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Roh, Jae-Whak

### Article

# Analysis of the impact of network characteristics on the industry's value-added rate

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ITPD 7.3

214

## Analysis of the impact of network characteristics on the industry's value-added rate

Iae-Whak Roh

Department of International Trade, Hansung University, Seoul, South Korea

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#### Abstract

**Purpose** – This study analyzed Korea's relations table through network analysis. In particular, among the centralities, eigenvector centrality, PageRank centrality and degree were used. The author studied which network characteristics affected the value-added rate.

Design/methodology/approach - A network analysis method was used.

**Findings** – It is the inward relationship that affects the value-added ratio of Korea's industries and the outward relationship has less influence. In particular, the inward relationship not only acts as a cost but also has an effect on the rate of added value recently.

**Research limitations/implications** – Since the three years of 2010, 2015 and 2019 are the target, the data are somewhat insufficient to generalize.

Practical implications - As for the value-added ratio of an industry, input is more important than output (sales). Therefore, where the input is received is very important.

Social implications - It is possible to increase the understanding of the determinants of the value-added rate of Korean industries.

Originality/value - (1) It was clarified which side is inward or outward in determining the industry in Korea. (2) The relationship between PageRank, eigenvector centrality and degree was analyzed in Korean cases. (3) Input is a cost and acts to increase added value.

Keywords Network analysis, PageRank, Eigenvector, Industrial relation table

Paper type Research paper

#### 1. Introduction

The industrial relation tables, also known as input–output tables, are statistical tables that show the interrelationships of inputs and outputs between industrial sectors and transactions directly related to the production of goods and services among these sectors. This table is used in economic analysis, forecasting and planning. For this reason, international organizations such as the OECD [1] and most countries publish their own input output tables. In Korea, the Bank of Korea publishes the input-output table every year [2] and calculates and publishes the multiplier coefficients derived from the table. The multiplier effect calculated from the table is an important indicator of economic operation. Moreover, these numbers play a crucial role in estimating the magnitude of impact each individual industry wields on the overall economy.

However, in recent years, since 2000, the analysis of network effects has gained attention as a promising approach to overcome various criticisms of calculating direct multiplier effects of industries. This has led to a surge in related research activities. The core idea revolves around viewing the input-output table as a comprehensive network, wherein inputs



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and outputs between national industries are interconnected. The objective is to discern how each industry sector impacts the overall economic performance by uncovering the intricate relationships within this network.

This network-based approach to analysis has found application in various domains. In the present study, the analysis will primarily leverage the network theory's fundamental concepts of 'nodes' (representing industrial sectors) and 'edges' (depicting the connections between these nodes).

In this study, our objective was to investigate the correlation between the structure and network topology of input and output relationships within each industry and the resulting value-added ratio (value added/output) for each sector (Iliopoulos *et al.*, 2020; Harvey and O'Neale, 2019). Furthermore, we sought to address the question of which network inputs and outputs hold greater significance in determining the value-added rate for industries within the Korean context.

As a general principle, it is foreseeable that industries with a higher presence of important nodes in their vicinity will exhibit an elevated value-added rate. This anticipation stems from the idea that nodes can augment their value added through connections with pivotal counterparts. This expectation rests on the premise that crucial nodes in proximity provide abundant opportunities for the focal node to enhance profitability (value added).

This study aims to offer insights into whether the input relationships or output relationships of an industry have a more pronounced impact on its value-added rate. While some overseas studies have applied similar principles in the realm of international trade (Iliopoulos *et al.*, 2020), empirical evidence specific to domestic input—output relationships within Korea is lacking. Thus, I would like to confirm its possibility through this study.

The methodology and approach taken in this study is similar to a number of studies in the field of international trade under the name of Global Power Network or Power Network (Henderson *et al.*, 2002). All of these studies examine the topological characteristic of position and the relational attributes of nodes to other sectors. Among the studies included in global production, some studies show that structural location affects the development of a country (Coe and Yeung, 2015), while others show that dominant actors have high profits (Iliopoulos *et al.*, 2020). In the end, what network research seeks is to identify the importance of nodes through the identification of centrality or the governance of nodes over a network through the identification of centrality.

This research will be conducted in the following sequential manner: to attain the outlined research objectives, it becomes imperative to discern the network characteristics specific to each industry. For this purpose, various forms of centrality metrics will be computed and juxtaposed for each industry node. Subsequently, an examination will be conducted to determine the correlation between the identified centralities and the value-added attributes of the respective nodes.

#### 2. Paper review

#### 2.1 Input-output table and network theory

The calculation of the Leontief multiplier effect has been widely used in economic analysis using input–output tables. However, it has faced criticism for its limitations in accounting for dynamic environments and its reliance on simplistic linear matrix manipulation methods (Goodwin, 1951). A recent notable critique of the Leontief approach was put forth by Oosterhaven in 2015. Despite these critiques, the Léontief multiplier is still widely employed by various countries and studies due to its inherent simplicity.

