Title	Capturing information on technology convergence, international collaboration, and knowledge flow from patent documents: A case of information and communication technology
Authors(s)	Lee, Changjun, Kogler, Dieter Franz, Lee, Daeho
Publication date	2019-07
Publication information	Lee, Changjun, Dieter Franz Kogler, and Daeho Lee. "Capturing Information on Technology Convergence, International Collaboration, and Knowledge Flow from Patent Documents: A Case of Information and Communication Technology" 56, no. 4 (July, 2019).
Publisher	Elsevier
Item record/more information	http://hdl.handle.net/10197/11176
Publisher's statement	This is the author's version of a work that was accepted for publication in Information Processing and Management. Changes resulting from the publishing process, such as peer review, editing, corrections, structural formatting, and other quality control mechanisms may not be reflected in this document. Changes may have been made to this work since it was submitted for publication. A definitive version was subsequently published in Information Processing and Management (56,4, (2019)) https://doi.org/10.1016/j.ipm.2018.09.007
Publisher's version (DOI)	10.1016/j.ipm.2018.09.007

Capturing Information on Technology Convergence, International Collaboration, and Knowledge Flow from Patent Documents: A Case of Information and Communication Technology

Changjun Lee[1], Dieter F. Kogler[2] and Daeho Lee[3]

Abstract

Recent advances in data-driven research approaches offer new and exciting perspectives and insights across a spectrum scientific fields concerned with technological change and the socio-economic impact thereof, while also providing the opportunity to address persistent gaps in existing theories. The present investigation suggests a novel approach to identify and analyse the evolution of technology sectors, in this case Information and Communications Technology (ICT), considering international collaboration patterns and knowledge flows and spillovers via information inputs derived from patent documents.

The objective is to utilize and explore information regarding inventors' geo-location, technology sector classifications, and patent citation records to construct various types of networks. This, in turn, will open up avenues to discover the nature of evolutionary pathways in ICT technology trajectories, and also provide evidence of how the overall ICT knowledge space, as well as directional knowledge flows within the ICT space, evolved differently. It is expected that this data-driven inquiry will deliver intuitive results for decision makers seeking evidence for future resource allocation and who are interested in identifying well-suited collaborators for the development of potential next-generation technologies. Further, it will equip researchers in technology management, economic geography, or similar fields with a systematic approach to analyse evolutionary pathways of technological advancements and further enable them to exploit existing and develop new theories regarding technological change and its socio-economic consequences.

Keywords: Knowledge Space, Technology Evolution, Knowledge Flows and Spillovers, Inventor Collaboration, Information and Communication Technology (ICT).

JEL codes: O33

---

[1] Spatial Dynamics Lab, University College Dublin, Dublin, Ireland. changjun.chris.lee@gmail.com

[2] Spatial Dynamics Lab, University College Dublin, Belfield, Dublin 4, Ireland. D04 V1W8
dieter.kogler@ucd.ie – ORCID: http://orcid.org/0000-0002-6744-5632 – Twitter: @dfkogler

[3] Interaction Science, Sungkyunkwan University, Seoul, Republic of Korea. daeho.lee@skku.edu

1. Introduction

Patent documents contain a wealth of unstructured data, including multidimensional information, and once extracted and processed enable scholars and experts to carry out a variety of exploratory analysis tasks depending on their purposes (Liu et al., 2011). The importance of knowledge as a key asset in an innovation-driven economy is well documented (Teece, 1998; Jaffe and Trajtenberg, 2002). A key challenge for decision-makers in charge of managing knowledge asset is the effective exploration and exploitation of technological opportunity via information that is stored in patent data (Abbas, Zhang, & Khan, 2014; Bonino, Ciaramella, & Corno, 2010; Codina-Filba et al., 2017).

The increasing dominance of teams (Wuchty et al., 2007) and levels of complexity in the creation of novel products and processes of economic value (Kodama, 1992; Patel and Pavitt, 1997) has also sparked interest in patterns of international collaboration as one effective way to create or recombine a new and useful knowledge (Guan & Chen, 2012; Hird & Pfotenhauer, 2017; Kim & Park, 2009; Rycroft & Kash, 2004; Wagner & Leydesdorff, 2005; Zhang, 2017). Consequently, understanding trends in patterns of international collaboration and knowledge flows among countries in specific technology sectors, alongside an understanding of how knowledge spillovers facilitate technology convergence processes, becomes a focal point in the study of the evolutionary patterns of technological change (Dosi and Nelson, 1994). Developing a multi-dimensional understanding and framework of analysis of a specific technology sector could be even more critical when it comes rapidly evolving sectors, such as Information and Communication Technology (ICT, hereafter).

Researchers have utilized patent documents to analyze technology trends (Khasseh et al., 2017; Kim, Suh, & Park, 2008; Yoon & Park, 2004), perform tasks of technology forecasting (Chen et al., 2017; Daim et al., 2006; G. Kim & Bae, 2017; Kyebambe et al., 2017; Yoon & Park, 2005), investigate relations among scientists (Jiang et al., 2017), and undertake strategic technology planning (Joung & Kim, 2017; Lee, Kim, & Shin, 2017; Yu & Zhang, 2017). However, we still lack in a holistic understanding of technological change that considers four distinct but interrelated dimensions and evolutionary paths that lead to advances in a specific technology sector, i.e. (1) technology convergence, (2) collaboration network, and knowledge flow among (3) technologies and (4) countries. To the best of our knowledge, no quantitative investigation concerning the evolutionary trajectories of a certain technology sector that employed all these four dimensions concurrently has been carried out so far. Considering recent developments, investigating trends in collaboration and knowledge flows among countries is of particular relevance when aiming to understand the position of a country's capacity in a specific technology sector.

The present investigation suggests a novel approach for identifying and analysing technology convergence, international collaboration patterns, and knowledge flows taking place within in a specific technology sector (ICT in this study) and among inventors residing in different countries from patent documents. Following this approach the objective is to discover the nature of evolutionary paths in ICT and further to study the potential different paths of inventor collaboration and knowledge flow patterns over time. To convert on this vision, data from the United States Patent and Trademark Office (USPTO) that provide information on inventors' location (i.e. in order to detect where exactly the invention originated from), technology classifications (i.e. to delineate the building blocks of an invention), and citations to prior art (i.e. to identify directional knowledge flows) are utilized. It is expected that this data-driven approach along with the present investigation will provide intuitive results for decision makers, such as R&D

managers among others, who are concerned with future resource allocation tasks or who are interested in finding potential well-suited collaborators in their quest for next-generation technology development tasks. Further, it is also expected that the suggested approach will provide a toolset for researchers to analyse the complex matter of technological change more systematically while also allowing them to test existing, as well as exploiting new, theories in this line of injury.

