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An Input-Output Network Structure Analysis Of Selected Countries

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Abstract

Network analysis is a very effective method which can be used in many different disciplines. It is possible to use network analysis in many areas of economics as well. Recently, input-output tables attracted economists who work in this area. Input-output tables give an important source of data for examining the productive significance of sectors since they reflect the intersectoral flows of intermediate goods. In this study, national input-output networks of selected nine countries which are in different levels of development and which have an important place in world trade are examined. This kind of an analysis may help us understand whether or not there is a connection between development levels and sectoral relationships.

Keywords: Input-output analysis, network analysis, complex systems.

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1 Introduction

Determining the production structure of countries and comparison of the production structures with other countries is the concern of many studies. This kind of analysis may form a base for international trade, may help to understand the mechanism of economic growth, and to analyze the economic problems which involves interdependence (Chenery and Watanabe, 1958). Determining strategies for development is related to determining the key sectors in the economy (Hewings, 1982).

The pioneering study on intersectoral linkages is considered to be the work by Hirschman (1958). This study together with studies by Rasmussen (1956) and Chenery and Watanabe (1958) are considered to be pioneering studies on analyzing the linkages between the sectors using input-output tables (Atan and Arslanturk, 2012). Input-output tables are balanced sheets which represent the intersectoral flows in monetary terms for a given year. They enable one to calculate the forward and backward linkages of the sectors and also to determine the effects of sectoral changes on the other sectors or on the whole economy.

Studies on the inter-sectoral connectedness in emerging economies generally focus on the control of services (Freytag and Fricke, 2017). For example, Tregenna (2008) analyzed sectoral linkages in South Africa and Rashid (2004) studied the Pakistani economy. Both showed that the manufacturing and the service sectors have an important role in the development of these countries. Hansda (2005) and Singh (2006) analyzed the Indian economy and showed the importance of the service sector (Freytag and Fricke, 2017).

Pure input-output analyses are later improved to qualitative input-output analyses and to Minimal Flow Analysis (MFA) ((Aroche-Reyes, 2002);(Schnabl, 1994); (West and Brown, 2003)). MFA makes

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use of graph theoretical methods. Aroche-Reyes (2002) determined the important coefficients in the input-output tables of Canada, USA and Mexico. He used both graph theoretical tools and qualitative input-output techniques. West and Brown (2003) analyzed the Taiwanese economy by using six input-output tables each containing 39 sectors in order to address the structural change in Taiwan.

A further improvement to input-output analyses is to add functional forms to the model. These models are referred to as the "production networks". Here, the diffusion of productivity shocks are analyzed (Liu, 2017). Liu (2017) gave examples of these studies: Long Jr and Plosser (1983), Horvath (1998, 2000), Dupor (1999), Shea (2002) and Acemoglu *et al.* (2012).

Network analysis is an effective tool for analyzing systems with interacting actors. Its applications can be seen in a wide range of disciplines including biology, sociology, finance, and economics. Economic systems include many interacting agents. Considering the interactions and including them in the models have a special importance since the behavior of the economy as a whole cannot be examined by the behavior of isolated individuals Michael and Battiston (2009) and also the models excluding the interaction patterns from their analysis may not provide a full understanding of certain phenomena (Jackson, 2010).

Gathering the two effective methods, namely the input-output and the network analyses, gives a powerful tool to examine the interrelated systems. It is possible, for example, to determine the position and the effectiveness of the sectors within the input-output network and this in turn gives us an insight of how the system works and how the effect of shocks or interventions on a certain sector may affect the others. We will give some examples of the studies using input-output networks.

The relationship between the individual industrial shocks and the overall macroeconomic fluctuations is the concern of many studies. The law of large numbers indicates that positive shocks in some sectors are offset by negative shocks in other sectors (Horvath, 1998). It was important to note that the applicability of the law of large numbers was dependent on the positions of the sectors in the input-output network. In fact, if the input-use matrix has only a few full rows and many sparse columns, indicating that there are small number of sectors providing intermediates to production in many sectors, the aggregate volatility will be high (Horvath, 1998). The model applied to the U.S. data shows that "as much as 80% of the volatility in U.S. gross domestic product growth rates could be the result of independent shocks to two-digit SIC sectors" (Horvath, 1998). Carvalho (2008) also analyzed the structure of input trade in the U.S. and saw that there were many specialized input suppliers together with general purpose sectors that are "hubs" in the economy. The presence of these hubs is shown to aggregate fluctuations.

Duan (2012) built a model to analyze the evolutionary dynamics of national economies. He tried to relate the overall economic dynamics to the dynamics of the individual industries. By examining an input-output network it is seen that all the nodes in the model have the same dynamic importance. Based on this, an economic evolution model which is based on the coupled dynamics of industry price, output quantity, and input-output network was built. Results showed that the model can reproduce the evolutionary dynamics of price, output quantity, and input-output network simultaneously.

Kuroiwa *et al.* (2014) decomposed the gross exports of China using Asian international input-output tables. He then analyzed the technological intensity of China's exports. This kind of analysis enables us to consider the imported intermediates within the exported goods. Removing the foreign content from the export values enables us to capture the value added by only the domestic factors of production. In fact, results show that due to these components, the technological intensity of China's exports was overestimated.

A study by Acemoglu *et al.* (2016) deals with the underlining reasoning of macroeconomic fluctuations due to the propagation of macroeconomic shocks through input-output and geographic networks. 392 industry input-output tables were analyzed for four types of industry-level shocks. The results show that all four shocks result in statistically and economically important propagation throughout the input-output network.

Foerster *et al.* (2011) constructed a model to explain the variability in aggregate U.S. industrial activity measured by the IP index (The Federal Reserve Board's Index of Industrial Production). They show that before 1984 about 20% of the variations in IP could be explained by sector-specific shocks, while 50% of the variations were explained in Great Moderation.

Input-output analysis takes a special place in measuring vertical specialization, namely the use of imported inputs in producing goods that are exported (Hummels *et al.*, 2001). Analyzing the input-output tables of 10 OECD countries Hummels *et al.* (2001) showed that from 1990 more than 21% of the total exports of these countries could be represented by vertical specialization exports. For smaller countries, and those outside the OECD database, vertical specialization was about 40 percent of the exports. Also, they showed that vertical specialization has grown about 30% since 1970.

They also developed a model which is an extension of the Dornbusch *et al.* (1977) model and concluded that vertical specialization can result in greater welfare gains from trade in two ways. First of all, a finer division of labor is possible with increased specialization in the individual stages of production. Secondly, with vertical specialization for any given trade barrier reduction, trade and the gains from trade will be greater.

In Hummels *et al.* (2001) it was assumed that a country's exports are entirely absorbed in final demand abroad. Johnson and Noguera (2012) relaxed this assumption and constructed a model which enables one to consider the case where a country's exports intermediates that are used to produce final goods absorbed at home. Bilateral exports decomposed into parts that "absorbed in the destination, embedded as intermediates in goods that are reflected back to the source country, or redirected to third countries embedded as intermediates in goods ultimately consumed there". This decomposed bilateral trade values together with input-output data is used to compute the value added content of bilateral trade. It is seen that the value added and gross trade flow differ significantly. This is a sign of heterogeneity in the production sharing relationships. The ratio of the value added to gross exports is a measure of the intensity of production sharing. It gives a measure of the domestic part of the exports. The variation in this ratio is due to bilateral production linkages, not variations in the composition of exports.

From here one can pass to the global chain. We paid attention to discuss the global chain rather than the international trade in national accounts. Trade statistics may be misleading since they attribute the whole value of the final good to the final exporter country. However, many countries may provide inputs to that good and the final production may be a small share of the whole value (Powers, 2012). Trade must be evaluated in terms of value-added and the position in the global chain must be considered. There are many studies on global chain (e.g (Bogataj *et al.*, 2011); (Dazhong, 2015); (Frohm *et al.*, 2017); (Neilson *et al.*, 2014)). In this study, we concentrated on the internal structure of the inter-industrial networks. Therefore, we did not go into the details of the international aspect.

Recognition of the importance of the inter-industrial relationships led the studies to construct models that can capture these relationships. Going beyond the analytical calculations, it is important to look at the picture in a network perspective. Classical models not considering the interaction patterns are unable to explain certain phenomena. Economic activities are highly influenced by network structure (Jackson, 2010).

In this study, we analyze the input-output network structure of selected countries with different development levels: China, Germany, Indonesia, India, Japan, Mexico, Russia, Turkey and USA. By displaying the flow of intermediates, we determined the core sectors in terms of both the inflows and the outflows of goods. We examined the relationship between the structures of the networks and the development levels of the selected countries.

In the next section the methodology used in this study is explained. In the following sections the outlook of the countries that are considered and the research results are given.

2 Data and Methodology

The data used in this study have been obtained from World Input-Output Database (WIOD). WIOD involves 43 countries (EU-28 and 15 major economies of the world such as Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Norway, Russia, South Korea, Switzerland, Taiwan, Turkey and the USA). Moreover, the data includes another region which is called ?rest of the world (RoW)? that represents the non-included part of the World economy. The data used in the analysis have been built by using National Input-Output Tables (NIOT) of selected countries from different level of development. A national input-output table covers 56 industries and products mostly at the two-digit ISIC Rev.4 level (Timmer *et al.*, 2016). We have condensed these 56 sectors into 18 sectors. NIOT structure and sectoral aggregation can be found in the Appendix.

The first step in understanding complex systems is the 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 them. In this context, policymakers have become interested in network analysis to determine the weaknesses of their concerns since these tools are applied to most real-world networks (Oecd, 2009).

A network is defined 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):

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

In weighted networks 1's in the matrix A_{ij} will be replaced by the weights that are assigned to the link between i and j.

One of the extents which are analyzed to get information about the topological properties of a network is connectivity. Connectivity is measured by node degree/node strength on the node-level. Higher node degree/strength means a stronger impact over the network (Howell, 2012). On the 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 can be 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 $0 \leq \rho \leq 1$.