In response to the shortcomings of the multiplier method, researchers have sought alternatives by interpreting input–output tables through a network perspective. Networks consist of various entities such as individuals, organizations and objects, collectively referred

to as actors. The arrangement of connections among these actors forms the network structure, and network analysis aims to describe and analyze this intricate framework. In this study, the annual input–output table published by the Bank of Korea serves as the basis for constructing a network among sectors. Exploring this networked structure holds the potential to yield valuable insights for identifying pivotal industries.

A representative study of network research using input–output tables utilizes the concept of "product space" (Hidalgo *et al.*, 2007). This study revealed that the trajectory of economic development is contingent on the ability to produce high-complexity products. It was observed that intricate products tend to emerge within denser networks, whereas simpler products often originate in less densely connected networks. This study established a link between the development and production of innovative products and the underlying network attributes. Furthermore, their investigation underscored that the achievement of economic development hinges on network characteristics that indicate the ease of transitioning toward essential products. By illustrating that developing countries encounter challenges in shifting toward the production of intricate products, they tried to find the conditions for economic development from the perspective of the economic production network's intrinsic features.

In 2008, a network-focused study related to input–output tables delved deeper into technical aspects. Bhattacharya *et al.* (2008) highlighted a critical gap in existing research, namely the oversight of considering the weight of each node. They underscored the necessity for weighted network studies, where the importance of the relationships between edges is duly acknowledged. Drawing inspiration from their work, this study intends to incorporate weighted centrality into our analysis.

The network theory extends beyond input–output tables and encompasses international trade. In this vein, Fagiolo *et al.* (2009) harnessed the weighted network approach when exploring international trade networks. Their investigation revealed remarkable stability in the network's statistical metrics, even when subjected to time series analysis. Of notable significance was their discovery of a strong correlation between the network's growth rate and its density.

In the field of global production, the network theory was introduced and developed into the Power Production Network theory. This theory focuses on quantifying and illustrating the extent to which an entity plays a pivotal role within the global production network or the broader global value chain. Central to this field of research is the concept of 'power.' Within production networks, the power manifests in two dimensions – as the dominance of a specific network position and the dominance of the exchange relationships among network participants. Essentially, the power signifies the capacity of a dominant actor to guide a production value chain and reshape the governance structure in its favor (Henderson *et al.*, 2002; Coe and Yeung, 2015).

Among the studies included in global production, some emphasize that the position in the structure affects the development of a country (Coe and Yeung, 2015), while others highlight the elevated profitability of dominant actors (Iliopoulos *et al.*, 2020). Consequently, it becomes intriguing to explore whether the Korean context reflects a heightened rate of gain in industries that hold dominance.

Recent research on global production network is progressively adopting a dynamic perspective investigating how changes in roles in the network over time, i.e. changes in dominance, affect technological progress and economic advantage relationships (Henderson *et al.*, 2002). On the other hand, some studies reveal the network structure of industries (McNerney *et al.*, 2013), which describe the linkages between industries in different countries.

#### 2.2 Review on degree, eigenvector and PageRank centrality

Degree refers to the number of edges connected to a node. If the number of edges connected to a node is large, it is considered as an important node. In research using degrees, degrees are

further classified and used by dividing them into in-degree, out-degree and total-degree, which means the number of incoming edges, the number of outgoing edges and the sum of the two. "In-degree" represents the extent to which a node receives connections from other nodes, while "out-degree" signifies the number of edges that emanate from the node and influence other nodes. The sum of these two is referred to as the "total degree." In this study, I also divided the degree into in-degree, out-degree and total-degree and compared them. An important study on this concept is Freeman (1977), which also presents other centrality methods as well.

Bonacich's (1987) study presents studies on the question of whether power is centrality and presents various measurement methods. He used the parameter  $\beta$ , which expresses the relationship with the outside, to explain the relationship between 'power' and 'centrality'. Considering this aspect, I will use degree, eigenvector centrality and PageRank centrality together in this study and predict that there is a certain relationship.

Eigenvector centrality considers not only the number of connected nodes but also their importance (Bonacich, 1987). A node's importance depends on its neighbor's centrality. Therefore, eigenvector centrality is the degree of connectivity calculated by weighting the centrality of other connected nodes.

In eigenvector centrality, the importance of a node is determined by the sum of the importance of the node and its connected neighboring nodes. The eigenvector centrality of node u can be expressed as,

$$\mathbf{EC}(\mathbf{u}) = \sum_{\mathbf{v} \in V \setminus \{\mathbf{u}\}} (\mathbf{a}_{\mathbf{u}\mathbf{v}} \cdot \mathbf{EC}(\mathbf{v})) \tag{1}$$

Having a high eigenvector centrality means that it is directly connected to important nodes since the eigenvector centrality of a node includes the importance of its neighbors. In this sense, finding an important industrial node in this study is the same task as finding a high eigenvector centrality considering neighboring industries.