The remainder of this study is organized as follows. Section 2 provides an outline of the data and the various methodological approaches employed in the present investigation. The subsequent section then highlights the findings of the study, while section 4 offers a discussion of results and some concluding remarks.

2. Data and Methods

2.1. Patent Documents and Data Sample

In order to conduct an international patent analysis, patent data from the USPTO were obtained. USPTO patent data publicly accessible and due to the size and competitiveness of the U.S. market these data are quite suitable for international technology and innovation studies (Jaffe, 1986; Jaffe & Trajtenberg, 2002; Lee, 2013). While the limitations of patent data are well known (Grilliches, 1998), they also provide a wealth of information. In the context of the present investigation information on inventors' geo-location, technology field classifications, and the patent citations are of relevance in order to delineate where exactly an invention originated from, which specific technology fields it is related to, and what technology classes provided essential knowledge inputs for the development of a novel product or process of economic value.

The focus is on patents applied for at the USPTO from 1980 to 2014, and there again only those patent documents related to Information and Communication Technology (ICT) fields. To filter ICT-related patents from the larger dataset, the International Patent Classification (IPC)-ICT concordance table developed by Inaba and Squicciarini (2017) was utilized. IPC is a patent classification tree based on fundamental knowledge and technology categories, and was originally established by the World International Property Organization (WIPO) and European Patent Office (EPO). The total number of USPTO patents applied for in the timeframe of interest, regardless of inventors' country of residence at the time of invention, is about 5.5 million. Once the IPC-ICT concordance table is applied, the sample results in about 1.8 million patent documents related to ICT technologies over the time period 1980-2014.

2.2. Capturing Knowledge and Collaboration space of countries in ICT

Figure 1 illustrates how to extract and reorganize the information of interest from patent documents. The example highlights 3 individual patents. Patent #1 and #3 were developed by three inventors respectively, while patent #2 only features 2 co-inventors. Patent #1 was co-invented by two individuals residing in the United States at the time of invention together with one inventor from Germany. Patent #2, on the other hand, was a collaboration between 2 inventors, one from the U.S. and another one from Japan. In addition to co-inventor collaboration patterns patent documents also provide insights into the technological fields are patent is allocated to. All three patents in the example displayed in Figure 1 are classified in 3 distinct technology classes, i.e. technology combinations (A, B, C), (B, C, E), and (B, E, F), respectively.

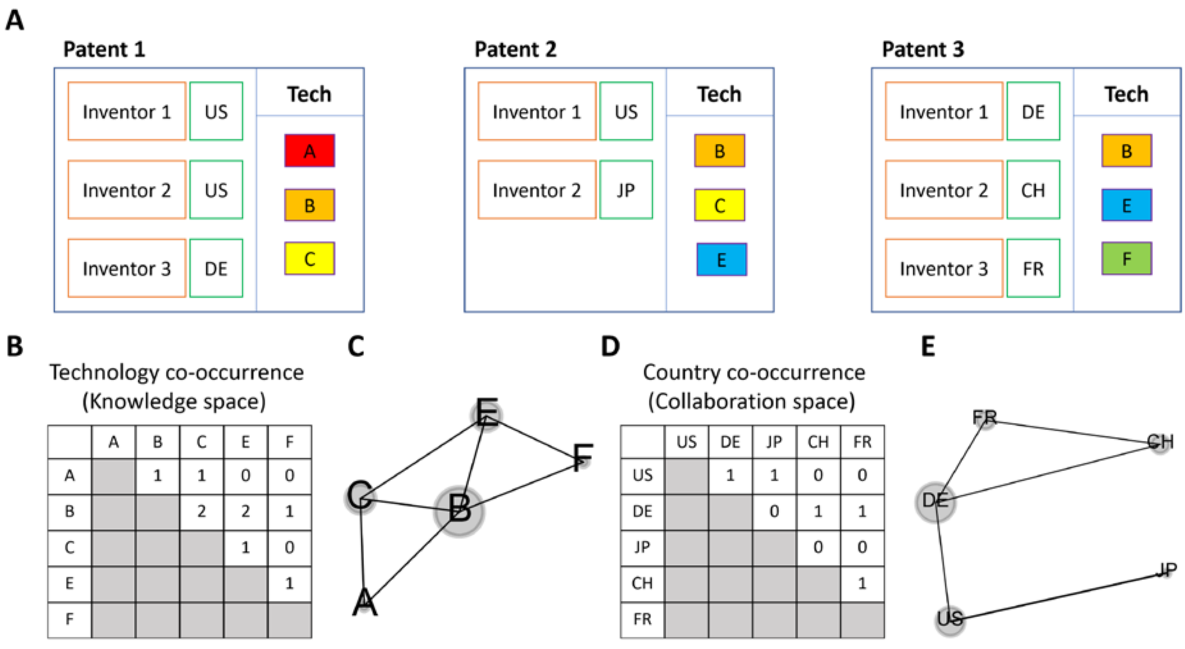


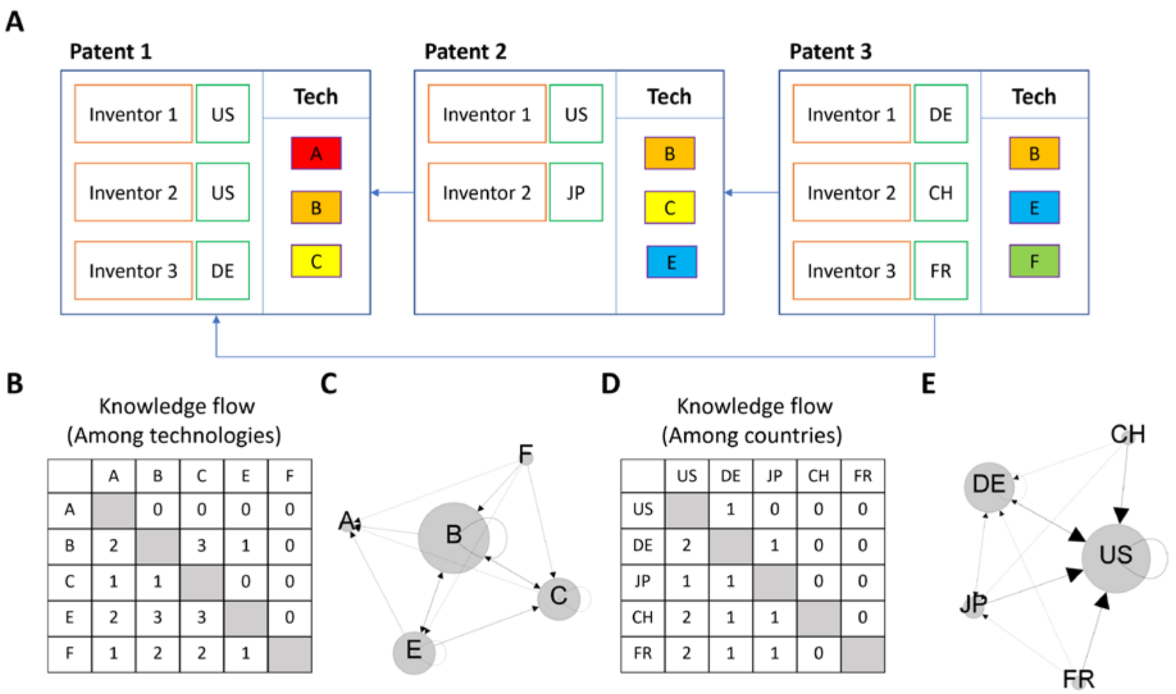
Fig 1. Example in knowledge space and collaboration network from patent document