Another term to be analyzed is clustering which refers to the relationship between two nodes which have links with a node in common. Clustering is also an indicator of transitivity in a network. The clustering coefficient can also be measured both in the node-level and in the network-level. The general clustering coefficient for a weighted network is formalized as follows (Opsahl and Panzarasa, 2009):

$$c_w = \frac{\text{Total value of closed triplets}}{\text{Total value of triplets}} = \frac{\sum_{\tau \Delta w}}{\sum_{\tau} w^{max}} \tag{3}$$

where T_i represents the count of triangles passing through the node i. The clustering coefficient in the network-level which is denoted as C is obtained by averaging c_i values. Clustering coefficients both in the node-level and in the network-level lie in the interval [0,1].

Degree distribution is another informative property about network topology. It has been indicated in the literature that most real-world networks such as movie networks, www, electrical power grid networks and citation networks follow power-law distribution (Barabási and Albert, 1999). These networks which follow power-law distribution are called 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 a 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 if one rescales and reshapes the distribution by focusing on a smaller part of the curve, the shape obtained will look like the previous shape. Finally, scale-free networks have small-world property which requires small average path length and a large degree of clustering.

It is known that power-law distributions belong to the class of fat-tailed distributions which have higher peaks and fatter tails when compared to Poisson distributions. Power-law distribution can be represented as follows (Hein *et al.*, 2006):

$$P(k) \approx k^{-\gamma} \tag{4}$$

In the statement above, $P(k)$ shows the probability of the occurrence of nodes with degree k in the network. 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 another words, a network with a lower value of γ has a higher quantity of super-nodes which have many links when compared to a network with a higher value of γ. It can also be interpreted as the higher exponent level implies less heterogeneity of connectedness (León and Berndsen, 2014).

One way to determine fat-tailed distributions is to look at the kurtosis. If the kurtosis has a positive value, then the distribution follows a fat-tail distribution (DeCarlo, 1997). It is also stated that most real world networks display right-skewed distributions 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 the skewness measure has a positive value, then the fat-tail is on the right and the distribution is right-skewed and vice versa (Lovric, 2010).

Centrality is another important topological property of a network. However, it is more convenient to examine assortativity/disassortativity in order to understand the importance of centrality. Assortativity means that nodes with high degree/strength tend to have links with nodes which have high degree/strength. However, nodes with high degree/strength tend to have a relationship with nodes with low degree/strength in the disassortative case (Reichardt, 2008). There are two ways to determine assortative/disassortative structures in a network. One way is to plot degree and ANND statistics on the same graph and to note the relationship between them. ANND is a statistic which shows how connected neighbors of node i are to one another (Fagiolo *et al.*, 2010). It is given by the formula (Xiang *et al.*, 2016):

$$\overline{k_{nn}}(k) = \sum_{k'} k' P(k'|k) \tag{5}$$

$P(k'|k)$ is the conditional probability that a vertex of degree k is connected to a vertex of degree k'. By replacing the expression for $P(k'|k)$ for this formula may also be stated as:

$$\overline{k_{nn}}(k) = \sum_{j} j \frac{e_{jk}}{\sum_j e_{jk}} = \sum_{j} j \frac{e_{jk}}{q_k} \tag{6}$$

It is possible to decide if there is a disassortative structure in a network. If the relationship between the degree and the ANND is positive, there is an assortative structure in the network. On the contrary, if the relationship between the degree and the ANND is negative, then there is a disassortative structure in the network.

The second way to determine an assortative/disassortative structure is to calculate the assortativity correlation coefficient. Newman defines the assortativity coefficient by adjusting the standard Pearson correlation coefficient as follows (Newman, 2010):

$$r = \frac{\sum_{ij} ij(e_{ij} - a_i b_j)}{\sigma_a \sigma_b} \tag{7}$$

where $a_i = \sum_j e_{ij}$ and $b_j = \sum_j e_{ij}$ are fraction of edges starting and ending at node i and node j, respectively and σ_a and σ_b are the standart deviations of the distributions of a_i and b_j. This 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 for a core-periphery structure in a network (Fuge *et al.*, 2014). The centrality measure enables one to determine the nodes in the core and the periphery. There is a number of centrality measures such as degree centrality, betweenness centrality, closeness centrality, eigenvector centrality etc. used to measure the importance of the nodes in a network.

HITS algorithm was developed by Kleinberg to calculate hub and authority centralities of web pages which are results of a specific query on the Internet. He based his analysis on a directed network in his original study. 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's aim was to calculate two different centrality measures for these distinct types of nodes.

(Kleinberg, 1999) noted that these authoritative pages which are related to the initial query should not only have large in-links, but it is also necessary for there 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 a mutually reinforcing relationship which means that a good hub is a node which points to many good authorities and a good authority is a node which is pointed to by many good hubs. Kleinberg used an algorithm, called 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 $y^{<p>}$. There are two operations ($\mathcal{I}$ and $\mathcal{O}$) which update these weights. $\mathcal{I}$ updates the x weights and $\mathcal{O}$ updates the y weights during the iterations. Kleinberg also expressed this mutually reinforcing relationship between hubs and authorities by equations as follows:

$$\begin{aligned} x^{<p>} &\leftarrow \sum_{q:(q,p)\in E} y^{<p>} \\ y^{<p>} &\leftarrow \sum_{q:(q,p)\in E} x^{<p>} \end{aligned} \tag{8}$$

As it is understood from Equation (8), the authority weight of a node is proportional to the hub weights of the nodes pointing to it. Similarly, the hub weight of a node is proportional to the authority weights of the nodes it points to.

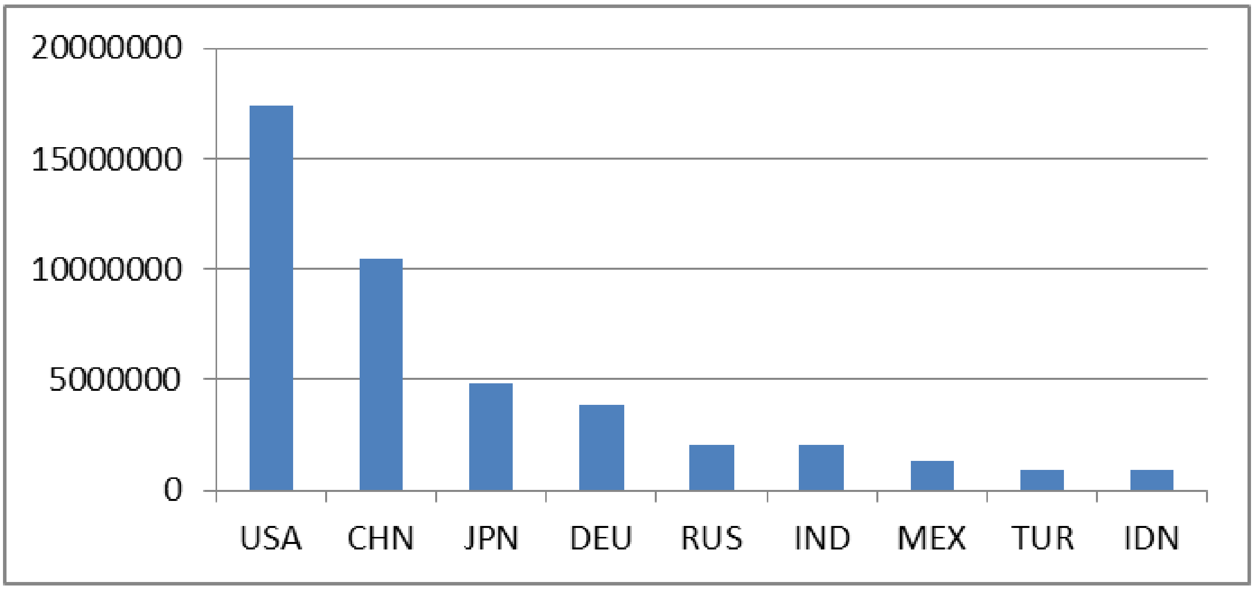
First of all, Kleinberg (1999) defined a vector y which elements consist of $y^{<p>}$ values and a vector x which elements consist of $x^{<p>}$. Assuming that $G = (V, E)$ with $V = p_1, p_2, ..., p_n$ and $\mathbf{A}$ is adjacency matrix of graph G, he proved that y and x converge to their equilibrium 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 method 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) explain the logic behind these hub and authority matrices(León and Perez, 2013). 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.

3 Country Outlooks

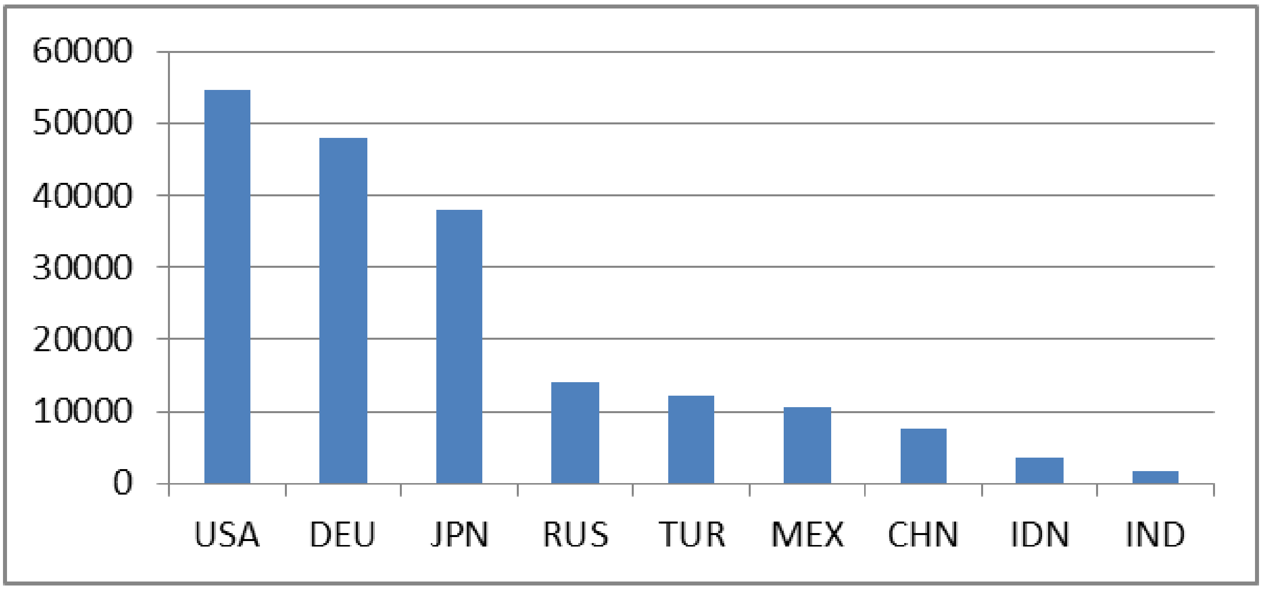
In this study, selected countries which are on different development levels are considered. Figure (1) shows the GDPs of these countries in terms of current million US dollars in 2014. The USA is well ahead in current GDP values. China, the closest follower of USA, has a GDP score which is 60% of USA's GDP. Japan's GDP is less than half of China's GDP. Indonesia has the lowest current GDP.



