>} &\leftarrow \sum_{q:(q,p)\in E} x^{<p>} \end{aligned} \tag{7}$$

As it is understood from the Equation (7), authority weight of a node is proportional to the hub weights of the nodes point to it. Similarly, hub weight of a node is proportional to the authority weights of the nodes it points to.

First of all, Kleinberg (1999) defined a vector y which elements consist of $y^{<p>}$ values and a vector x which elements consist of $x^{<p>}$. Assuming that $G = (V, E)$ with $V = p_1, p_2, ..., p_n$ and $\mathbf{A}$ is adjacency matrix of graph G, he proved that y and x converge to their equilibrium values $y*$ and $x*$ (which are hub centrality and authority centrality, respectively) at the end of this iteration process. He concluded that $x*$ (authority centrality vector) is the principal eigenvector of $\mathbf{A}^\top\mathbf{A}$ and $y*$ (hub centrality vector) is the principal eigenvector of $\mathbf{A}\mathbf{A}^\top$.

Kleinberg (1999)'s algorithm uses the way which is used to calculate eigenvector centrality. However it eliminates zero-centrality problem of eigen-pair analysis by calculating hub and authority centralities of nodes simultaneously and iteratively depending on that mutually reinforcing relationship. León and Perez (2013) summarized this iterative process as the estimation of eigenvector centrality of two modified versions of adjacency matrix. On this basis, $M_{hub} = \mathbf{A}\mathbf{A}^\top$ and $M_{auth} = \mathbf{A}^\top\mathbf{A}$ can be called as hub matrix and authority matrix of which eigenvector centralities refer to hub centrality and authority centrality, respectively (Kolaczyk, 2009).

León and Perez (2013) explains the logic behind these hub and authority matrices like that. Multiplication of a directed (non-symmetrical) adjacency matrix with transpose of itself enables one to identify second-order adjacencies. Clearly, in the case of M_{auth}, multiplication of $\mathbf{A}^\top$ with $\mathbf{A}$ sends weights backwards towards the pointing node. However, multiplication of $\mathbf{A}$ with $\mathbf{A}^\top$ sends weights forwards towards to the pointed node. Since M_{hub} and M_{auth} are symmetrical matrices with non-negative elements, hub and authority centrality vectors will also contain positive and non-zero scores.

4 Data and Results

4.1 Data

The data used in this study have been obtained from WIOD database. The data used in the analysis have been built by using World Input-Output Tables (WIOT). A WIOT is a set of national input-output tables which are connected to each other by bilateral international trade flows. Time series of WIOT includes EU-27 and 13 major economies of the world such as Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey and the USA. Additionally, the data contain another region which is called "rest of the world (RoW)" for the non-included part of the World economy. However, we have excluded the RoW part. WIOT data also cover 35 industries mostly at the two-digit ISIC Rev.3 level (Timmer *et al.*, 2015). We have condensed these 35 sectors into 18 sectors depending on the sectoral aggregation of Wong (Wong, 2014). Inorder to observe only intermediate good flows among foreign sectors, zero was placed in the matrix replacing inter-country flows. WIOT structure and sectoral aggregation can be found in Appendix 1 and 2, respectively.

4.2 Findings

First of all, when the basic indicators of global input-output networks showing intermediate product flow of domestic sectors are observed, it is apparent that although the number of nodes did not change, the number of links increased for both years. This indicates that input flow has become more globalized, which also can be observed through the density coefficient. Because the coefficient of density which is the ratio of the possible count of connectivity in the network rose from 0.90 to 0.93. When compared to complete networks where the density coefficient is equal to 1 and all possible connections are made, global production network, although not fulfilling all total network requirements could be declared close to complete. Besides all of these, it could be stated that network transitivity and connectivity increased from 1995 to 2011.

Table 1: Some Basic Indicators

	1995	**2011**
Nodes	720	720
Links	469642	482042
Transitivity	0.96531	0.970763
Reciprocity	0.880268	0.917881
Density	0.907205	0.931158

Another important aspect is; the distribution in network analysis is coherent with the power-law distribution. Because this distribution, indicates the heterogeneous structure of the network connections. A method to derive an idea to determine the coherence to power-law distribution is to check skewness and kurtosis values. Skewness and kurtosis values according to this are shown in the Table (2).