To understand the relationship between ICT technology sub-classes and their recombination patterns, the knowledge space methodology (Kogler et al, 2013) is applied by constructing a technology class (or country) co-occurrence matrix. Following the work by Hidalgo, Klinger, Barabási, and Hausmann (2007), a variety of scholars have used this methodological approach to outline the relatedness between industries (Neffke, Henning, & Boschma, 2011), products (Hidalgo et al., 2007), and knowledge (Kogler, Essletzbichler, & Rigby, 2017). In order to construct an ICT knowledge space the technology class co-occurrence matrix in ICT-related patents needs to be developed first. For instance, technology class B and C occur together in Patent 1 and 2, but class A and E never co-occur in any patent in our example. Figure 1-B and 1-C show the co-occurrence matrix and the network visualization thereof based on the information derived from the three patents three patent documents in this example.

The co-occurrence matrix approach is also utilized to construct the international collaboration space. In a similar fashion like previously with the knowledge space methodology, a country co-occurrence matrix that counts each pair of inventor's resident countries found in every patent document of interest is constructed. For instance, the U.S. and Germany co-occur in Patent #1 (in other words a collaboration between U.S. and German inventors took place while developing this invention). Similar, in patent #2 there was a collaboration between an inventor residing in the U.S. and one who was located in Japan at the time of invention. Patent #3 features 3 inventors from 3 different countries and thus we find 3 instances of international collaborations, i.e. Germany and Switzerland, Switzerland and France, and Germany and France. Following this approach the international collaboration matrix is shown in Figure 1-D. This co-occurrence matrix can be also translated into a network visualization, which is displayed in Figure 1-E.

2.3. Capturing Knowledge Flow among Technologies and Countries from patent

While there is no direction between pairs of technologies or countries in co-occurrence matrix, there exists both a source and a target in knowledge flow. In other words, knowledge flow shows the origins of the knowledge and the destinations where it flows towards. We use the information on the technology elements and patent citations to capture the knowledge flow in the two, technology and country, dimensions. Figure 2 illustrates an example of the process in capturing knowledge flow among technologies and countries from the patent. Assuming the knowledge (or the technology) in Patent #1 is influenced by Patent #2 and #3, and Patent #2 is created by applying the knowledge in Patent #3, the knowledge flow among countries can be started from Germany, Switzerland, and France, via US and Japan, arrived to US and Germany (see Figure 2-D and E). Also, we can find the direction of the knowledge flow among technologies, which flows from Tech (B, E, F), through (B, C, E), to (A, B, C). For instance, knowledge flow from Tech C to B happens only once in Patent #2 to #1, and flow from Tech B to C happens three times in Patent #3 to #2, #3 to #1, and #2 to #1 (see Figure 2-B). This technology flowing direction is visualized in Figure 2-C.



	A	B	C	E	F
A		0	0	0	0
B	2		3	1	0
C	1	1		0	0
E	2	3	3		0
F	1	2	2	1	

	US	DE	JP	CH	FR
US		1	0	0	0
DE	2		1	0	0
JP	1	1		0	0
CH	2	1	1		0
FR	2	1	1	0	

Fig 2. Example in knowledge flow among technologies and countries from patent document

2.4. Evolutionary trajectories of each network

To understand the evolutionary trajectories of above four spaces; (1) technology co-occurrence matrix, (2) country co-occurrence matrix, (3) technology flow matrix, and (4) country knowledge flow matrix, we exploit those four matrices over five-year periods; 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2009, and 2010-2014. By using those 28 (4×7) adjacency matrices, we visualize and observe how the four spaces have evolved over the periods. This helps us easily gain some intuition and ideas, however, we still need a help from some numbers with regards to the overall network properties for further understanding, thus using basic indicators in network analysis studies such as the number of nodes, edges, network density, average path length, and average cluster coefficients. The large numbers of nodes and edges mean that many technologies (or countries) are participating during the periods, and their combinational links are diverse, respectively. Network density is calculated as the sum of the weight of edges divided by every possible combination of edges, representing the degree of connectivity. Average path-length is calculated by summing the shortest path between all pairs of nodes and dividing by the total number of pairs. It represents how long it takes for a node to get to another node on average. Average clustering coefficient is the ratio of existing edges connecting a node's neighbors to each other to the maximum possible combination.

2.5. Trends analysis with network indices

We apply the several network indices with the attributes of nodes and edges to capture the trend of technology convergence, collaboration, knowledge flow among technologies, and countries. Edge weight, A_{ij}, which is the value of the cell in the co-occurrence between *i* and *j* or knowledge flow from *i* to *j*, enables us to capture the trend of distinguished convergent combination between technologies.

Centralities are the most representative indicator in network analysis. We use weighted degree and betweenness centrality to track the evolutionary trajectories in top-tiered technologies in ICT as the knowledge spaces have evolved. Weighted degree centrality, $\mathrm{C_{WD}}(v)$, is the sum of edge weight to a node, measured by each node. Co-occurrence matrix does not consider the in-or-out-degree centrality because there is no meaning in the direction of the links. Knowledge flow matrix, however, the direction of links by nodes has different implications whether they are in-coming or out-going links, thus in-degree, $\mathrm{C_{WD-in}}(v)$, and out-degree, $\mathrm{C_{WD-out}}(v)$, centralities are measured separately. We can also capture the tendency of being source technology (or country) in knowledge flow by using the directional information (in this study, it is patent citation). Here, we use out-degree ratio to the overall degree, $\mathrm{ODR}(v)$.

$$\mathrm{C_{WD}}(v) = \mathrm{C_{WD-in}}(v) + \mathrm{C_{WD-out}}(v) \qquad \text{eq. (1)}$$
where, $\mathrm{C_{WD-in}}(v) = \sum_i A_{iv}$, $\mathrm{C_{WD-out}}(v) = \sum_j A_{vj}$

$$\mathrm{ODR}(v) = {\mathrm{C_{WD-out}}(v)} \Big/ {\mathrm{C_{WD}}(v)} \qquad \text{eq. (2)}$$