SOURCE: World Bank

Figure 1: GDP Values in Current Million $

When the per capita GDP is considered, China falls into seventh position. The first three countries are USA, Germany and Japan, respectively. In fact, these countries hold their positions in the top three throughout the period considered, although the second and third place show changes between Germany and Japan. Even the closest follower Russia has much lower per capita GDP values, being two fifth of Japan's per capita GDP in 2014. The lowest score is for India. Up to 2008, Indonesia was a close follower of India, but since 2008 the difference between the per capita GDP's of India and Indonesia has increased in favor of Indonesia (Figure (2)).



SOURCE: World Bank

Figure 2: Current GDP Per Capita ($)

The ranking of share of agriculture in GDP is inversely related to the ranking of per capita GDP for the countries in the first and second places (Figure (3)). So, the largest agricultural share is observed for India and India is followed by Indonesia. The lowest values are observed for USA, Germany and Japan with around one percent of GDP.

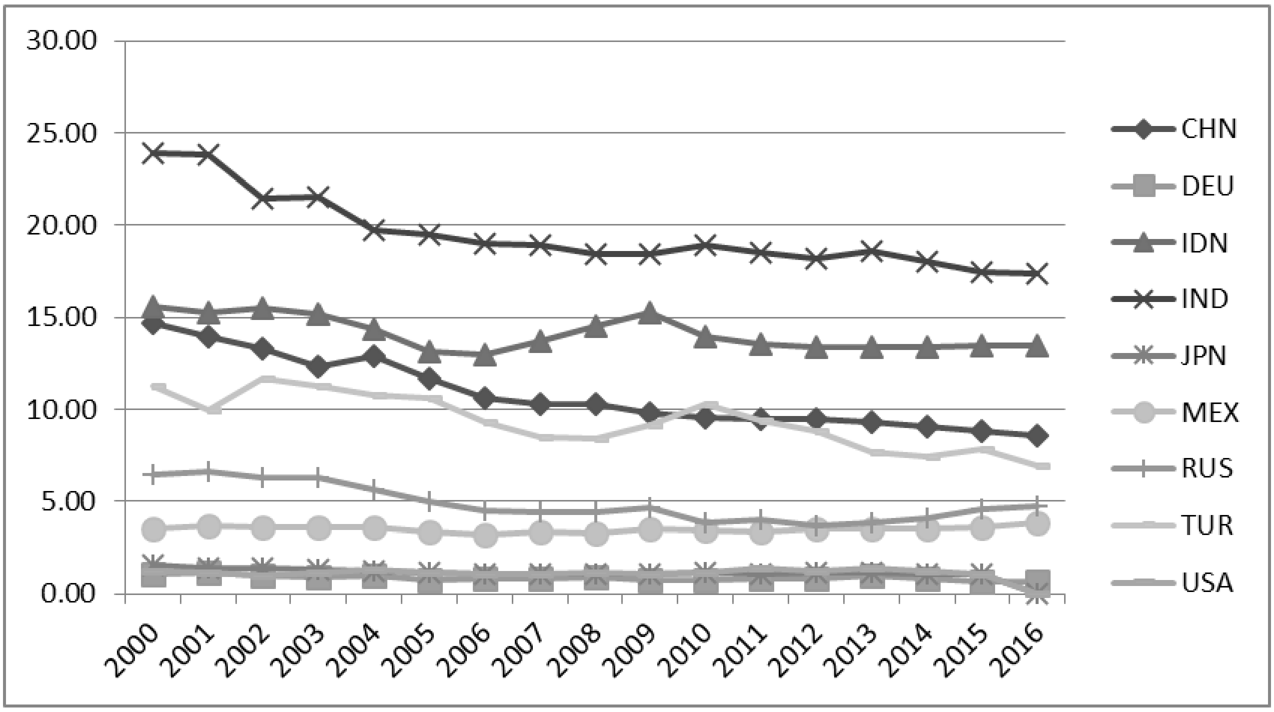


Figure 3: Agricultural Shares in GDP (2000-2014).

As expected for the developed countries, the service sector's share in GDP is much higher than for the developing countries. The highest share is observed for USA with 75% in 2014. USA is followed by Japan and Germany with 69% and 62% in 2014, respectively. The lowest share is observed in Indonesia at 42% in 2014. Service sector GDP shares are very close for China and India. Both countries saw an increase from around 40% in 2000 to 48% in 2014 (Figure (4)).

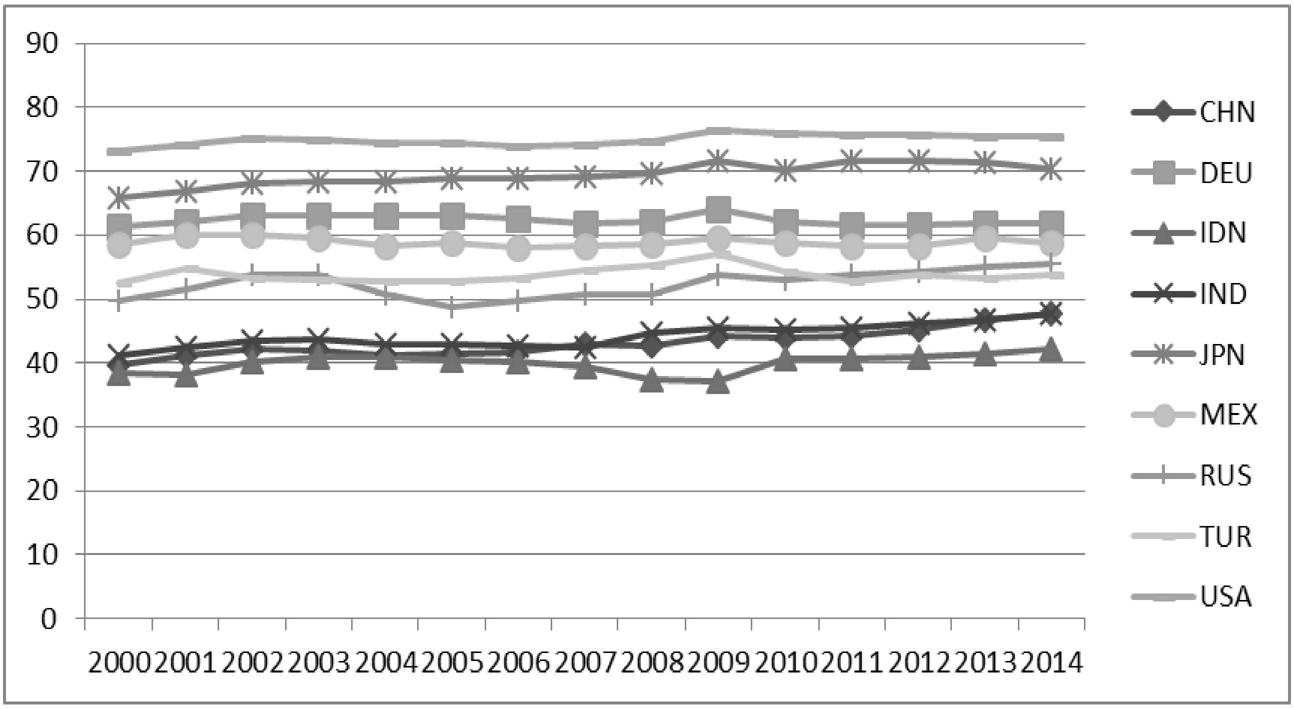


Figure 4: Service Sector Shares in GDP (2000-2014).

4 Results

In this analysis we aim to determine the input-output structure of the intersectoral relationships in the selected countries. Network analysis posses some useful measures in this manner.

The first measure considered is the density coefficients which are also indicators of connectivity (Table (1)). When the density coefficients of countries are considered, the density values of Germany, Japan and the USA are equal to 1, meaning that all possible connections are made and the input-output network structures of these countries represent a complete network structure. However, the density coefficients of other countries are less than 1, meaning that some domestic sectors in these countries are not connected to one another in terms of intermediate good flow.

As mentioned above, another important property of a complex network is assortativity/disassortativity which is also an indicator of the core-periphery structure. If the assortativity correlation coefficient is less than zero then there is a disassortative structure, meaning that there is a core-periphery structure in the network. If the assortativity correlation coefficient is greater than zero, then there is an assortative structure in the network. Values in Table (2) indicate that assortativity correlation coefficients have a negative value for all countries each year. Thus, it can be concluded that all the countries have a core-periphery structure in their national input-output structures. This structure, together with the density coefficients, implies that there are some core (hub) sectors and some periphery sectors in the national input-output network and these hubs and peripheries are generally connected to one another.