Another important measurement adopted in this study, PageRank, was published in Brin and Page (1998) and is still being used as an algorithm for scoring web pages. As a criterion for scoring search results, an indicator showing the importance of pages were needed, and PageRank was developed and has been used as an index that measures the importance of a page and pages including all the relationship between web pages.

A simple concept can be expressed as follows:

$$PR(A) = (1 - d) + d\left(\frac{PR(T1)}{C(T1)} + \dots + \frac{PR(T_n)}{C(T_n)}\right)$$
(2)

Here, T1, T2, ... Tn indicates pages. Therefore, these pages can be interpreted as referring to an industrial node. Basically, this formula assumes that PR(A), that is, the rank of A page is determined by the page ranks of other linked pages (T1, T2, ... Tn). Here, d is a damping factor and C(T1) means the total number of outgoing links from T1. PR(T1)/C(T1) means that the PageRank of T1 is divided by the number of edges going out of T1. Thus,  $\frac{PR(T1)}{C(T1)} + \ldots + \frac{PR(T_n)}{C(T_n)}$  are all PageRank connected to Page A and each page ranks is divided by its own number of outgoing edges. Therefore, the sum of the PageRank of all connected pages is 1. For PageRank, an adjacency matrix is created, then a stochastic matrix expressed as a probability is constructed and then a page rank is created. The solution to the condition in which the matrix is stabilized becomes the PageRank.

In this study, I will introduce PageRank centrality as one of the methods for measuring centrality. This idea can be applied to measure the importance of an industry node by considering the importance of other nodes connected to it. It is expected that this method will

bring a difference compared to the existing centrality measures such as eigenvector centrality and degree centrality are considered in this paper.

There have been numerous studies that leverage PageRank centrality. A seminal work in this domain is by Harvey and O'Neale (2019). Additional notable contributions include those by del Río-Chanona *et al.* (2017) and Kireyev *et al.* (2022). Harvey and O'Neale (2019), employ and juxtapose both PageRank and eigenvector centrality alongside a conventional multiplier. The experimental results reveal that betweenness centrality and closeness centrality, both rooted in network 'paths,' exhibit a semblance of similarity. In contrast, eigenvector centrality exhibits a correlation akin to that of the traditional multiplier's outcomes. Furthermore, Harvey and O'Neale (2019) significantly influence this present research, as it utilizes the national input–output tables of various countries. Notably, it directly employs the input–output table as the requisite adjacency matrix for network analysis.

del Río-Chanona *et al.* (2017) calculate PageRank and weighted degree, which measures the strength of a node, and then reconstruct a secondary network based on these. They conducted a dynamic study using import and export data between countries over a 15-year period, and the results of their analysis concluded that political and geographic conditions play a very important role in a country's economic performance.

Another PageRank-focused study was conducted by Kireyev *et al.* (2022), who also examined the international trade market (world input–output table). They devised a novel index that segments international trade into distinct communities. PageRank was then employed to categorize these communities into different sectors to identify key players. The centrality metrics employed encompass not only product PageRank but also money PageRank, Hubs Rank and Authority Rank. The findings indicate that the US-centric community retains importance, although it has somewhat diminished, while network analysis reveals the growth of the Chinese-centric community.

#### 3. Data and measurement

This study uses data from the Korean industrial relations table, published by the Bank of Korea. The experimental comparison uses multi-year data, specifically from the years of 2019, 2015 and 2010. The Bank of Korea's annual report on the industrial relations table encompasses 32 input sectors and 32 output sectors, collectively capturing the supply and demand dynamics of the entire economy.

Within the input sectors, a further division is made into intermediate inputs, value-added inputs and gross inputs, all categorized according to specific industries. The concept of 'gross inputs' is harmonized with gross outputs, following the principle of balancing supply and demand. The value-added rate employed in this study is computed as the quotient of value added and total input for each industry (Iliopoulos *et al.*, 2020).

An essential component of network analysis is the adjacency matrix, which describes the connections and relationships between individual nodes. In this study, the industrial relations table, also known as the input–output table, is employed as the adjacency matrix (lliopoulos *et al.*, 2020).

Industrial relation tables are notable for their remarkably dense input–output relationships within each industry, forming a network where all nodes are interconnected (McNerney *et al.*, 2013). There are two ways to deal with this high-density table. The first solution is to treat values below a certain number as zero. The second solution is to tolerate the centrality of many identical values that result from not treating them as zeros. However, this latter choice often complicates the assessment of centrality levels, limiting our ability to distinguish between them (Harvey and O'Neale, 2019).