We also use eigenvector centrality, $\mathrm{C_E}(v)$, to measure overall influence of the nodes across the networks (Newman, 2008). Compared to the way of calculation for degree centrality where each neighbor contributes equally to centrality, a node's eigenvector centrality is calculated with considering the relative scores assigned to all other nodes based on the concept that connections to high-scoring nodes indicates higher influence than the equal number of connections to low-scoring nodes. Eigenvector centrality of a node is calculated by proportional value to the sum of scores of its neighbors (see Equation 3). Therefore, a high eigenvector score means that a technology (or a country) is connected to many technologies (or countries) with high eigenvector scores.

$$\mathrm{C_E}(v) = \frac{1}{\lambda}\sum_{t\in M(v)} \mathrm{C_E}(t) = \frac{1}{\lambda}\sum_{t\in G} A_{vt} \times \mathrm{C_E}(t) \qquad \text{eq. (3)}$$

where $M(v)$ is a set of the neighbors of v, and λ is a constant

Betweenness centrality, $C_B(v)$, is measured by the number of the shortest paths that pass through each node (see Equation 4). Betweenness centrality indicates how a node is well bridging other nodes or communities through the node, measured by each node. A node with the highest betweenness centrality is the most connective technology in the knowledge space, the biggest platform country in the collaboration space, and the most effective transferring knowledge and country in the knowledge flow spaces.

$$C_B(v) = \sum_{i \neq v \neq j \in V} \frac{\sigma_{ij}(v)}{\sigma_{ij}}$$

eq. (4)

where σ_{ij} is the number of shortest paths from *i* to *j*, and $\sigma_{ij}(v)$ is the number of shortest paths from *i* to *j* that passes through node *v.*

2.6. Trend analysis based on positioning each node using centralities

We apply a matrix based on eigenvector and betweenness centrality to identify the positions of the nodes in the collaboration space and knowledge flow among countries (see Figure 3). Unlike C. Lee and Kim (2018) adopted weighted degree centrality for building a positioning matrix, we use eigenvector centrality partnered with betweenness centrality to reflect overall influence of the nodes in the networks more effectively as eigenvector centrality, compared to weighted degree centrality, weights more for each node's overall influence of network rather than the node itself. Thus, if a technology (or a country) has both high eigenvector and betweenness centralities, we classify the node into a global hub of the entire network system because it has a highly influential power as well as a high possibility of overlapping with other technologies (or countries). However, if a node has a high eigenvector but low betweenness centrality, the node is likely to be a local hub of a community because it has a strong influence but only in a specific local community. In addition, if a node has low eigenvector centrality but high betweenness centrality, the node is likely to be a bridge node linking between other local communities, meaning that the technology (or the country) is not influential but it could be a bottleneck or a gatekeeper when the important information is transferred from one community to the other.

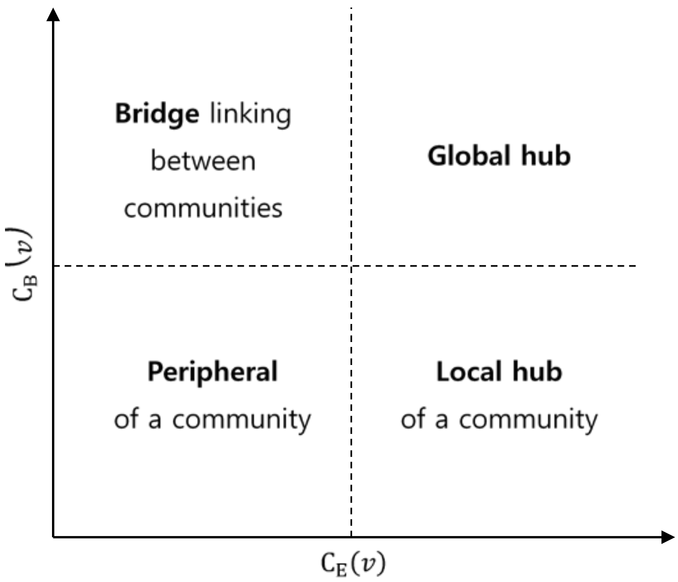


Fig 3. Network positioning matrix

3. Findings

3.1. Evolutional paths of Knowledge Space and flow in ICT

Table 1 shows the descriptive statistics of the knowledge space and flow in ICT by periods. All networks have twelve nodes, which represent that twelve technology areas of ICT; *High speed network, Mobile communication, Security, Sensor and device network, High speed computing, Large-capacity and high speed storage, Large-capacity information analysis, Cognition and meaning understanding, Human-interface, Imaging and sound technology, Information communication device, Electronic measurement,* and *Others*, are connected each other at least once, thus there are no isolated nodes in both networks. Network densities in both networks have been increased from 54 to 2,069 and from 1,587 to 2,938,818 as the weights of the edges have grown in the fixed number of nodes. An increasing trend of network density in knowledge space means that ICT technology has become more complicated and has been invented in variously combined manner (rigorous recombination), whereas, an increasing trend of network density in knowledge flow space means that the amount of the knowledge in- and out-flowing among the sub-technological fields in ICT has grown rapidly.

Table 1. Descriptive statistics of the networks (Knowledge space and flow in ICT)

Period	80-84	85-89	90-94	95-99	00-04	05-09	10-14
Knowledge space in ICT							
No. nodes	12	12	12	12	12	12	12
No. edges	124	132	132	131	132	132	132
Net. Density	54	88	205	520	919	1,328	2,069
Knowledge flow in ICT							
No. nodes	12	12	12	12	12	12	12
No. edges	132	132	132	132	132	132	132
Net. Density	1,587	4,595	21,971	290,898	232,707	793,250	2,938,818

Figure 4 shows the evolutional paths of ICT knowledge space and knowledge flow space every other 5 years. In knowledge space, the distance between technologies indicates technical relatedness between them measured by the degree to which they co-occur frequently. Thus, the short distance means high technical relatedness, so that they are more likely to be combined together than other pairs. During 1980-1984, the four technologies such as *information communication devices, high speed network, large-capacity and high speed storage,* and *imaging and sound technologies* are located in the center of knowledge space. Since 1990, however, technologies related to *security* and *large-capacity information analysis* had grown rapidly and combined with the previous big four technologies. During 2000-2004, sensor technologies like *Human-interface* or *Computer input-output and Others* started growing, and the recent period of 2010-2014 shows a big growth of *mobile communication*.