Years	China	Germany	Indonesia	India	Japan	Mexico	Russia	USA	Turkey
2000	0.886	1.000	0.944	0.879	1.000	0.974	0.784	1.000	0.889
2001	0.886	1.000	0.958	0.879	1.000	0.974	0.784	1.000	0.889
2002	0.886	1.000	0.958	0.879	1.000	0.974	0.784	1.000	0.889
2003	0.886	1.000	0.958	0.879	1.000	0.974	0.784	1.000	0.889
2004	0.886	1.000	0.958	0.879	1.000	0.974	0.784	1.000	0.889
2005	0.886	1.000	0.902	0.879	1.000	0.974	0.784	1.000	0.889
2006	0.886	1.000	0.993	0.879	1.000	0.974	0.784	1.000	0.889
2007	0.886	1.000	0.993	0.879	1.000	0.974	0.784	1.000	0.889
2008	0.889	1.000	0.993	0.879	1.000	0.928	0.784	1.000	0.889
2009	0.889	1.000	0.993	0.879	1.000	0.928	0.784	1.000	0.889
2010	0.889	1.000	0.987	0.879	1.000	0.974	0.784	1.000	0.889
2011	0.889	1.000	0.987	0.879	1.000	0.928	0.784	1.000	0.889
2012	0.889	1.000	0.987	0.879	1.000	0.928	0.784	1.000	0.889
2013	0.889	1.000	0.987	0.879	1.000	0.931	0.784	1.000	0.889
2014	0.889	1.000	0.987	0.879	1.000	0.925	0.784	1.000	0.889

Table 1: Density Coefficients

Years	China	Germany	Indonesia	India	Japan	Mexico	Russia	USA	Turkey
2000	-0.061	-0.059	-0.073	-0.061	-0.059	-0.060	-0.067	-0.059	-0.063
2001	-0.061	-0.059	-0.069	-0.060	-0.059	-0.059	-0.067	-0.059	-0.063
2002	-0.062	-0.059	-0.070	-0.061	-0.059	-0.059	-0.067	-0.059	-0.063
2003	-0.061	-0.059	-0.070	-0.059	-0.059	-0.060	-0.067	-0.059	-0.063
2004	-0.061	-0.059	-0.072	-0.059	-0.059	-0.059	-0.067	-0.059	-0.063
2005	-0.061	-0.059	-0.077	-0.058	-0.059	-0.058	-0.067	-0.059	-0.063
2006	-0.062	-0.059	-0.057	-0.058	-0.059	-0.059	-0.067	-0.059	-0.063
2007	-0.062	-0.059	-0.057	-0.059	-0.059	-0.058	-0.067	-0.059	-0.063
2008	-0.063	-0.059	-0.057	-0.059	-0.059	-0.069	-0.067	-0.059	-0.063
2009	-0.063	-0.059	-0.056	-0.059	-0.059	-0.055	-0.067	-0.059	-0.063
2010	-0.063	-0.059	-0.049	-0.059	-0.059	-0.058	-0.067	-0.059	-0.063
2011	-0.063	-0.059	-0.049	-0.059	-0.059	-0.070	-0.067	-0.059	-0.063
2012	-0.063	-0.059	-0.048	-0.060	-0.059	-0.064	-0.067	-0.059	-0.063
2013	-0.063	-0.059	-0.049	-0.059	-0.059	-0.061	-0.067	-0.059	-0.063
2014	-0.063	-0.059	-0.049	-0.058	-0.059	-0.065	-0.067	-0.059	-0.063

Table 2: Assortativity Correlation Coefficients

Another important aspect is the fitness of degree/strength distribution in the network analysis to the power-law distribution. This distribution indicates the heterogeneous structure of the network connections. One method to determine the fitness for a power-law distribution is to check skewness and kurtosis values. These values determined for the countries of interest are shown in Table 3. As mentioned in methodology, positive skewness and kurtosis values imply right-skewed and fat-tail distribution, respectively. By studying the values in Table 3, we see that all countries have positive skewness and kurtosis values for all years.

Years	China		Germany		Indonesia		India		Japan		Mexico		Russia		USA		Turkey	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
2000	0.94	3.14	2.29	8.00	1.38	4.14	0.81	2.14	0.90	2.49	1.21	3.15	1.53	4.35	1.72	5.43	1.01	2.45
2001	0.84	2.83	2.27	7.87	1.29	3.84	0.81	2.17	0.90	2.50	1.16	3.03	1.49	4.11	1.66	5.21	1.04	2.59
2002	0.83	2.80	2.30	7.99	1.15	3.27	0.79	2.12	0.90	2.49	1.17	3.14	1.50	3.99	1.64	4.94	1.26	3.31
2003	0.93	3.10	2.29	7.95	1.15	3.08	0.83	2.17	0.88	2.43	1.22	3.31	1.36	3.45	1.65	4.96	1.31	3.37
2004	0.93	3.14	2.35	8.30	0.99	2.67	0.89	2.33	0.86	2.39	1.10	2.92	1.29	3.31	1.65	4.99	1.33	3.44
2005	0.96	3.16	2.38	8.46	0.87	2.34	0.97	2.46	0.80	2.20	1.09	2.84	1.23	2.94	1.60	4.83	1.33	3.43
2006	0.99	3.29	2.41	8.64	0.92	2.36	0.94	2.35	0.78	2.12	1.12	2.88	1.25	3.01	1.56	4.63	1.42	3.75
2007	1.11	3.72	2.45	8.80	0.95	2.48	0.90	2.27	0.79	2.16	1.10	2.84	1.25	3.08	1.53	4.50	1.42	3.84
2008	1.06	3.55	2.46	8.82	0.99	2.58	0.90	2.30	0.82	2.20	1.04	2.65	1.29	3.14	1.47	4.34	1.51	4.23
2009	1.18	4.18	2.55	9.47	1.01	2.58	0.94	2.38	0.88	2.43	1.12	3.01	1.31	3.17	1.56	4.44	1.34	3.87
2010	1.19	4.40	2.56	9.54	1.08	2.83	0.93	2.38	0.83	2.31	1.13	2.94	1.29	3.14	1.57	4.58	1.37	3.91
2011	1.25	4.59	2.55	9.43	1.09	2.86	0.92	2.33	0.83	2.28	1.11	2.81	1.24	2.96	1.53	4.43	1.56	4.45
2012	1.21	4.47	2.57	9.60	1.02	2.59	0.98	2.61	0.83	2.28	1.10	2.79	1.27	3.03	1.55	4.49	1.61	4.62
2013	1.16	4.36	2.65	9.94	1.02	2.67	1.14	3.17	0.84	2.34	1.15	2.98	1.29	3.13	1.61	4.75	1.61	4.62
2014	1.05	4.03	2.63	9.88	1.05	2.79	1.20	3.34	0.83	2.33	1.16	3.04	1.39	3.49	1.66	4.89	1.65	4.71

Table 3: Skewness and Kurtosis Measures

Years	China			Germany			Indonesia			India			Japan			Mexico			Russia			USA			Turkey		
	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value	Exponent of power-law	KS statistic	p-value
2000	4.84	0.14	1.00	2.00	0.12	0.96	2.48	0.18	0.94	1.76	0.18	0.66	2.05	0.16	0.83	1.70	0.18	0.64	1.71	0.16	0.82	2.02	0.15	0.82	1.90	0.15	0.84
2001	4.42	0.17	0.99	2.03	0.11	0.98	2.70	0.15	0.99	1.70	0.17	0.73	2.07	0.17	0.79	1.70	0.19	0.58	1.77	0.15	0.85	2.22	0.16	0.83	1.81	0.13	0.90
2002	2.13	0.18	0.66	2.00	0.11	0.99	2.58	0.17	0.96	1.68	0.17	0.71	2.07	0.18	0.75	2.01	0.17	0.86	1.92	0.14	0.89	2.21	0.17	0.76	1.67	0.16	0.78
2003	3.78	0.16	0.99	2.00	0.11	0.98	2.23	0.18	0.89	1.74	0.17	0.72	2.09	0.18	0.74	2.34	0.19	0.91	1.88	0.15	0.91	2.35	0.18	0.66	1.72	0.17	0.70
2004	2.52	0.18	0.78	1.97	0.17	0.81	1.40	0.22	0.32	1.78	0.15	0.83	2.09	0.17	0.80	2.75	0.22	0.76	1.76	0.13	0.97	2.27	0.18	0.66	1.94	0.18	0.79
2005	2.40	0.19	0.72	1.96	0.14	0.91	2.19	0.22	0.74	1.82	0.15	0.83	2.08	0.17	0.76	2.67	0.22	0.76	1.79	0.13	0.96	2.16	0.17	0.74	2.14	0.23	0.66
2006	2.47	0.19	0.72	1.96	0.13	0.92	1.99	0.22	0.68	1.85	0.15	0.81	2.06	0.18	0.69	1.57	0.23	0.33	1.80	0.14	0.96	2.07	0.16	0.79	1.95	0.16	0.88
2007	2.69	0.19	0.73	1.96	0.13	0.92	1.49	0.19	0.53	1.83	0.15	0.84	2.05	0.19	0.66	15.58	0.23	0.99	1.75	0.15	0.89	2.13	0.16	0.81	2.02	0.15	0.96
2008	2.79	0.14	0.96	1.91	0.15	0.86	1.57	0.21	0.41	1.75	0.15	0.82	2.03	0.19	0.67	1.50	0.28	0.20	1.87	0.13	0.97	2.16	0.13	0.93	1.93	0.20	0.62
2009	2.85	0.13	0.98	2.67	0.16	0.97	1.58	0.21	0.40	1.77	0.14	0.90	2.09	0.17	0.76	2.31	0.19	0.89	1.73	0.13	0.97	2.17	0.16	0.78	1.71	0.18	0.72
2010	2.92	0.15	0.95	2.82	0.14	0.99	6.32	0.22	0.99	1.84	0.15	0.83	2.07	0.17	0.75	2.08	0.21	0.78	1.71	0.14	0.93	2.08	0.13	0.94	1.88	0.19	0.70
2011	3.54	0.13	1.00	2.97	0.19	0.91	5.12	0.21	0.98	1.76	0.14	0.87	2.05	0.17	0.76	2.02	0.21	0.78	1.86	0.17	0.87	2.01	0.11	0.99	1.92	0.17	0.85
2012	3.99	0.14	1.00	2.71	0.17	0.99	1.75	0.23	0.56	1.76	0.16	0.75	2.06	0.17	0.78	1.46	0.28	0.13	1.86	0.17	0.83	2.03	0.12	0.97	1.62	0.17	0.75
2013	3.96	0.16	1.00	2.67	0.18	0.98	1.50	0.22	0.33	1.77	0.13	0.91	2.06	0.16	0.81	2.20	0.18	0.90	1.74	0.16	0.84	2.07	0.13	0.96	1.85	0.18	0.75
2014	4.26	0.18	0.97	2.46	0.22	0.94	5.09	0.16	1.00	1.78	0.14	0.88	8.23	0.17	1.00	2.17	0.19	0.88	1.90	0.16	0.88	1.94	0.11	0.99	1.80	0.17	0.83

Table 4: K-S Test Results

This gives an idea as to the fitness of the power-law distribution. Still there is a need to improve the fitness to power-law distribution statistically. Therefore, the Kolmogorov-Smirnov (K-S) test has been applied to the out-strength series. The results can be seen in Table 4.