Table 2: Skewness and Kurtosis Measures

	1995	**2011**
Skewness	4.442653	4.694878
Kurtosis	28.45125	33.0651

As mentioned above, positive kurtosis value indicates the distribution's coherence with fat-tail distribution and positive skewness value indicates that the distribution is on the right side of the fat-tail distribution. Hence, the values in the table indicates power-law distribution coherence for both years. Nevertheless, we have to test the degree of distribution at hand for power-law distribution statistically too. Hence K-S test was applied to the data. Results derived from the test are in the Table (3).

Table 3: K-S test results

	1995	**2011**
alpha	1.744516	1.885968
p-value	0.0008373	0.2498211
K-S statistic	0.1197972	0.0676574

In this test, H_0 hypothesis represents distribution's coherence with power-law distribution, H_1 hypothesis represents the distribution's coherence with the power-law distribution. p value above 0.05 indicates being out of the H_0 red area. Briefly, H_0 hypothesis which indicates the possibility of the distribution's coherence with the power-law distribution is undeniable. Here the interesting point is; although there was no coherence in 1995, power-law distribution coherence is evident in 2011. The deduction is based on the p value which increased from 0.0008 to 0.249 between 1995 and 2011. This change in the p value can be interpreted as the transition of the links from non-heterogeneous to heterogeneous between 1995 and 2011 in the global production network. Hence, it is reasonable to deduce that, in the course of time in global production network while some links in some of the countries grew to have vast connections, the others lost ground. Briefly, in the past years certain hubs emerged in the global production network.

As mentioned in methodology section, another important topological property is; the network's assortativity/disassortativity inclined structure. The correlation coefficient to determine assortativity or dissassortativity are -0.0122521 for 1995 and -0.006824 for 2011.

According to this, although it is not a perfect disassortativity, still the disassortativity is evident. As mentioned above, disassortative structure is an indicator of core-periphery structure. In this sense, it is plausible to say that global production network has a core-periphery structure.

In core-periphery context, centrality measurement is used to determine the central sectors in the network. As abovementioned, Kleinberg (1999)'s hub and authority centralities is used in this analysis. Since, hub represents nodes with outgoing links and the links in the matrix represent export, hub centrality measurement can also be titled as export centrality. Similarly, as authority represents nodes with many number of incoming links, authority centrality measurement can be titled as import centrality. Kleinberg (1999)'s method provides an export centrality and an import centrality value for each node. Hence, it makes possible to see which countries became dominant in which sectors, and the development of their export and import centralities from 1995 to 2011.

The hub centrality values of countries which provide input to global production network for each sector for 1995 and 2011 are in the Table 5. Here the hub centrality of the countries represents the centrality of the countries in terms of their intermediate goods input to global production network. In the most general sense, Far East Asian countries stand out as electrical equipment, chemicals, metal industry, business, machinery industry, transport equipment and textile industry input providers in global production network.

If explained from general to specific, in electrical equipment Taiwan and South Korea following Japan and USA in 1995 rose to top in 2011. The countries which dropped under these two, meaning Japan and USA are followed by China constitutes the first 5 important input providers.

Germany, the leader of chemical materials sector of 1995 was replaced by South Korea in 2011. Countries like China and Taiwan, which were nonexistent in the top 10 list of 1995 rose to 3rd and 6th positions respectively. Germany and Netherlands lost their centrality as far as their inputs to global production network concerned.

A very similar situation is valid for the metal industry. As of 1995 none of the Far East Asian countries were in the top 10 list of this sector; in 2011 South Korea, Taiwan and China resided in positions 3rd, 5th and 6th respectively. Canadian metal industry lost ground both in centrality and in ranking. Japanese metal industry preserved its centrality score, rose in the ranking and became the most important input provider as of 2011.

As far as business activities concerned England, the leader of 1995 dropped to being 4th in 2011 and left its leading position to USA. Parallel to this China, which was nowhere among the top 10 in 1995, rose to being the 2nd most important input provider in 2011.