In this study, to accurately capture the network's attributes, an adjustment was made to enhance the representation of its characteristics. Specifically, all values below 5% of the maximum value in the adjacency matrix table were set to zero. This decision serves to

ITPD

7.3

accentuate the network's salient features. Another rationale behind treating values at 5% or less as zeroes lies in the nature of the eigenvector and PageRank adopted in this study. eigenvector and PageRank produce many identical values when the density of the adjacency matrix increases.

Within the realm of various centrality measures, this study opts for three specific measures: degree centrality, eigenvector centrality and PageRank centrality. Degree centrality, a wellestablished tool denoting a node's influence, has been addressed in prior research (Harvey and O'Neale, 2019). Meanwhile, PageRank and eigenvector centrality has been employed in studies by del Río-Chanona *et al.* (2017), Kireyev *et al.* (2022) and Harvey and O'Neale (2019).

Both PageRank and eigenvector centrality emphasize the significance of neighboring nodes. However, there is a distinction in how they weigh incoming connections. PageRank assigns greater importance to incoming edges compared to eigenvector centrality, which treats incoming edges more evenly. Notably, eigenvector centrality does not differentiate between incoming and outgoing edges. Consequently, given PageRank's emphasis on incoming nodes over eigenvector centrality, a comparative analysis of their outcomes will establish whether incoming or outgoing nodes have a more substantial impact on the value-added rate.

Each centrality values are calculated based on the adjacency matrix which is the industrial relation table. The centralities used in this study are in-degree, out-degree, total-degree, eigenvector centrality and PageRank centrality. Then, the calculated centrality and the calculated value-added returns are tested with correlation coefficients (Harvey and O'Neale, 2019). Other studies that correlate centrality with primary objective measures such as value added and profit rates in network research include Harvey and O'Neale (2019), del Río-Chanona *et al.* (2017) and Kireyev *et al.* (2022). Harvey and O'Neale (2019) use both PageRank and eigenvector. In del Río-Chanona *et al.* (2017), PageRank and weighted degree, which measures the strength of a node, are first calculated and then correlated.

#### 4. Simulation results

#### 4.1 Calculating the value-added rate

Numerous studies within network analysis have directed their attention toward value added or profit share, exploring these dimensions extensively (Harvey and O'Neale, 2019). This study, too, centers its analysis on value added Table 1, presented below, showcases the calculated value-added rates for 32 industries, utilizing data sourced from the Bank of Korea for the years of 2010, 2015 and 2019. Employing the industrial relation table, we compute the value-added rate and rank them for each year.

Leveraging the calculated value-added rates, we establish rankings for each year. Rank 1 designates the industry with the highest value-added ratio, while rank 32 signifies the industry with the lowest value-added ratio. The final column in the table displays the variation in ranking values, reflecting the difference between the 2019 and the 2010 ranking. An increase in value (+) denotes a decrease in rank of value added, while a decrease in rank (-) signifies an increase in rank of value added.

In terms of value added, the leading industries in 2010 encompassed computers, primary metals, motor vehicle transportation equipment, textiles and leather and food and beverages sectors. In 2015, the top five industries include transportation equipment, textiles and leather, primary metals, food and beverages sectors and other manufacturing sectors. Come 2019, the spotlight turned to primary metals, textiles and leather, transportation equipment, coal and petroleum and chemicals. Notably, primary metals, textiles and leather, transportation equipment and food and beverages emerge as the consistent frontrunners, consistently securing positions among the top five industries in Korea based on value added.

In 2010, the industries with the lowest value-added rates were real estate, education, utilities, business support services and service for manufacturing. By 2015, the sectors with