In this test, H0 hypothesis represents the distribution's coherence with power-law distribution and H1 hypothesis represents the opposite. The p value above 0.05 indicates being outside the H0 red area, indicating H0 to be undeniable. When we look at the p-values, we can conclude that the out-strength of all countries for all years follow the power-law distribution, meaning that there is a heterogeneous structure in the national input-output networks of countries in terms of sectoral connectedness.

As mentioned in the above section, another important topological property is the network's assortativity/disassortativity inclined structure. The correlation coefficient used to determine assortativity or dissassortativity is given in the table below.

Although it is not a perfect disassortativity, still the disassortative structure exists. As mentioned above, a disassortative structure is an indicator of a core-periphery structure. In this sense, it is safe to say that the input-output network of each country has a core-periphery structure.

In the case of core-periphery structure, the centrality measure is used to determine the central sectors in the network. Kleinberg's hub and authority centrality measures have been used in this analysis. Since, hub represents nodes with many outgoing links and the links in the matrix represent export, hub centrality measure can be referred to as export centrality. Similarly, as authority represents nodes with many incoming links, authority centrality measure can be referred to as import centrality.

Hub centrality measures show the position of the sectors as suppliers of intermediates. Network visualizations are formed using this measure. Networks for each country for the period are sketched. Here only the ones which give notable results are shown. Pictures of the networks are especially useful in observing the strength of the links between the sectors. Also, comparing the link structures for different years is easier by network visualization. Below, the hub centrality results together with some of the network views are shown.

Hub centrality measures for China indicate that the most central intermediate good supplier sectors are the chemical sector and the metal sector having an increasing impact (Figure 5). The service sector is third with a decreasing value. In terms of authority centrality measure, the most central intermediate good user sector is construction. Services and electrical equipment follows the construction sector.

The impact of the sectors as intermediate good suppliers is seen in Figure (5). Here, the nodes are the sectors and the links represent the flow of intermediate goods. The thickness of the links reflects the amounts of the flow. So, we have a directed and weighted network. The size of the nodes corresponds to the magnitude of the hub centralities. According to the network visualization, the most hub-central sector is the chemical sector both in 2000 and 2014. It is followed by the metal and the services sectors.

By comparing the connections, for the year 2000 to the year 2014, we see that China showed a significant increase in the amount of intermediate good flows between the national sectors. The most prominent links in 2000 (chemical - construction, chemical - services, agriculture - food, metal - construction) became even thicker in 2014. There were also others, such as links between metal and mining, metal and machinery, and food and services that were weaker in 2000, but became stronger in 2014.

In Germany, the service sector was the largest hub during the period. Professional, scientific and technical activities were the second hub with a decreasing value and the sales sector was third with an almost stable value during the period. On the other hand, the sales sector is the largest authority in the national input-output structure of Germany. The service sector follows with decreasing value. Only the service and the public utility sectors have increasing hub centrality values during the period. All of the other sectors (except for metal and machinery) have decreasing hub values. The values of the metal and the machinery sectors remained stable.

By analyzing the strength of the connections one can observe that there was a significant change

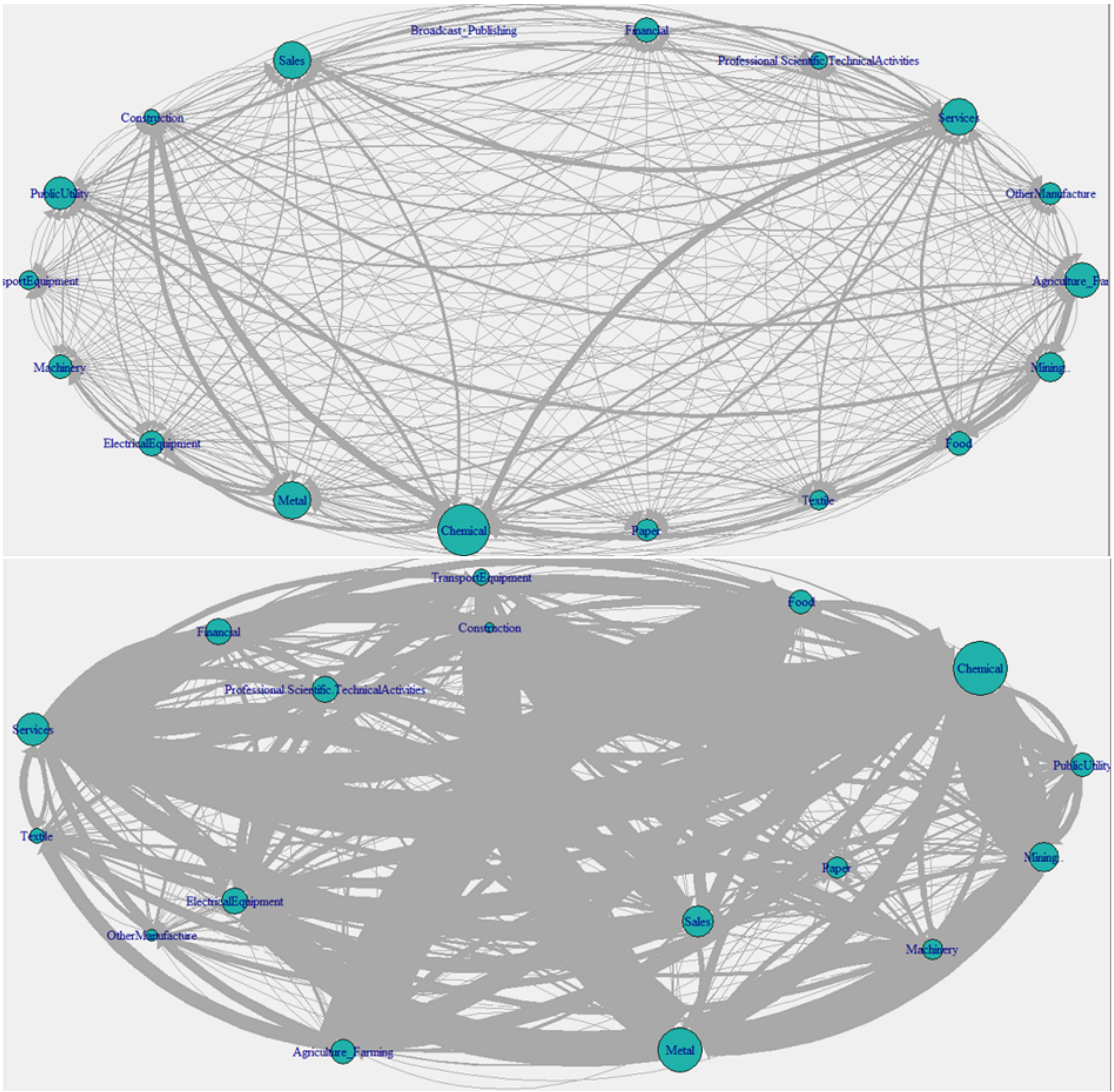


Figure 5: Hub Centralities for China, 2000 and 2014

in the connections of the service sectors from 2000 to 2014. The existing links strengthened while new strong connections were generated such as services - chemical, services ? machinery, transport equipment - metal, transport equipment - sales, etc. On the other hand, the links of the agricultural and farming sector, and the broadcast and publishing sector weakened. In Indonesia, the largest central supplier sector is agriculture-farming. This sector had a severe decline in 2006 when a strong earthquake and tsunami occurred. Sales, chemical and mining sectors follow this sector. The largest central intermediate good user sectors are food, construction, services and chemical.

When comparing the 2000 values to the 2014 values, we see that in 2000 there is no connection coming forward, the connection strengths are close to each other. In 2014, however, there are some additional hub-central sectors such as services, mining and chemical, and some connections gain importance. Connections between chemical - mining, chemical-construction, chemical - services, services - sales, agriculture and farming and food sector, construction and metal, and construction and sales strengthened in 2014 when compared to 2000.

In India, sales, chemical and agriculture-farming have had a high impact as input suppliers to the national economy while construction, food, services and textiles have had a high impact as an input user for the national economy (Figure (6)).