Although the top three positions occupied by Japan, Germany and USA in 1995 did not change in 2011, South Korea which was not even in the top 10 in 1995, appeared as the 4th input provider for global production network in machinery industry in 2011. Taiwan and China became the 6th and 7th in 2011 In transportation sector, even though Russia and USA preserved their positions for both years, China and South Korea outrun Netherlands, France, England and Germany and became the 3rd and 4th respectively.

In textile industry, for both years China is the leading figure. Both in 1995 and 2011 Italy follows China as the 2nd. In 2011, India and Taiwan rose in ranking in providing intermediate goods in textile sectors.

Nevertheless, Far East countries' centrality remained rather low in providing input to transport equipment, paper, mining, finance and agriculture sectors. If the table examined closely, it will be seen that USA and Japan are the most important transport equipment input providers. Canada which was the 3rd in 1995 left its place to Germany and Mexico in 2011 in transport equipment market. As of 2011 China and South Korea outrun England and Italy.

The mining sector leader of 1995, Canada was dethroned by Australia in 2011 and dropped to being the 2nd. Russian mining sector preserved its 3rd position in both years. Briefly, Far East countries emerge in this industry group too. It could be stated that, this situation is related to country's

Table 4: Change of hub centralities of countries from 1995 to 2011 in terms of sectoral separation

Electrical Equipment				Transport equipment				Chemical			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
JPN	0.4445	TWN	0.5086	USA	0.2843	USA	0.0292	DEU	0.2325	KOR	0.1102
USA	0.2665	KOR	0.3123	JPN	0.2126	JPN	0.026	JPN	0.1503	JPN	0.0938
KOR	0.2529	JPN	0.2419	CAN	0.1655	DEU	0.025	NLD	0.1415	CHN	0.0754
TWN	0.1916	USA	0.1708	DEU	0.1242	MEX	0.0163	FRA	0.1413	USA	0.0728
DEU	0.1209	CHN	0.1309	MEX	0.075	CAN	0.0119	USA	0.1408	DEU	0.0703
GBR	0.103	DEU	0.0774	FRA	0.0702	CHN	0.0101	CAN	0.1376	TWN	0.0653
CAN	0.1017	MEX	0.0315	GBR	0.0634	FRA	0.0091	GBR	0.1208	CAN	0.0566
CHN	0.0846	FRA	0.0274	ITA	0.0389	KOR	0.009	BEL	0.1186	NLD	0.0381
FRA	0.0812	GBR	0.0143	ESP	0.0281	GBR	0.0086	ITA	0.0869	GBR	0.0356
MEX	0.0784	CAN	0.0139	AUT	0.0195	ITA	0.0044	ESP	0.0425	FRA	0.0332
Paper				**Metal**				**Business**			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
CAN	0.1722	USA	0.0162	CAN	0.133	JPN	0.1224	GBR	0.102	USA	0.0326
USA	0.0391	CAN	0.013	JPN	0.1284	USA	0.0732	FRA	0.0853	CHN	0.029
FIN	0.0244	DEU	0.0039	DEU	0.0991	KOR	0.0612	USA	0.0633	DEU	0.0242
DEU	0.0242	CHN	0.0035	USA	0.0602	DEU	0.0434	NLD	0.0624	GBR	0.0202
SWE	0.0195	BRA	0.0033	FRA	0.0578	TWN	0.0413	CAN	0.0399	NLD	0.0153
GBR	0.0184	FIN	0.0027	BEL	0.0539	CHN	0.037	DEU	0.0351	FRA	0.0151
FRA	0.0155	RUS	0.0025	ITA	0.0475	AUS	0.03	ITA	0.0304	SWE	0.0108
IDN	0.0123	SWE	0.0024	GBR	0.0453	CAN	0.0264	BEL	0.0263	CAN	0.0104
NLD	0.0111	IDN	0.0023	RUS	0.0397	RUS	0.0216	SWE	0.0222	ITA	0.0095
BRA	0.0111	JPN	0.0017	NLD	0.0355	GBR	0.0177	TWN	0.0177	BEL	0.0086
Mining				**Machinery**				**Transport**			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
CAN	0.0886	AUS	0.5677	JPN	0.0649	DEU	0.0521	RUS	0.0411	RUS	0.0343
MEX	0.0609	CAN	0.1877	DEU	0.0631	JPN	0.0471	USA	0.0402	USA	0.0223
RUS	0.0537	RUS	0.1625	USA	0.0505	USA	0.0295	NLD	0.029	CHN	0.0139
GBR	0.0341	MEX	0.1121	ITA	0.0318	KOR	0.0202	FRA	0.0287	KOR	0.0134
AUS	0.0283	BRA	0.1102	CAN	0.0259	ITA	0.0169	GBR	0.0213	AUS	0.0087
IDN	0.0183	IDN	0.096	GBR	0.0257	TWN	0.0126	DEU	0.0212	FRA	0.0055
NLD	0.0123	GBR	0.0187	FRA	0.0198	CHN	0.011	BEL	0.0198	DEU	0.0049
USA	0.0107	USA	0.014	TWN	0.0106	CAN	0.0074	KOR	0.0166	BEL	0.0048
CHN	0.0085	IND	0.0106	SWE	0.0104	FRA	0.0073	CAN	0.0159	NLD	0.0041
DEU	0.004	NLD	0.0097	NLD	0.0095	GBR	0.0064	TWN	0.0144	JPN	0.0041
Textile				**Financial**				**Agriculture**			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
CHN	0.0294	CHN	0.0114	USA	0.029	USA	0.0112	USA	0.0122	USA	0.0043
ITA	0.0242	ITA	0.002	LUX	0.0116	GBR	0.0054	CAN	0.0098	BRA	0.0031
KOR	0.0125	IND	0.0016	GBR	0.0092	IRL	0.0053	FRA	0.006	CAN	0.0023
DEU	0.0088	TWN	0.0014	IRL	0.0045	DEU	0.0019	NLD	0.0056	IND	0.002
FRA	0.0083	USA	0.0013	CAN	0.0037	NLD	0.0017	IND	0.0056	AUS	0.0013
BEL	0.0077	JPN	0.0012	FRA	0.0033	ESP	0.0006	MEX	0.005	RUS	0.0009
USA	0.0075	KOR	0.0012	BEL	0.0026	IND	0.0006	AUS	0.0044	IDN	0.0008
TWN	0.0072	MEX	0.0009	IDN	0.0024	AUS	0.0005	CHN	0.0041	MEX	0.0007
IND	0.0066	IDN	0.0009	MEX	0.0023	ITA	0.0005	TWN	0.0038	TWN	0.0007
IDN	0.0066	CAN	0.0008	ITA	0.002	BEL	0.0005	BRA	0.0035	FRA	0.0006