11PD 7,3	Name of industry	Value added in 2010	Rank in 2010	Value added in 2015	Rank in 2015	Value added in 2019	Rank in 2019	Rank difference between 2010 and 2019		
	age	0.52	20	0.54	25	0.51	21	1		
	min	0.52	26	0.52	21	0.01	19	-7		
	fod	0.3	5	0.25	4	0.26	5	0		
220	txt	0.25	4	0.19	2	0.2	$\tilde{2}$	-2		
	pap	0.33	11	0.31	10	0.32	12	1		
	peT	0.33	12	0.31	9	0.25	4	$-\hat{8}$		
	chm	0.32	10	0.29	6	0.27	7	-3		
	nmt	0.31	9	0.31	11	0.31	10	1		
	met	0.19	2	02	3	0.19	1	-1		
	mfb	0.34	13	0.36	14	0.36	14	1		
	com	0.15	1	0.33	12	0.00	16	15		
	elc	0.31	7	0.3	8	0.28	9	2		
	mac	0.31	8	0.29	7	0.31	11	3		
	trE.	0.25	3	0.19	1	0.22	3	0		
	otM	0.3	6	0.28	5	0.28	8	2		
	reP	0.59	28	0.49	19	0.53	22	-6		
	elt	0.42	15	0.37	15	0.27	6	_9		
	wat	0.44	18	0.53	23	0.56	26	8		
	con	0.43	17	0.42	17	0.44	17	0		
	sal	0.55	22	0.55	26	0.53	24	$\overset{\circ}{2}$		
	trP	0.39	14	0.39	16	0.36	15	1		
	acc	0.42	16	0.35	13	0.34	13	-3		
	tel	0.52	19	0.54	24	0.56	27	8		
	fin	0.56	23	0.59	28	0.59	28	5		
	rel	0.82	32	0.76	31	0.73	31	-1		
	sci	0.53	21	0.51	20	0.5	20	-1		
	aux	0.71	29	07	30	0.68	29	0		
	adm	0.73	30	0.77	32	0.76	32	$\overset{\circ}{2}$		
	edu	0.78	31	0.69	29	0.70	30	_1		
	soC	0.56	25	0.53	22	0.53	23	-2		
	otP	0.59	27	0.55	27	0.55	25	-2		
<b>—</b> • • • •	otS	0.56	24	0.44	18	0.45	18	$-\bar{6}$		
Table 1.	Note (a): In 2010, 2015 and 2010 the levels of value added wave measured and represented as makings. The									
Kanking and change in	e m <b>Note(5)</b> . In 2010, 2013 and 2019, the levels of value added were measured and represented as ranking bound by a solution of the solution							teu as rankings. The		
ranking by value	ast counting shows now much unterence occurred in industry rankings based on the passage of time between 2010 end 2010									
2015  and  2010	Source(s)	Author's cale	ulations with	n data from t	he Bank of I	Korea				
2010 anu 2019)	Source(s). Aution's calculations with data from the Dank of Korea									

the lowest value-added rates were utilities, real estate, business support services, education and financial services. Progressing to 2019, the industries with the lowest value-added rates encompassed public administration, real estate, education, business support services and financial services. It is notable that public service, real estate service, education service and business support services consistently fell within the lowest value-added groups over the three-year span. These sectors collectively belong to the service industry, in which Korea's value-added ratios are generally evaluated as relatively low.

The shift in value-added rankings presented in last column of table highlights notable changes within industries from 2010 to 2019. Industries demonstrating the most significant upward trajectory in value-added rankings (indicated by a negative sign signifying increased importance) include electric power and gas sectors (-9), followed by oil industry (-8), mining industry (-7) and the repair of manufacturing equipment sector (-6). Conversely, sectors experiencing the most notable decline in value-added rankings (indicated by a positive sign) encompass the computer industry (15) and the water and power industry (8).

These shifts prompt inquiries into the factors underpinning the alterations in industry rankings. This exploration delves into the causes of these shifts and poses the intriguing question of which network-related factors contribute to these transformations.

#### 4.2 Calculation of centralities

Table 2 below displays the computed values for each major centrality, arranged chronologically for the years of 2010, 2015 and 2019. Additionally, the three-year average PageRank values (not presented in Table2) unveil sectors with notable centrality patterns. Notably, transportation equipment, construction, wholesale and retail as well as the food services and accommodation service industry emerge with high centrality, whereas manufacturing, wholesale and industrial equipment repair, water and waste recycling, business support services and arts sector exhibit lower centrality.

	2010 Eigen	2015 Eigen	1019 Eigen	2010 Page	2015 Page	1019 Page	2010 In-degree	2015 In-degree	1019 In-degree
age	0.24	0.09	0.10	0.02	0.01	0.01	2	1	1
min	0.00	0.00	0.00	0.01	0.01	0.01	0	0	0
fod	0.49	0.31	0.44	0.03	0.03	0.03	2	2	4
txt	0.22	0.25	0.22	0.02	0.02	0.02	3	3	3
pap	0.00	0.00	0.00	0.01	0.01	0.01	0	0	0
peT	0.00	0.00	0.00	0.01	0.01	0.01	1	1	1
chm	0.40	0.45	0.55	0.05	0.05	0.04	4	7	7
nmt	0.00	0.00	0.02	0.01	0.01	0.01	0	0	1
met	0.03	0.00	0.10	0.02	0.01	0.02	3	2	3
mfb	0.09	0.07	0.11	0.01	0.01	0.01	2	2	2
com	0.71	0.72	0.64	0.05	0.05	0.04	7	7	7
elc	0.24	0.25	0.26	0.02	0.03	0.02	3	3	3
mac	0.30	0.03	0.39	0.03	0.01	0.03	5	3	7
trE	1.00	1.00	0.95	0.09	0.08	0.06	9	9	9
otM	0.00	0.00	0.00	0.01	0.01	0.01	0	0	0
reP	0.00	0.00	0.00	0.01	0.01	0.01	0	0	0
elt	0.00	0.00	0.00	0.01	0.01	0.01	1	1	1
wat	0.00	0.00	0.00	0.01	0.01	0.01	0	0	0
con	0.84	0.74	0.98	0.06	0.06	0.08	9	9	11
sal	0.70	0.78	1.00	0.13	0.12	0.10	7	7	8
trP	0.22	0.23	0.20	0.09	0.06	0.04	3	3	3
acc	0.75	0.73	0.96	0.06	0.06	0.07	5	4	4
tel	0.37	0.35	0.47	0.04	0.03	0.03	4	2	4
fin	0.22	0.14	0.40	0.02	0.03	0.04	3	3	5
rel	0.25	0.23	0.41	0.07	0.08	0.09	2	3	3
sci	0.44	0.58	0.75	0.06	0.06	0.06	6	7	8
aux	0.00	0.00	0.00	0.01	0.01	0.01	0	0	0
adm	0.00	0.00	0.05	0.01	0.01	0.01	0	0	1
edu	0.12	0.15	0.19	0.02	0.02	0.02	1	1	1
SOC	0.21	0.50	0.75	0.01	0.03	0.04	1	2	3
otP	0.00	0.00	0.00	0.01	0.01	0.01	0	0	0
otS	0.00	0.15	0.14	0.01	0.04	0.03	0	1	1