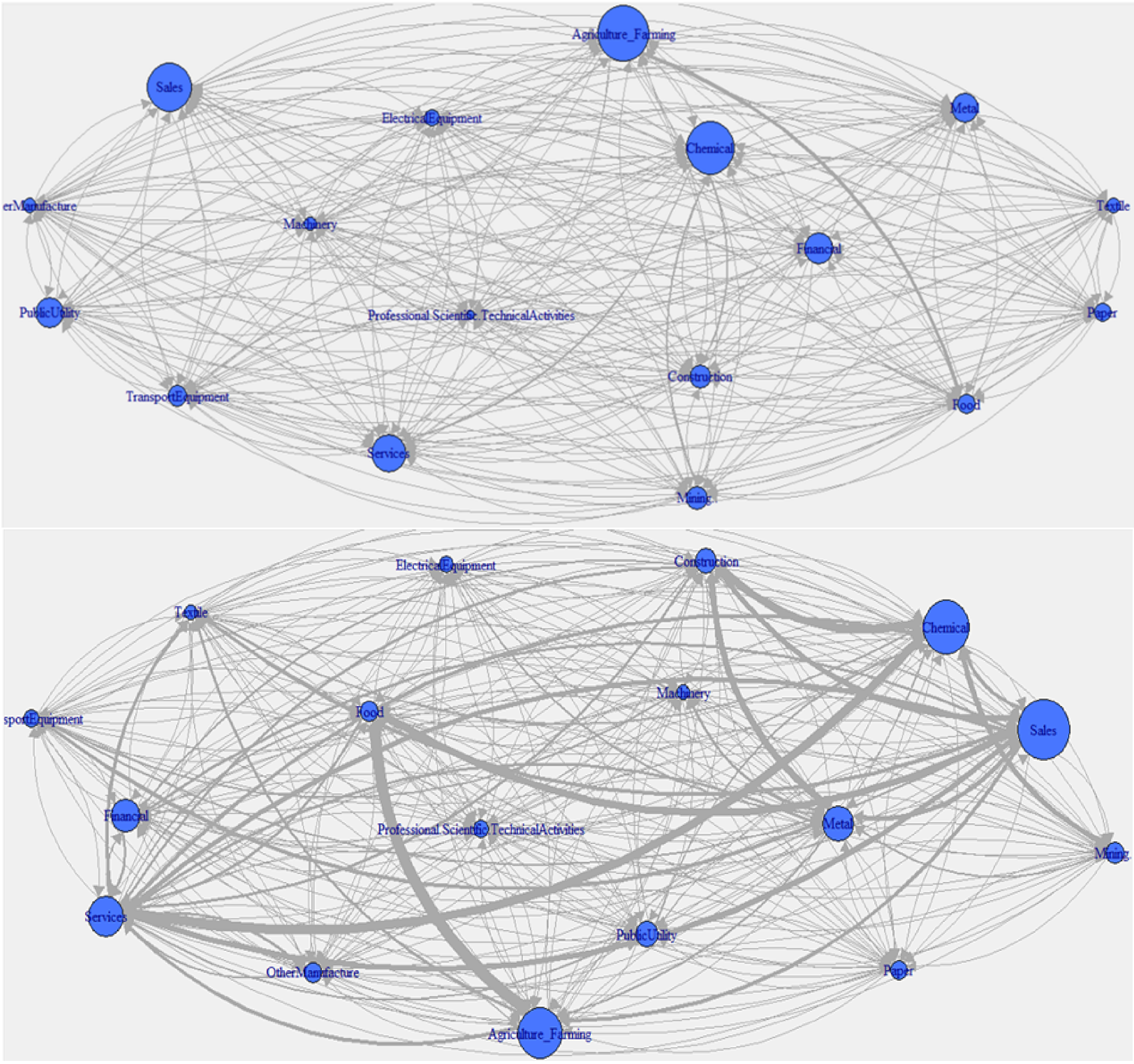


Figure 6: Hub Centralities for India, 2000 and 2014

Comparing the years 2000 and 2014 in terms of hub centralities, we cannot see a significant change in the hub-central sectors of the Indian input-output network. However, the importance of the links changed. There are some connections which were not distinguishable from the other connections in 2000 but became prominent in 2014 such as services - chemical, construction - chemical, construction - metal, sales - food, sales - services, chemical - mining.

In Japan, the professional, scientific and technical activities, sales, chemical and finance are the most important input suppliers to the domestic economy. Hub centrality values for professional, scientific and technical activities and chemical sectors increases during the period while hub centrality values for sales and finance sectors decreases. In terms of authority centrality, the service sector is the most important input user for the domestic economy having an increasing value. Construction and sales sectors follow the service sector with lower and decreasing values during the period.

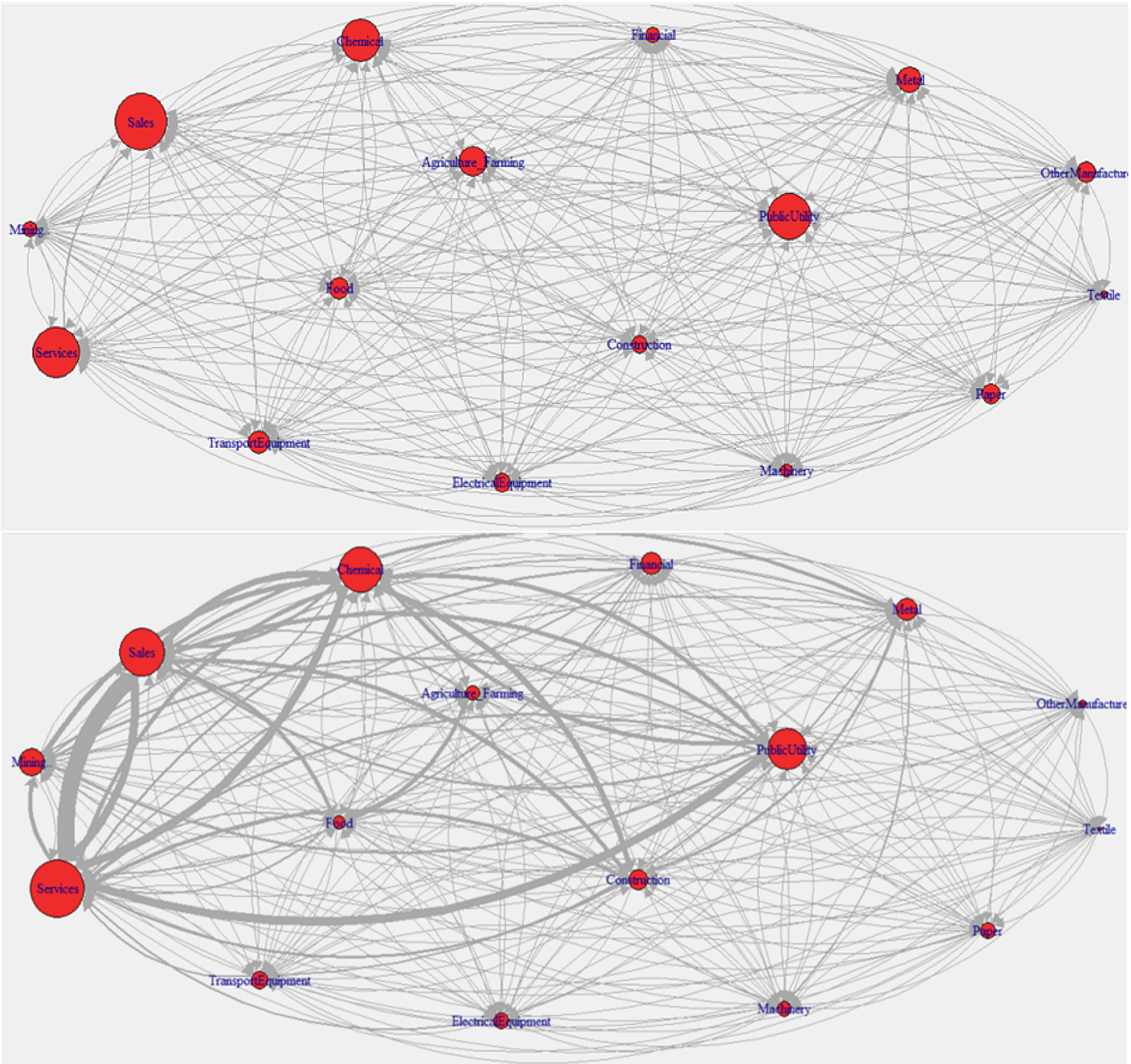


Figure 7: Hub Centralities for Russia, 2000 and 2014

Sectoral connections did not change significantly from 2000 to 2014. Some connections, such as agriculture and farming - food, construction - metal, services - sales, services - finance became weaker in 2014.

In Mexico, the most central input supplier sector is the mining sector with an increasing value of hub centrality for the greater part of the period. Sales and chemical sectors also had a high impact on the national input-output structure as an input provider. However, their values remained almost same by the end of the period, although values fluctuated during the term. When it comes to authority centrality, the chemical sector, services and food sector have the highest values.

There are two apparent sectoral connections (mining - chemical and agriculture and farming - food) in the Mexican national input-output structure in 2000. By 2014, some connections also become apparent such as sales - services, chemical - services. In Russia, there are four top sectors in terms of hub centrality: services, chemical, sales and public utility sectors. While the hub centrality of the sales sector in general shows a decreasing pattern, the chemical sector is generally increasing. There is a visible decline in the hub centralities for the agriculture and farming sector (Figure 7).

When comparing the hub centralities for the year 2000 and 2014, one can observe that the food sectors, other manufacturing sectors and public sectors showed declining centrality measures while the centrality for the mining sector increased. The sectoral connections became much more apparent among the major sectors such as services, sales, chemical and public utility. For example, there was a significant increase in the services - sales connection. Connections such as services - public utility, services - chemical, services - mining, construction - chemical represent other important relationships.

In Turkey, at the beginning of the period, the agriculture-farming sector has the highest hub centrality value. Hub centrality goes into a sharp declining period after 2005, and then increased for the years 2009 and 2010. Afterwards, it declined again. Up to 2006, the agriculture sector was the main intermediate supplier, but after 2011 the service sector replaced the agriculture sector as the main intermediate supplier. Thereafter, service sectors have had the highest hub centrality.

Sales and chemical sectors follow the service sector. Professional, scientific and technical activities sector has shown an increasing trend. As for the authority centrality, the most important input user sector by year 2014 was the sales sector. Services, food and textile sectors follow.

Finally, when we studied the hub centrality for the USA, the professional, scientific and technical activities sectors were the largest hub central sectors and they were followed by the chemical, financial and services sectors. In contrast to the increasing value of the chemical and professional, scientific and technical activities sectors, the financial sector had a decreasing hub value. There was a decline in the hub value for the financial sector in 2008. In 2009, the hub value for the financial sector showed a recovery but the hub value for this sector declined again in 2010. This decline may be the result of the bailout in the US economy after the outbreak of the financial crisis.

The connections of the finance sector with other sectors do not show a change between 2007 and 2009. On the other hand, there was an increase in the value of the connections for the finance sector when comparing the year 2000 to the year 2014. In fact, there was an increase in all the values for the connections from the beginning to the end of the period. When it comes to authority values, the sales sector was the largest central input user from the domestic economy.

One can observe that for all the countries, the chemical sector is in the first five sectors in hub centrality measure. As development levels increase, the role of agriculture as an exporter declines. For USA, Germany and Japan, the professional, scientific and technical activities sectors and the finance sectors had important places as suppliers.

By analyzing the authority centralities, it can be seen that the construction and the service sectors have an important role. In the developed countries, the sales sector accompanies these sectors, while in developing countries we see the food sector accompanying construction and the service sectors. We mentioned that the chemical sector was an important exporter sector. Here we see that it is important as an importer sector as well. Different from hub centrality, we see the transportation sector as one of the most important sectors in terms of import.