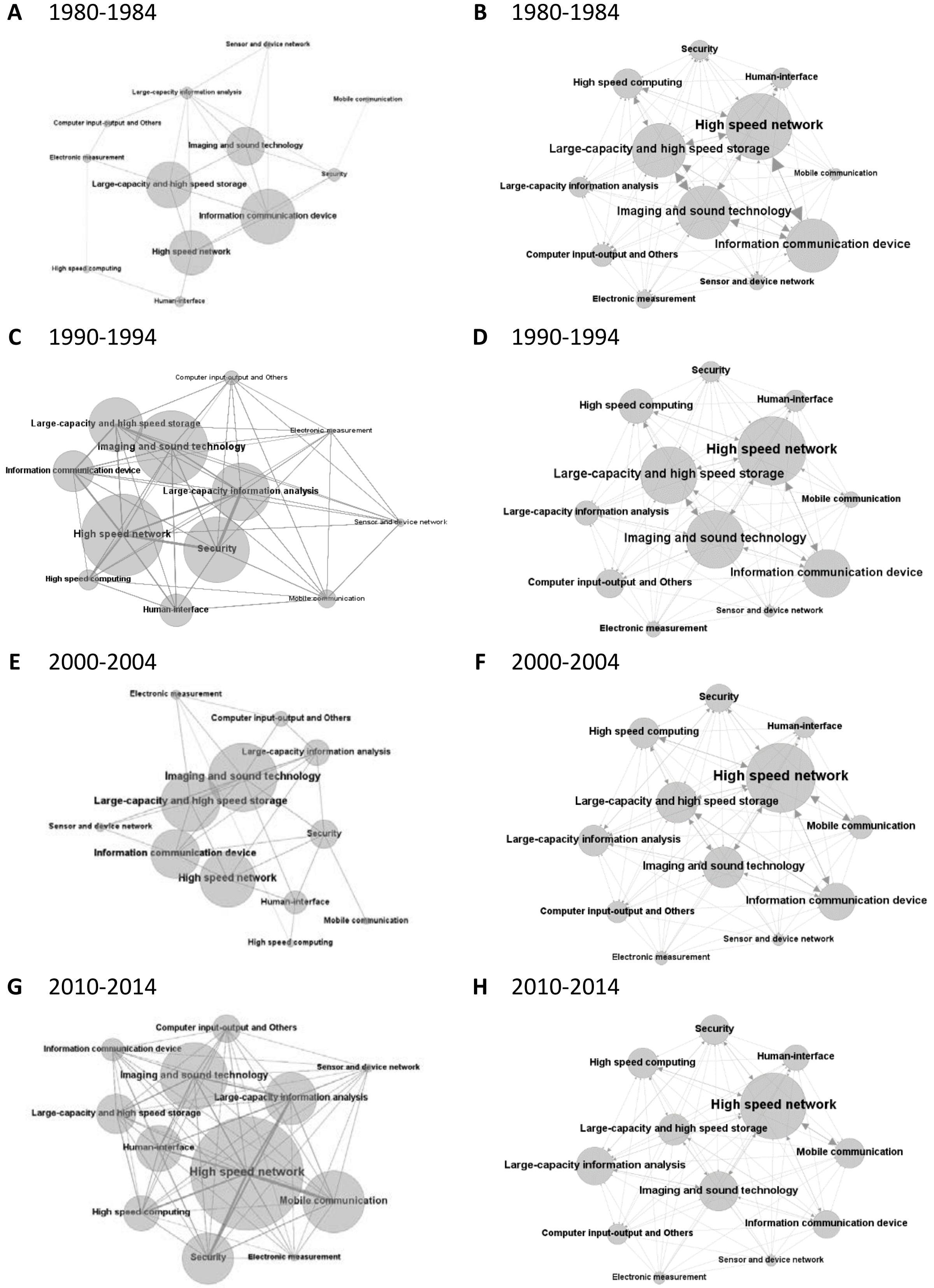


Fig 4. Evolutional path of knowledge space and flow in ICT sector
Note: **A**, **C**, **E**, and **G** indicate an evolutionary path of knowledge space, and **B**, **D**, **F**, and **H** indicate an evolutionary path of Knowledge flow.

While the knowledge space has changed dramatically, the evolutional path of knowledge flow space seems not changed over the periods. It might be caused by the factor of the knowledge of which foundations or sources are hardly replaced. Once a technology is used as a base knowledge, then the technology would be cited repeatedly as the knowledge complexity has increased. *High speed network* has been used the source of knowledge over the period. At the first period of 1980-1984, we found the specific technology pairs where both paired technologies highly affect each other. For example, *high speed network* and *information communication device* are influenced by each other, and *large-capacity and high speed storage* and *imaging and sound technology* are citing each other as well. However, the trend did not last longer until the period of 1990-1994. We hardly find a strong evidence of which technologies are more based on the others because most technologies ended up being connected and citing each other. The fact which has not been changed is that the four technologies such as *high speed network*, *information communication device*, *large-capacity and high speed storage*, and *imaging and sound technology* are knowledge sources for the other technologies like *electronic measurement* and *sensor and device network*.

Aggregated edges' weight by period hints the relationship between the technologies and their evolution. Table 2 shows the trends in top five convergent ICT technologies and their weights in the knowledge space network (the left-sided) and also top five direction of ICT technology flow in the knowledge flow network (the right-sided). The most frequent convergent combination during 1980-1984, combined between *High speed network* and *information communication device technologies*, had made the top five convergent lists until the period of 2000-2004, and disappeared after then. Whereas, the combination between *high speed network* and *mobile communication* combination had not been in the list until 1994, but suddenly emerged to the second rank and have kept the first tier up to the period of 2010-2014.

In knowledge space, the two technologies; *high speed network* and *Information communication device* are co-occurred frequently in 1980s, but there is no information on the direction of knowledge flow. The right-side of the Table 2 shows the top five direction of the knowledge flow in ICT. During the period of 1980-1989, it turns out that the knowledge flow is mostly bi-directional instead of unilateral until the period of 1990-1994. For example, during the period of 1980-1984, the first rank was the flow from *Imaging and sound technology* to *Large-capacity and high speed storage,* and second rank was the opposite direction between the two. The period of 1985-1989 has the same relationship between the two. This trend was changed since 1990. During the period of 1995-1999, most of knowledge flowed from *high speed network* technology to various technologies. In other words, *high speed network* technology became the famous knowledge source for other technologies.

Node attributes (several centralities in this paper) give useful information such as each sub-technologies' recombination and positionings in ICT. Figure 5 shows how each technology's weighted degree centrality has been changed over the years. Figure 5-A and -B represent the trend of the weighted degree in the knowledge space and the knowledge flow respectively. Most technologies are in the increasing trends in both graphs, with similar orders. We found two ICT technologies mismatched in the two networks; *Imaging and sound* and *Computer input-output* technologies. *Imaging and sound* technology has kept the second rank with high growth rate in knowledge space but has been laggard with slow growth rate in knowledge flow. This can be translated into that *Imaging and sound* became famous for convergent technology but not contributed much to the ICT knowledge flow in the way of being source or target of knowledge. On the other hands, *Computer input-output* technology has been skyrocketed in knowledge flow network but has grown slowly in knowledge space network. This means that it contributed a lot to being source or target of knowledge creation rather than being a convergent counterpart.