**Note(s):** This table shows eigenvector centrality, PageRank centrality and in-degree centrality for 31 different industries in the years of 2010, 2015 and 2019. Eigenvector centrality indicates how many important nodes a node is connected to, while PageRank primarily represents the influence of incoming nodes. In-degree, on the other hand, reflects the number of directly connected nodes **Source(s):** This table is calculated by the author

Table 2.Calculated centralities(2010, 2015 and 2019)

industry's value-added rate

Analysis on

Moreover, the average of the three-year eigenvector centralities (not provided in the table) highlights the most centralized industries, led by wholesale and retail merchandise brokerage services, trailed by real estate services and transportation equipment services. Conversely, sectors such as miscellaneous manufacturing, manufacturing forestry, mining, wood and paper printing, business support services, arts and sports and social assistance appear to possess comparatively lower centrality levels.

As you can see from the relationship between value added and degree in the Table 3 of next section, the degree that is highly related to value added is in-degree, not out-degree or total-degree. Therefore, in Table 2, only important in-degrees are indicated.

Considering the in-degree centrality, the most centralized industry is the construction industry, closely followed by the transportation equipment sector, wholesale and retail trade service, professional, scientific and technical services and computer-assisted optical instruments. On the other end of the spectrum, the least centralized industries are miscellaneous manufacturing, manufacturing processing and repair, water and waste disposal and business support services.

Collectively, the analyses of eigenvector, PageRank and in-degree centrality converge to highlight the foremost industries in Korea. Notably, transportation equipment and computer electronics emerge as the most pivotal, followed by construction services and wholesale and retail sale and commodity brokerage services. This consensus is grounded in three years of comprehensive data. The industries with the next highest centrality are professional, scientific and technical services, along with food and accommodation services.

Conversely, the industries displaying the lowest overall centrality encompass miscellaneous manufacturing, manufacture-processing and industrial equipment repair, water, waste-water and recycling and business support services.

The above analysis has identified the industries with high centrality in Korea have been identified. The natural progression from this point is to investigate whether the value-added rates of Korea's industries demonstrate an uptick when they interact with industries of notable centrality. Notably, industries such as transportation equipment, computer and electronic equipment, construction, wholesale and retail trade, professional, scientific and technical services as well as food and accommodation, emerge as pivotal players. This inquiry still needs to be explored.

#### 4.3 Value-added rate and centrality

Table 3 below provides a comprehensive overview of the correlation coefficients between various types of centrality and the value-added ratio, as measured by established studies

	Rate-	Rate-	Rate-	Rate-	Rate-	Eigen-	Page–	Page-	Eigen-	Eigen-	Eigen-
	page	in	out	total	eigen	total	in	out	in	out	page
2010 2015 2019	$-0.04 \\ 0.04 \\ 0.12$	$-0.34 \\ -0.26 \\ -0.19$	$-0.04 \\ 0.02 \\ -0.01$	$-0.23 \\ -0.16 \\ -0.12$	$-0.26 \\ -0.17 \\ -0.04$	0.72 0.72 0.74	0.78 0.81 0.76	0.50 0.44 0.44	0.93 0.89 0.88	0.25 0.26 0.35	0.78 0.83 0.85

**Note(s):** Rate-page is the correlation coefficient between value-added rate and PageRank, rate-in is the correlation coefficient between value added rate and in-degree, rate-out is the correlation coefficient between value-added rate and out-degree, rate-total is the correlation between value-added rate and total degree and rate-eigen is the correlation between value-added rate and eigenvector centrality, page-in indicates the correlation coefficient between PageRank and in-degree and page-out indicates the correlation coefficient between PageRank and in-degree represents the correlation coefficient between eigenvector and PageRank. A high correlation coefficient indicates a strong relationship between two measured variables **Source(s)**: Additionally, this table was calculated by the author

#### Table 3.

Correlation between value-added rates and different types of centralities

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(Harvey and O'Neale, 2019; Iliopoulos *et al.*, 2020; del Río-Chanona *et al.*, 2017). Within the scope of this study, centrality is quantified through computations of in-degree, out-degree and total degree, alongside PageRank and eigenvector metrics. The ensuing table succinctly compiles the computed values for the years of 2010, 2015 and 2019.