We may analyze the hub centralities on a sectoral basis as well. In agriculture, India, Indonesia and Turkey have the highest hub centralities. Except for two years (2005 and 2006), Indonesia has had the highest value. In 2005 and 2006 Turkey came in first place, but it was in third after 2006. One can see the hub centralities for 2014 for agriculture in Figure (8).

Throughout the period the agricultural hub values for China and Russia declined steadily. After 2010 the largest decline in agricultural hub centralities are seen for Turkey. But still Turkey had the

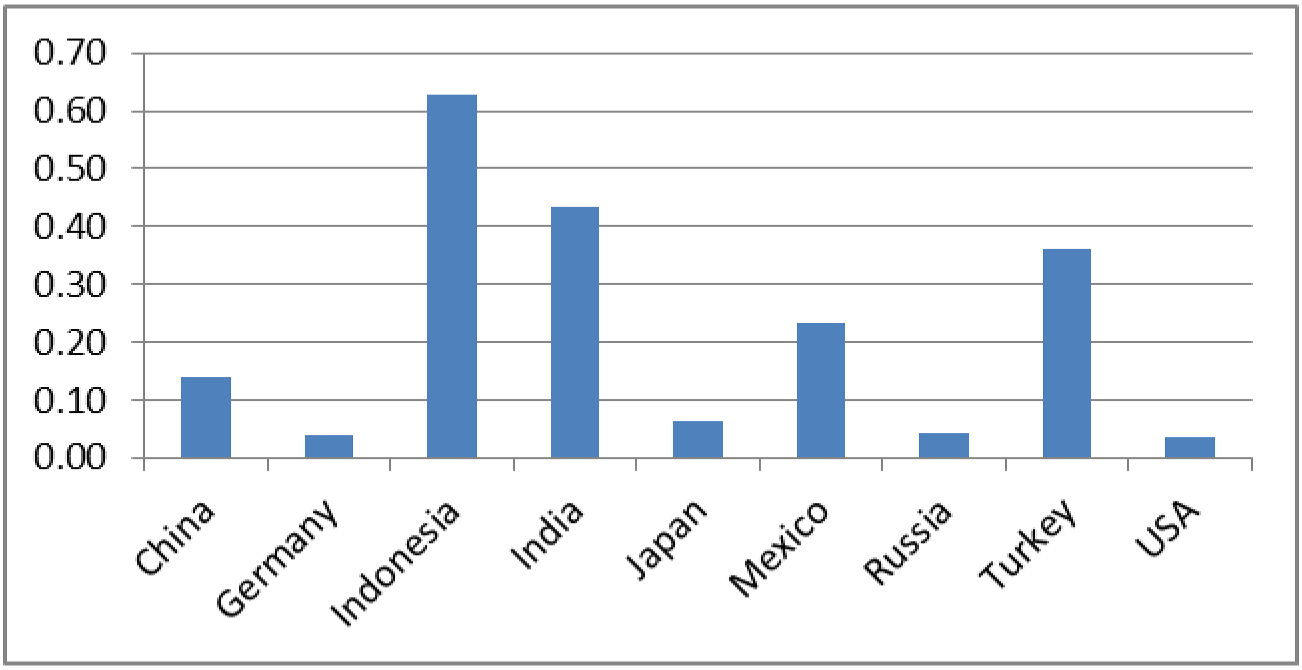


Figure 8: Agriculture Sector Hub Centralities, 2014

third highest agricultural hub centrality in 2014.

In Germany, Russia and USA, there were very small changes in the centrality values over time. Also, these countries had much smaller hub centralities than the hub centralities in other countries. In Russia, the centrality values were small showing a decreasing trend in the given period.

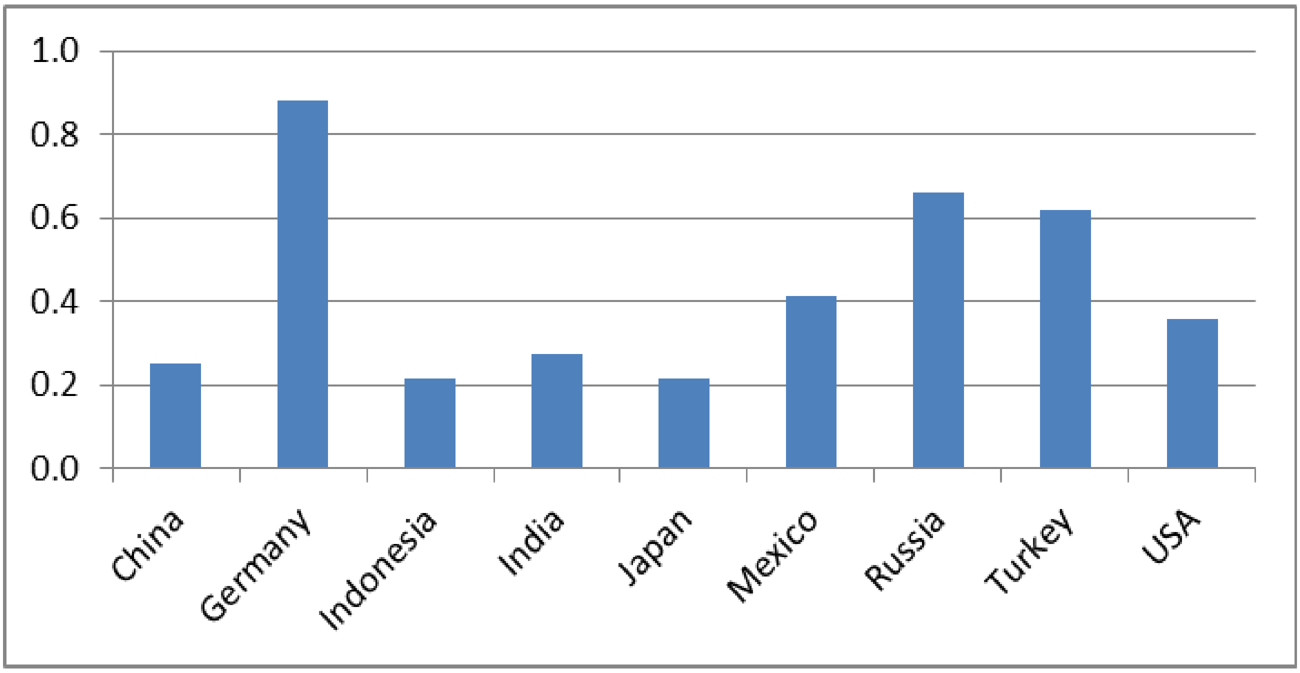


Figure 9: Service Sector Hub Centralities, 2014

Looking at the service sector, one can see that Germany had significantly high hub centralities throughout the period. Up to 2011, Russia took second place because between 2011 and 2013 Turkey showed higher hub values than Russia. Values in 2014 indicated that Turkey had promising hub centrality figures when compared to the developing countries under consideration (Figure 9).

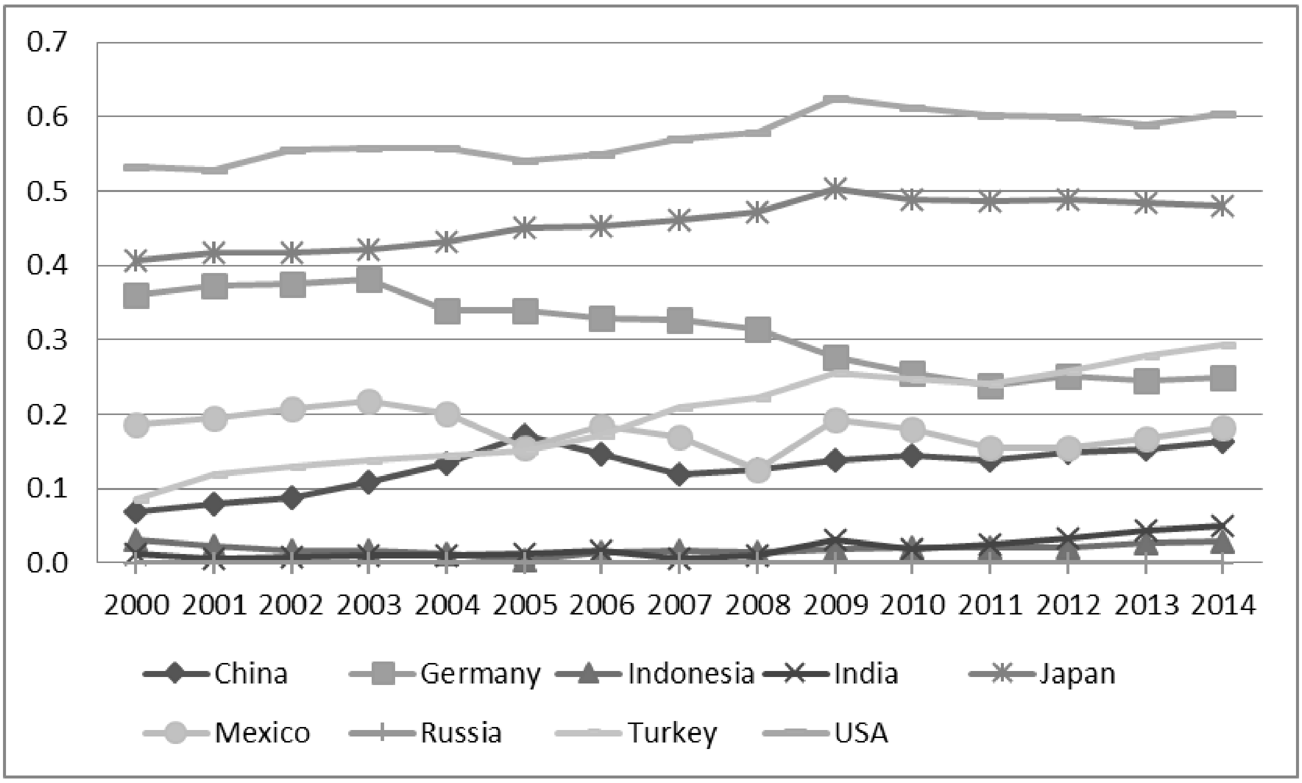


Figure 10: Professional, Scientific and Technical Activities Hub Centralities

Professional, scientific and technical activities sectors turned out to be the largest hub in the US economy (Figure 10). This position did not change even during the crisis. Furthermore, this sector's hub centrality in USA was considerably larger than the hubs of the other countries. India and Indonesia fell far behind the others. In Turkey, the sector's centrality measure showed an increasing trend. In fact, in 2013, the sector's centrality measure for Turkey exceeded the value for Germany. On the other hand, in Germany, the sector serves as an important importer to the other sectors. The greatest authority centrality is for Germany (Figure 11).