Table 2. Trends in Top 5 convergent technologies and technology flow in ICT sector

Period	Knowledge space in ICT			Knowledge flow in ICT		
	Weight	Convergent technologies (A-B)		Weight	Technology Knowledge Flow (A → B)	
80-84	833	High speed network	Information communication device	8134	Imaging and sound technology	Large-capacity and high speed storage
	665	Imaging and sound technology	Large-capacity and high speed storage	8108	Large-capacity and high speed storage	Imaging and sound technology
	555	Imaging and sound technology	Information communication device	7487	Information communication device	Large-capacity and high speed storage
	548	Information communication device	Large-capacity and high speed storage	7226	High speed network	Information communication device
	473	High speed network	Large-capacity and high speed storage	7206	Information communication device	High speed network
85-89	1244	Imaging and sound technology	Large-capacity and high speed storage	33572	Imaging and sound technology	Large-capacity and high speed storage
	1165	High speed network	Information communication device	25381	Large-capacity and high speed storage	Imaging and sound technology
	755	Information communication device	Large-capacity and high speed storage	18987	High speed network	Large-capacity and high speed storage
	740	Imaging and sound technology	Information communication device	18893	High speed network	Information communication device
	604	High speed network	Imaging and sound technology	18093	Imaging and sound technology	High speed network
90-94	2910	Imaging and sound technology	Large-capacity and high speed storage	164776	High speed network	Security
	2066	High speed network	Information communication device	143077	High speed network	Imaging and sound technology
	1718	High speed network	Imaging and sound technology	128565	Imaging and sound technology	Large-capacity and high speed storage
	1521	Information communication device	Large-capacity and high speed storage	124978	Imaging and sound technology	High speed network
	1292	High speed network	Large-capacity and high speed storage	111018	High speed network	Human-interface
95-99	6426	Imaging and sound technology	Large-capacity and high speed storage	2928540	High speed computing	Computer input-output and Others
	4774	High speed network	Mobile communication	2532435	High speed network	Security
	4469	High speed network	Imaging and sound technology	1956090	High speed computing	Security
	3969	High speed network	Information communication device	1694052	High speed network	Computer input-output and Others
	3479	Information communication device	Large-capacity and high speed storage	1451001	High speed network	High speed computing
00-04	11704	High speed network	Mobile communication	1728288	High speed network	Security
	8399	Imaging and sound technology	Large-capacity and high speed storage	1167235	Large-capacity information analysis	Security
	7286	Large-capacity information analysis	Security	999882	Security	High speed network
	6938	Information communication device	Large-capacity and high speed storage	955874	High speed network	Large-capacity information analysis
	6384	High speed network	Information communication device	933365	Mobile communication	High speed network
05-09	21283	High speed network	Mobile communication	5906331	High speed network	Large-capacity information analysis
	11377	Imaging and sound technology	Large-capacity and high speed storage	5120550	High speed network	Security
	10684	Large-capacity information analysis	Security	5064852	High speed network	High speed computing
	9936	High speed network	Security	3843908	Security	Large-capacity information analysis
	8478	High speed network	Imaging and sound technology	3634971	Large-capacity information analysis	Security
10-14	34294	High speed network	Mobile communication	21941332	High speed network	Large-capacity information analysis
	15608	High speed network	Security	21646633	High speed network	Security
	12360	High speed computing	High speed network	21017758	High speed network	High speed computing
	11749	Imaging and sound technology	Large-capacity and high speed storage	20861449	High speed network	Computer input-output and Others
	11532	Imaging and sound technology	Large-capacity information analysis	14176313	Mobile communication	Large-capacity information analysis

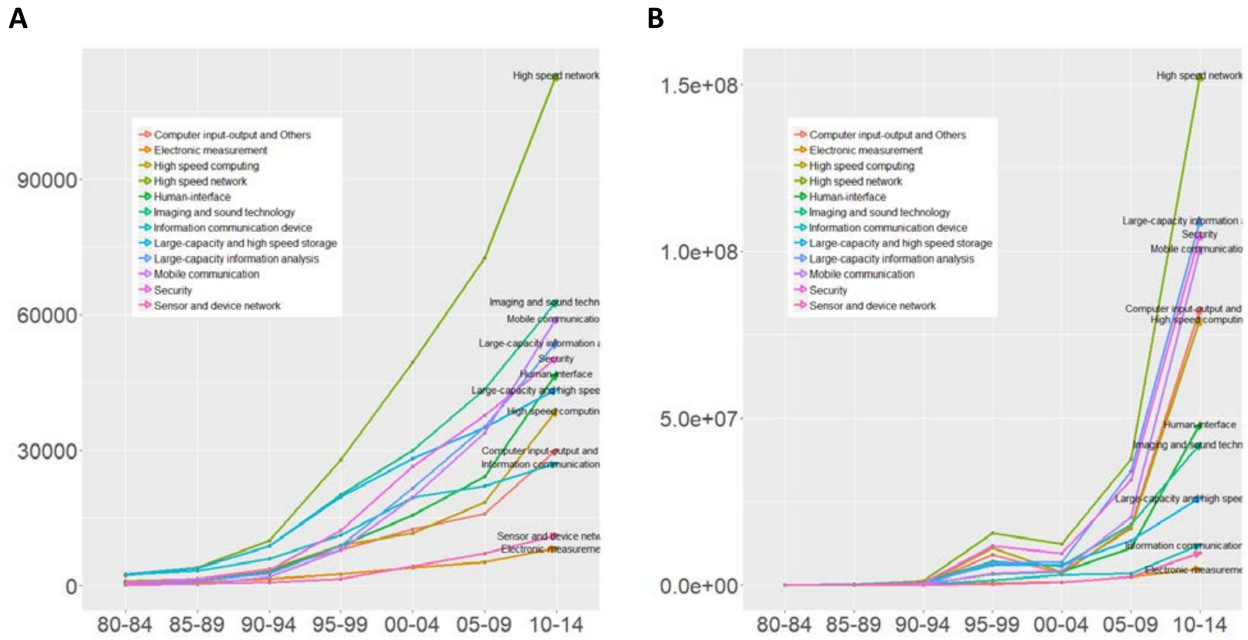


Fig 5. Trends in weighted degree by technologies in ICT sector
Note: Fig. 5 represents trends in $\mathrm{C_{WD}}(v)$ by ICT technologies in knowledge space (**A**) and knowledge flow space (**B**).