intermediate goods supply potential.

A similar situation is valid for financial intermediation relations. USA occupies the most prominent centrality in both years for financial intermediation input supply. In 1995 Luxembourg followed USA whereas England rose to second position in 2011. In general it is reasonable to say that, for both years European countries preserved their dominant centralities.

On the other hand Far East countries, besides their low-cost input, took advantage of their low-cost labor to achieve a relatively favored position in supplying a number of final goods. This state requires Far East countries' sectorial import centrality to elevate in time. Because these countries' production processes are in dire need of intermediate goods.

This condition can be observed in table (5) which shows the import centrality of countries on sectorial basis. In the table for countries' import centrality for sectors, if a country has a high import centrality in a sector, it is an implication of country's centrality as a user of intermediate goods.

In this context USA, the electrical equipment leader of 1995 left its leading position to China in 2011. Aside this industry, China outrun USA in metal, machinery and textile industries too. Although China did not outrun ABD in transportation, chemicals and paper industries, became the second most important intermediate goods importing country. Another striking issue in the table is; while Turkish textile sector was not in top 10 in 1995, became the 5th intermediate goods importer in 2011. This situation can only be explained with Far East Asian countries' centrality in intermediate goods supply for low-cost raw materials and intermediate goods industries.

Like Grazzini *et al.* (2015), we also found that western countries had remain central in the business and finance sectors while Far East Asian countries had substituted with them in terms of other sectors during the period.

5 Conclusion

Network analysis which is vastly used in economics, found a new application area in input-output tables. With this analysis it is possible to pinpoint the important intermediate goods suppliers and users of the network. Advantage of employing network analysis and the algorithm used in this process provides the possibility of analysis with advanced indicators rather than first degree indicators.