In Table 3, the first column showcases the evolving relationship between the value-added ratio and PageRank centrality. The correlation coefficients (-0.04, 0.04 and 0.12) exhibit a gradual and notable progression, with the sign transitioning gradually from negative to positive. PageRank calculates a node's centrality by taking into account the amount of incoming input from its significant neighbors. Outgoing edges are only partially considered at this time. The shifting magnitude of the correlation coefficient, rising from 0.04 to 0.12, indicates a growing significance of inputs from pivotal neighboring industries in determining centrality. This transformation is underpinned by a shift in the coefficient's sign, symbolizing that inputs have evolved from being a cost to now contributing positively to value added. This observation underscores the notion that an industry's substantial influx of inputs from vital sectors translates into more than just cost increment; it leads to a positive influence that surpasses the cost, thereby elevating the industry's value-added rate.

In summary, the observations from the first column indicate that initially, an augmented number of incoming connections from neighboring significant nodes lead to cost escalation. However, this effect transitions from negative to positive, making a more substantial contribution to added value as recently as 2019.

In this context, a wealth of studies (Harvey and O'Neale, 2019; Iliopoulos *et al.*, 2020; del Río-Chanona *et al.*, 2017) underscore the pivotal role of PageRank, even though many of these investigations encompass cross-country examinations of global networks.

The second column within Table 3 introduces a distinct perspective by contrasting it with the first column. While the first column weighs the significance of incoming nodes using PageRank, the second column's in-degree solely considers the sheer quantity of incoming edges. In this case, the second column underscores that in-degree displays a notably high negative correlation (-0.34, -0.26 and -0.19) with the value-added ratio for each industry, representing the highest values among the presented Table 3 data.

The count of input edges assigned to each industry can be understood as encompassing materials, parts, equipment and the like, procured from a diverse array of other industries. This interaction inherently functions as a cost due to the nature of incoming inputs for the respective industry. As anticipated, this suggests a negative impact on the value-added ratio, a deduction that is corroborated by the consistently negative and notably high values observed. In essence, this relationship emerges lucidly, firmly indicating that the value-added rate of Korean industries diminishes as they forge more connections with input-oriented sectors. To succinctly summarize, the evidence underscores that heightened interconnections with input industries lead to a lower value-added rate.

Turning our attention to the third column, which represents out-degree, we note that its correlation with the value-added rate is not as robust in absolute terms when compared to indegree (-0.04, 0.02 and -0.01). Out-degree essentially signifies the provision of input into other interlinked industries, suggesting that diversification in output utilization yields only marginal impact on augmenting the value-added rate (-0.04, 0.02 and -0.01). A notable observation arises in 2015, where an out-degree of 0.02 implies an elevated outflow of products (sales), aligning with expectations that it might enhance the value-added rate. However, for the remaining years, 2010 and 2019, the correlation coefficients between outdegree and value-added rate reveal negative values of -0.04 and -0.01, respectively. These values, measured in absolute terms, remain exceedingly low, suggesting that the influence of out-degree on value added is marginal. In essence, it becomes evident that out-degree exerts limited influence in determining the value-added rate.

The total-degree in the fourth column is actually the inclusive sum of out-degree centrality and in-degree centrality. Out-degree holds less sway compared to in-degree, which stands as the predominant determinant. This observation underscores that it is indeed in-degree, rather than out-degree that shapes the character of total-degree.

In the fifth column, eigenvector centrality reveals a trend of diminishing negative influence over time (-0.26, -0.17 and -0.04). Eigenvector centrality gauges the extent to which the significance of a specific node hinges on the prominence of other interconnected nodes. Consequently, these figures signify a progressive decline in the influence of connections to neighboring pivotal nodes. A negative correlation coefficient indicates that if a node is linked to a significant neighboring node, its influence is initially negative. In 2010, a pronounced and negative correlation is evident, which then diminishes by 2015, eventually exhibiting minimal impact in 2019. In essence, the inference is that being connected to numerous important nodes fosters a negative impact on the node in question. Nonetheless, this negative influence from neighbors is observed to wane as we approach more recent periods.