As Figure 5 shows the trend with the absolute weighted degree values, we can also figure out the absolute difference between technologies but hardly capture the relative dynamics among the technologies. In this sense, Figure 6 may help us to understand the technology dynamics and forecasting better by showing the trends in the rank of weighted degree and eigenvector centralities in ICT sector. Figure 6-A and -B refer to the ranking dynamics of weighted degree centrality in knowledge space and flow respectively, and Figure 6-C and -D refer to the ranking dynamics of eigenvector centrality in both spaces. We highlight the two technologies; *Mobile communication* and *Large-capacity information analysis,* are most fast growing technologies in all centralities and spaces. What is interesting when comparing the two spaces, the increasing rate in ranking of *Mobile communication* is faster than *Large-capacity information analysis* in knowledge space, but the opposite holds in knowledge flow space, which means that the main power of growth in *Mobile communication* technology is driven by being fused with other technologies rather than adopting or affecting other technologies. *Information and communication device* technology is in decreasing trend in both spaces. Trend of eigenvector centralities has no distinguished differences compared to weighted degree centralities.

3.2. Evolutional paths of Collaboration Space and Knowledge flow in ICT

Table 3 shows the descriptive statistics of the collaboration space and knowledge flow among countries in ICT by periods. Nodes have been growing in both networks. Only 87 countries made international collaborations during the period of 1980-1984, but nowadays about more than 180 countries are participating to collaborate or contributing to the knowledge flow in ICT sector. Network density in both networks have increased from 0.114 to 1.482 and from 3.36 to 24.83, representing that collaboration has become more multinational and also knowledge flow has become more dense among countries as ICT technology is getting more complicated.

Average path length in both networks has been decreased from 2.51 to 2.11 in the collaboration space and from 2.02 to 1.93 in the knowledge flow space. Decreasing trends in average path length hint how the two spaces have co-evolved. Transferring knowledge (or information) has become faster in knowledge flow network as many countries have been more connected in collaboration space network where they can find and reach the proper collaborative partners easier than before. The evidence of which average clustering coefficient in both networks has been increased steadily leads us to the interpretation that local communities have been forming slowly within the both collaboration and knowledge flow networks.

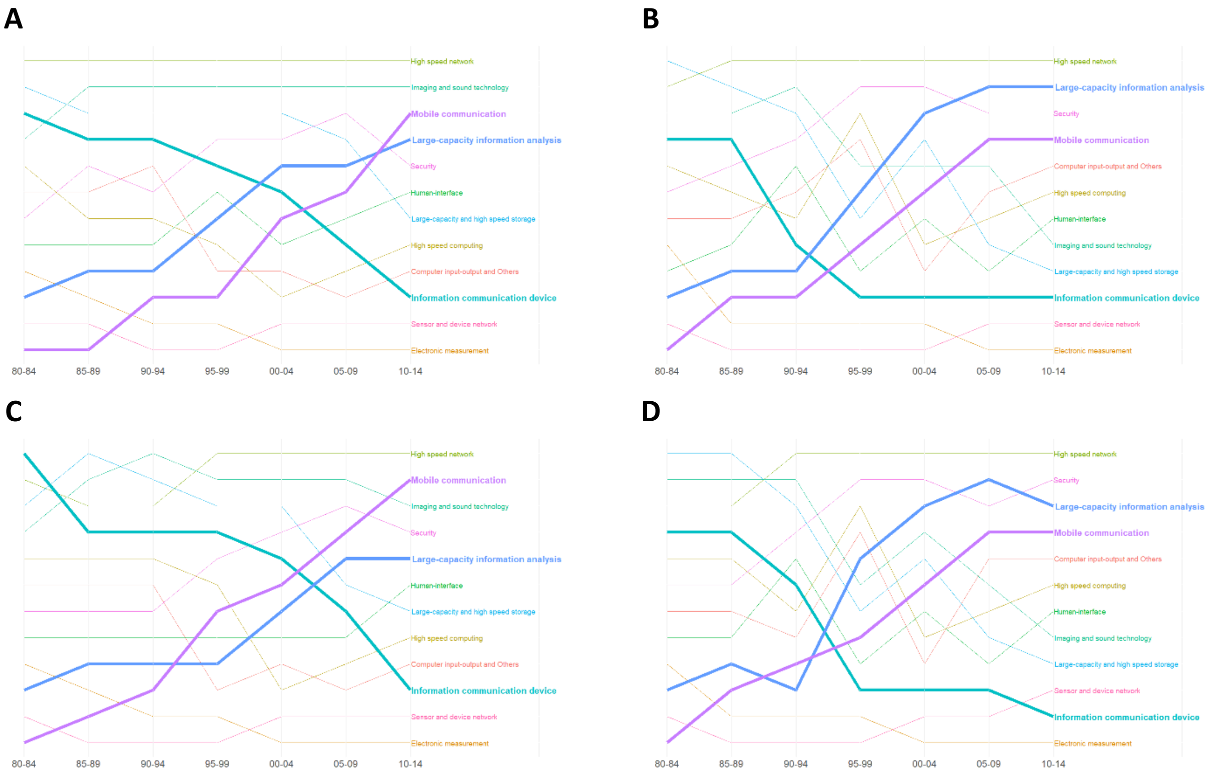


Fig 6. Ranking dynamics of centralities in knowledge space and flow among ICT technologies
Note: Fig. 6 represents ranking dynamics of $C_{WD}(v)$ in knowledge space (**A**) and knowledge flow space (**B**), and $C_E(v)$ in knowledge space (**C**) and knowledge flow space (**D**).

Table 3. Descriptive statistics of the networks (Collaboration space and knowledge flow among countries)

Period	80-84	85-89	90-94	95-99	00-04	05-09	10-14
Collaboration space in ICT							
No. nodes	87	97	119	162	183	183	184
No. edges	268	362	563	1,091	1,659	2,019	2,189
Net. Density	0.114	0.185	0.269	0.442	0.758	1.152	1.482
Ave. Pathlength	2.510	2.420	2.310	2.300	2.220	2.100	2.110
Ave. CC	0.197	0.238	0.247	0.306	0.341	0.363	0.385
Knowledge flow among countries in ICT							
No. nodes	108	119	134	175	199	188	189
No. edges	612	849	1,215	2,297	3,101	3,143	3,407
Net. Density	3.360	6.220	9.560	17.64	18.47	18.75	24.83
Ave. Pathlength	2.020	2.000	1.970	1.950	1.960	1.950	1.930
Ave. CC	0.232	0.269	0.305	0.331	0.363	0.387	0.419

Figure 7 shows the evolutional paths of collaboration space and knowledge flow in ICT sector every other 5 years. During the period of 1980-1984, the prominent nature of the two networks is that a few countries compared to the recent networks joined collaboration and knowledge flow and four or five countries such as United States (US), Japan, Germany, France, and United Kingdom led the collaboration or knowledge creating scene. What can be clearly seen in this period is that most of ICT knowledge flows between US and Japan. However, there has been gradual rise in the number of participating countries during the period of 1985-2004. US and Japan are no longer the only countries collaborating and flowing knowledge between each other. The distribution of collaboration and knowledge flow had become more even, but there had been still uneven distribution across the world, rather been concentrated to about ten to twelve countries. For example, the countries positioned at the periphery of the network such as South Korea has been emerged in the knowledge flow scene since 2000. Currently, more countries are crowded in the center of the collaboration space and the knowledge flow sources and channels are becoming more diverse.