Essentially, findings derived in this work are just the first step of the network analysis. Methodologically, the more advanced step of network analysis is to study the consequences of probable demand/supply shocks via simulations. This method has been applied to financial networks especially after the global crisis, recently its application to global production network via input-output matrices is being studied. Findings derived from the network analysis are used to create the above mentioned simulations.

The comparison of 1995 and 2011 carried out in work shows that; the importance of Far East Asian countries increased in the course of time for import and export for intermediate goods in this complex network. However, western countries have maintained their places as a central exporter and importer in terms of business and finance sectors.

Another result to be emphasized is; input-output network, within the period, has become a scale-free network which means that there are a lot of insignificant sectors whereas there are less central sectors as input exporter/importer for the world production network. This reduces the robustness of the network; that is, the global production network has become more vulnerable to any demand or supply shock.

Table 5: Change of authority centralities of countries from 1995 to 2011 in terms of sectoral separation

Electrical equipment				**Transport equipment**				**Chemical**			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
USA	0.41662	CHN	0.65069	USA	0.33844	USA	0.0586	USA	0.23909	USA	0.21943
TWN	0.18697	KOR	0.10368	CAN	0.28137	CHN	0.04164	DEU	0.1417	CHN	0.1812
KOR	0.17323	TWN	0.07725	DEU	0.10395	MEX	0.02516	FRA	0.12587	JPN	0.17619
DEU	0.14393	MEX	0.07371	FRA	0.10158	DEU	0.02458	ITA	0.11441	KOR	0.08318
MEX	0.13113	USA	0.0597	MEX	0.08168	CAN	0.01934	BEL	0.09624	FRA	0.06083
JPN	0.12995	JPN	0.05818	GBR	0.07397	FRA	0.01739	GBR	0.09061	ITA	0.05899
CHN	0.11593	DEU	0.05617	BEL	0.05776	KOR	0.01697	NLD	0.07984	NLD	0.04691
GBR	0.10101	CZE	0.02638	ESP	0.04714	JPN	0.01357	JPN	0.07202	DEU	0.03401
FRA	0.08566	BRA	0.01863	KOR	0.04614	GBR	0.01278	KOR	0.06077	TWN	0.02921
CAN	0.07109	FRA	0.01601	JPN	0.03495	BRA	0.00586	TWN	0.06061	BEL	0.02464
Financial				**Electricity**				**Paper**			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
USA	0.02488	USA	0.01128	FRA	0.01761	JPN	0.07659	USA	0.13378	USA	0.01439
CHN	0.01092	LUX	0.00366	USA	0.01152	CHN	0.04124	DEU	0.02663	CHN	0.01364
GBR	0.01038	GBR	0.00306	DEU	0.01085	ITA	0.03378	JPN	0.02265	DEU	0.00312
FRA	0.00744	CHN	0.00251	JPN	0.0101	KOR	0.02866	GBR	0.01878	JPN	0.00288
CAN	0.00524	DEU	0.00214	ITA	0.00771	USA	0.02231	CAN	0.01656	IRL	0.00273
JPN	0.00416	CAN	0.00191	CHN	0.0075	TWN	0.01743	FRA	0.01616	CAN	0.0025
NLD	0.00393	NLD	0.00178	BEL	0.00587	GBR	0.00996	ITA	0.01552	FRA	0.00184
BEL	0.00254	JPN	0.0015	GBR	0.00574	DEU	0.00866	NLD	0.01149	GBR	0.00145
LUX	0.0022	IRL	0.0013	NLD	0.00476	FRA	0.00712	BEL	0.00879	MEX	0.00138
KOR	0.00211	KOR	0.00087	ESP	0.00375	ESP	0.00702	KOR	0.00842	ITA	0.00134
Metal				**Machinery**				**Business**			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
USA	0.13212	CHN	0.56937	USA	0.09859	CHN	0.0737	USA	0.09013	USA	0.0415
DEU	0.06489	KOR	0.10605	DEU	0.06383	USA	0.02488	FRA	0.04033	CHN	0.03874
FRA	0.04258	JPN	0.07978	JPN	0.03522	DEU	0.02115	CHN	0.03412	FRA	0.00922
ITA	0.042	USA	0.03415	ITA	0.02883	JPN	0.01584	DEU	0.0277	GBR	0.00692
JPN	0.0386	DEU	0.03305	TWN	0.0288	KOR	0.01169	NLD	0.02023	AUS	0.00611
KOR	0.03785	TWN	0.03303	KOR	0.02815	CAN	0.00938	BEL	0.01628	DEU	0.00575
CHN	0.03499	CAN	0.02634	GBR	0.0268	TWN	0.008	ITA	0.01571	NLD	0.00492
BEL	0.03314	FRA	0.01497	CHN	0.02625	ITA	0.00661	GBR	0.01557	JPN	0.00483
GBR	0.03243	IND	0.01381	FRA	0.0235	FRA	0.00618	MEX	0.01076	MEX	0.00455
TWN	0.02621	ITA	0.0134	CAN	0.01767	GBR	0.00606	SWE	0.00995	IRL	0.00452
Transport				**Textile**				**Agriculture**			
	1995		**2011**		**1995**		**2011**		**1995**		**2011**
USA	0.06882	USA	0.03351	USA	0.02793	CHN	0.0115	FRA	0.0272	CHN	0.00898
GBR	0.04124	CHN	0.03123	ITA	0.01761	USA	0.00262	USA	0.01971	USA	0.00619
DEU	0.03584	GBR	0.01295	DEU	0.01657	IND	0.00206	DEU	0.0146	BRA	0.00437
FRA	0.02625	DEU	0.0123	CHN	0.01513	ITA	0.00193	CHN	0.01423	FRA	0.00391
ITA	0.02387	MEX	0.01064	KOR	0.01384	TUR	0.00182	GBR	0.00964	DEU	0.0028
NLD	0.02128	AUS	0.00664	BEL	0.01279	IDN	0.00178	CAN	0.00922	MEX	0.00262
CAN	0.01946	FRA	0.00592	TWN	0.01101	KOR	0.00175	NLD	0.00696	CAN	0.00257
MEX	0.01716	IND	0.00591	FRA	0.01012	DEU	0.00146	JPN	0.00654	IDN	0.00158
JPN	0.01675	JPN	0.00582	GBR	0.00948	TWN	0.00125	BRA	0.00636	JPN	0.00147
AUS	0.01506	KOR	0.00579	NLD	0.0079	MEX	0.00106	ESP	0.00596	AUS	0.00131