In the ninth column of the table, eigenvector and in-degree exhibit robust correlation coefficients (0.93, 0.83 and 0.85), indicating that eigenvector centrality encompasses both incoming and outgoing nodes, with a notable emphasis on in-degree. A parallel observation is reported in an international study (del Río-Chanona *et al.*, 2017), highlighting similar findings. Another international study, conducted by Kireyev *et al.* (2022), similarly underscores the high correlation between eigenvector and PageRank.

The final column of Table 3 highlights the notable correlation coefficients between PageRank and in-degree (0.78, 0.81 and 0.76). This strong correlation is to be anticipated, given PageRank's consideration of incoming edges, aligning well with our expectations and affirming consistent results.

As a result of targeting Korea's industrial relation table, it was found that eigenvector centrality, PageRank centrality and in-degree showed a high correlation with each other, and therefore, incidentally, it was found that the incoming edge plays a very important role compared to the outgoing edge.

#### 5. Conclusion

This study uses industrial relation tables (input–output table) of Korea and the network analysis approach. This approach differs from traditional studies which use industrial relation tables to measure multiplier effects. This study aims to examine the relationship between industrial sectors of Korea from the perspective of network analysis. I am trying to explore the characteristics of a network that influence the value-added rate by analyzing the correlation coefficients values between various centrality measures reflecting the network's characteristics and the value-added rate. A side result of this study is to find out which of the incoming edge and outgoing edge plays a more important role for the increase in the value-added ratio.

As far as I know, there is no study that has taken a comprehensive approach using PageRank, degree and eigenvector among the tasks that reveal the factors that play a decisive role in the value-added ratio mentioned above through network analysis. At the same time, to my knowledge, there is no clear study on the role of incoming and outgoing edges in the Korean industry. Therefore, the contribution of this study can be said to clarify these two themes.

The methodology employed three years' worth of data from the Korean industrial relation table (input-output table), thereby striving for consistent findings across this span. Initially, we computed the value-added rate and gauged eigenvector centrality, PageRank centrality and degree centralities for each industry. Subsequently, we calculated correlation coefficients between these centrality measures and the value added.

ITPD 7,3

The experimental findings reveal several key insights. Firstly, the inputs a given industry receives from various other industries can manifest as costs, exerting a downward pressure on its rate of value added. This negative relation is particularly evident, clear and discernible.

Secondly, as we approach the more recent period (specifically, the year 2019); a progressively positive shift becomes discernible indicating that inputs are assuming an increasingly pivotal role within Korean industries. The shift of correlation coefficient values representing the value-added rate and inputs from negative to positive signifies a significant implication. It demonstrates that despite inputs traditionally entailing costs in recent years, the receipt of substantial inputs from influential nodes can exert a favorable impact on valueadded growth. In essence, this indicates that industries benefit from a heightened valueadded rate when receiving substantial inputs from key sectors, even when these inputs are classified as costs in contemporary years. Consequently, the elevation of materials, components, devices and similar factors to a higher performance level has the potential to enhance an industry's value-added rate, even in the face of their categorization as costs.

Thirdly, when it comes to out-degree, the correlation is not as noticeable in terms of absolute values as it is with in-degree. This means that the value-added rate of Korean industries is more affected by the inputs they receive rather than the outputs they provide. This observation has important implications for understanding the Korean economy's dynamics.

Lastly, our findings underscore that higher PageRank or eigenvalue does not necessarily translate to a higher value-added rate, as observed when comparing industry centrality with their respective value-added rates. In essence, the receipt of inputs from major industries boasting high centrality does not uniformly amplify an industry's value-added rate or does the provision of outputs to such major industries. This insight constitutes another crucial facet in understanding the intricacies of the Korean economy. Importantly, this result diverges from the findings of Iliopoulos *et al.* (2020), who posit a correlation between dominant firms and higher profits. Notably, such overseas studies are rooted in global networks, thereby highlighting the need for further analogous investigations within the Korean context.

This research still has many areas that need improvement. This is because there are not many results available for our country in this field. Therefore, it is acknowledged that caution is needed in interpretation. For example, one of the reviewers of the paper pointed out the limitations of interpreting profit rate as a ranking method, and as a result, centrality may not have adequate explanatory power. This is also considered a factor to be taken into account in the future.

In additionally, this network-centered research is believed to be helpful in understanding the global structure of networks in South Korea. It is also considered a very good approach to finding solutions in case of external pressures and obstacles, and it is expected to be useful in its application. Therefore, this research can be seen as valuable.

#### Notes

- 1. https://www.oecd.org/sti/ind/input-outputtables.htm
- 2. https://www.bok.or.kr/portal/bbs/P0000559/view.do?nttId=10065068&menuNo=2&pageIndex=1

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Analysis on industry's value-added rate

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#### Further reading

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#### **Corresponding author**

Jae-Whak Roh can be contacted at: jwroh@hansung.ac.kr