Despite the decline in 2008, the finance sector of USA had the highest hub centrality. Japan followed USA. In Turkey, although there were many ups and downs during the period in 2014, Turkey became the third highest valued country in terms of hub centrality of the service sector. India followed close behind Turkey (Figure 12).

Hub centralities in the sales sector remains very close for Indonesia, India, Japan, Mexico, Russia and Turkey, while USA, Germany and China have much smaller hub centralities in 2014 (Figure 13).

5 Conclusion

Analyzing input-output networks gives a very useful outlook on sectoral relationships. Data gained from the input-output tables are analyzed with the help of network tools. In this study we aimed to display the input-output network structure of selected countries between 2000 and 2014. Analyses indicate that all the countries considered possess a core-periphery structure for all years. This structure indicates that there are some hubs in the network.

Determining the hubs is related to a centrality analysis. Hub centralities indicate that as the development level increases, the role of agriculture as an exporter declines. In fact, there is a considerable difference in agricultural hub centralities between developed and developing countries.

Of the most developed countries considered here, namely USA, Germany and Japan, it was observed that the professional, scientific and technical activities sectors and the finance sector had an important place as suppliers. In Turkey, we observed that professional, scientific and technical activities sectors showed the highest increasing rates when compared to other countries and while Turkey was in fifth place among the other countries in 2000, Turkey placed third after 2011.

By analyzing the authority centralities, it can be seen that the construction and the service sectors have an important role. In the developed countries, the sales sector accompanies these sectors, while in developing countries we see the food sector accompanying the construction and the service sectors. The chemical sector is an important sector both in terms of being an exporter and an importer. Different from hub centrality, we see the transportation sector as one of the most important sectors in terms of import.

The inersectoral linkages are observed for all countries throughout the period. Changes in the structure and length of connections are given and some of the network visualizations are shown.

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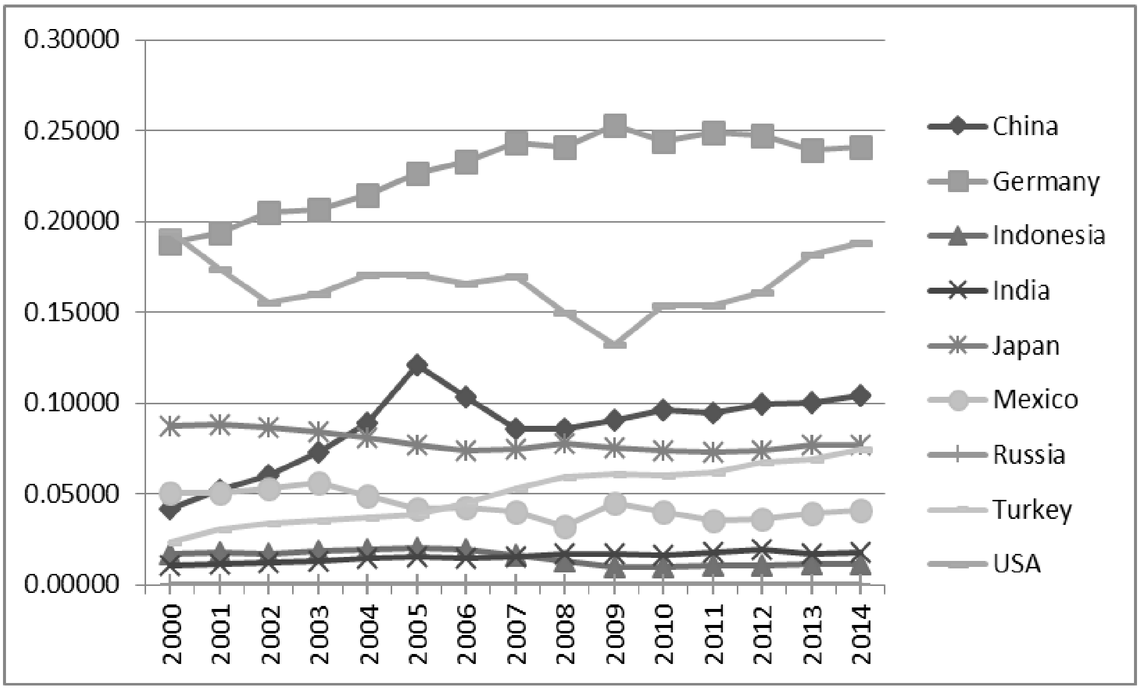

Figure 11: Professional, Scientific and Technical Activities Authority Centralities

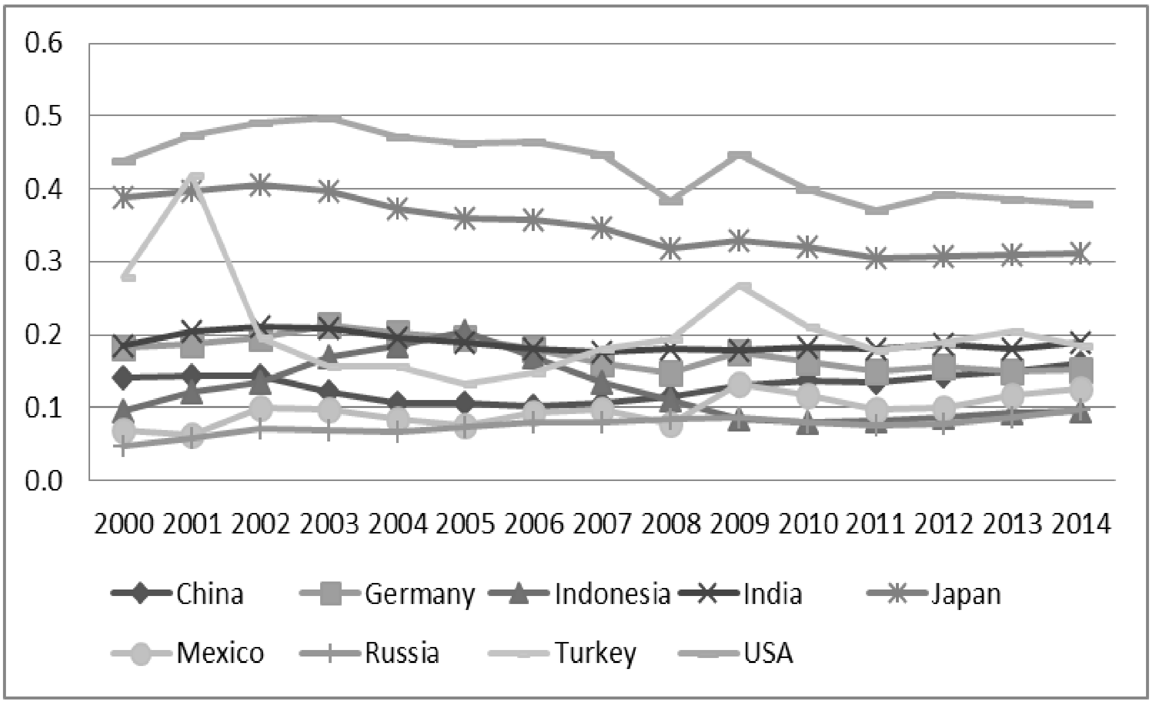

Figure 12: Finance Sector Hub Centralities

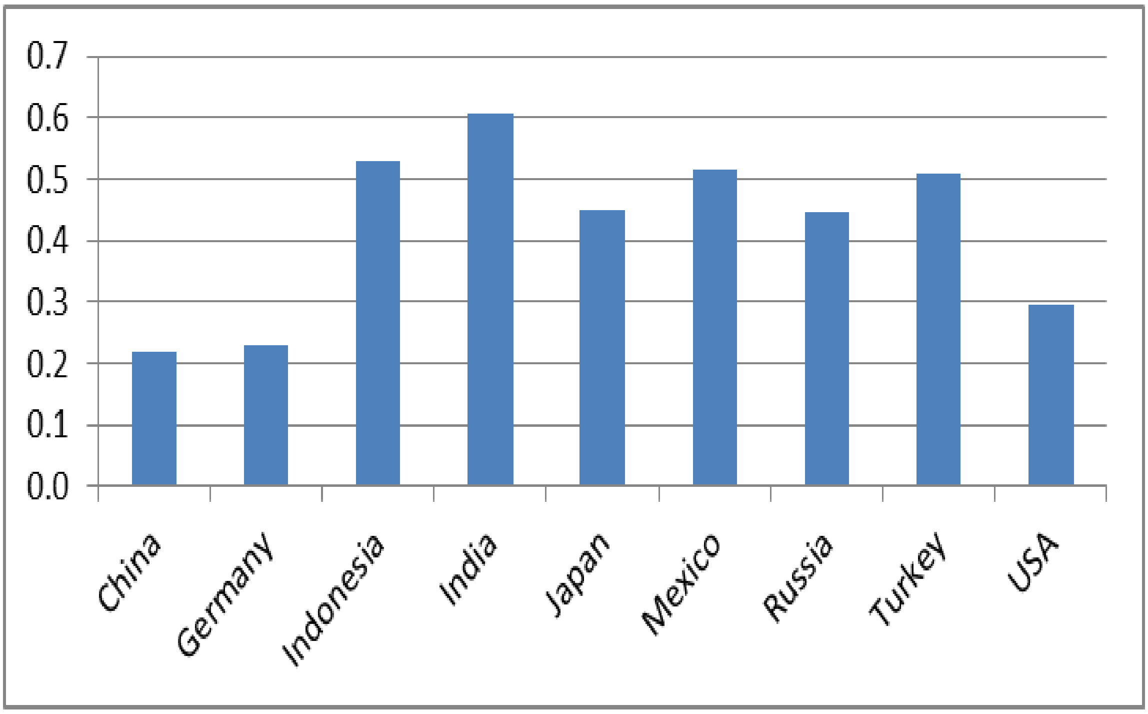

Figure 13: Sales Sector Hub Centralities, 2014