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Appendix I: WIOT Structure

			Use by country-industries							Final use by countries			Total use
			Country 1			...	Country M			Country 1	...	Country M	
			Industry 1	...	Industry N	...	Industry 1	...	Industry N		...		
Supply from country-industries	Country 1	Industry 1											
		...											
		Industry N											
	......												
	Country M	Industry 1											
		...											
		Industry N											
Value added by labour and capital													
Gross output													

Appendix II: Sectoral Aggregation

Sector	**Abbreviation**
Agriculture, Hunting, Forestry and Fishing	Agriculture
Mining and Quarrying	Mining
Food, Beverages and Tobacco	Food
Textiles and Textile Products	Textile
Leather, Leather and Footwear	
Wood and Products of Wood and Cork	Paper
Pulp, Paper, Paper , Printing and Publishing	
Coke, Refined Petroleum and Nuclear Fuel	Chemical
Chemicals and Chemical Products	
Rubber and Plastics	
Other Non-Metallic Mineral	
Basic Metals and Fabricated Metal	Metal
Machinery, Nec	Machinery
Electrical and Optical Equipment	Electrical
Transport Equipment	Trans. Equip.
Manufacturing, Nec; Recycling	Manufacturing
Electricity, Gas and Water Supply	Electricity
Construction	Construction
Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	Sales
Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	
Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	
Hotels and Restaurants	
Inland Transport	Transport
Water Transport	
Air Transport	
Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	
Post and Telecommunications	
Financial Intermediation	Financial
Real Estate Activities	Business
Renting of M&Eq and Other Business Activities	
Public Admin and Defence; Compulsory Social Security	Others
Education	
Health and Social Work	
Other Community, Social and Personal Services	
Private Households with Employed Persons	