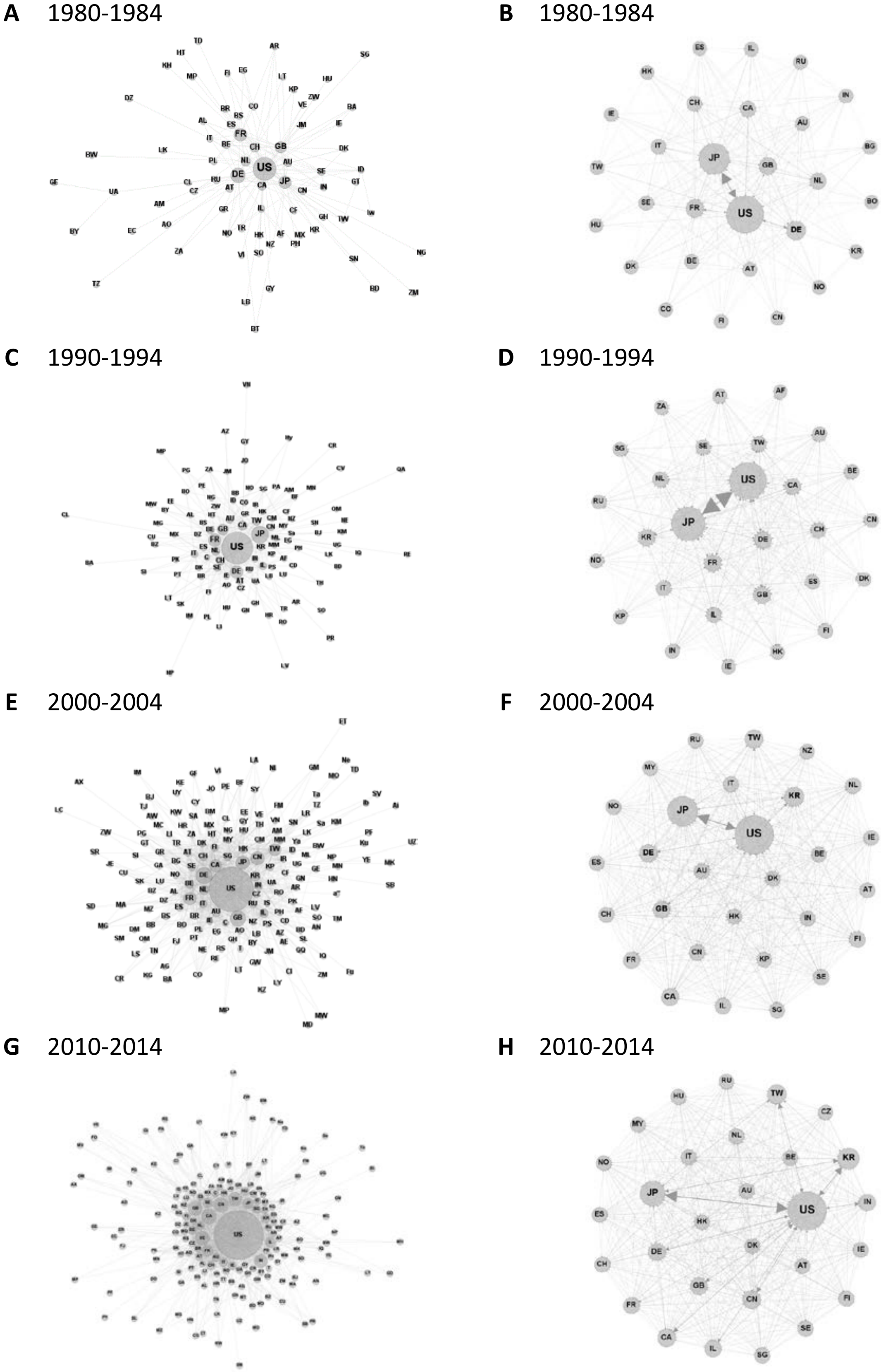


Fig 7. Evolutional paths of collaboration space and knowledge flow in ICT sector
Note: **A**, **C**, **E**, and **G** indicate an evolutionary path of collaboration space, and **B**, **D**, **F**, and **H** indicate an evolutionary path of Knowledge flow space among countries.

Table 4 shows the trends in Top 5 international collaboration partners in ICT sector. As shown in Figure 7, since 1980 United States has been a global hub in collaboration space and also in knowledge transfer network. The collaboration between US and Japan had been one of the most frequent collaboration until 2009, but is not in the top 5 collaboration list in the period of 2010-2014. Other collaborations such as US-Germany, US-Canada, and US-U.K. have stayed strong. What stands out in this scene is the collaborations between China and Taiwan, and US and India. China-Taiwan collaboration, which were not appeared in the top ranks before, suddenly made fifth during 1995-2004. US-India collaboration emerged in 2005-2009 as the third, and made the most popular collaboration in the period of 2010-2014.

Table 4. Trends in Top 5 international collaboration partners in ICT sector

Period	Collaboration space in ICT			Knowledge flow in ICT		
	Weight	Collaboration partner (A-B)		Weight	Technology Knowledge Flow (A → B)	
80-84	61	United States	Japan	8649	United States	Japan
	51	United States	United Kingdom	7132	Japan	United States
	49	United States	Germany	1742	United States	Germany
	37	United States	Canada	1673	Germany	United States
	32	United States	Netherland	1457	France	United States
85-89	184	United States	Japan	20712	United States	Japan
	114	United States	Canada	19708	Japan	United States
	83	United States	United Kingdom	3136	Germany	United States
	74	United States	Germany	2680	United States	Germany
	65	Japan	Germany	2569	United Kingdom	United States
90-94	517	United States	Japan	43930	Japan	United States
	224	United States	United Kingdom	33915	United States	Japan
	172	United States	Canada	5029	United Kingdom	United States
	168	United States	Israel	4292	Germany	United States
	158	United States	Germany	3846	France	United States
95-99	1179	United States	Japan	107446	Japan	United States
	694	United States	Canada	81122	United States	Japan
	690	United States	United Kingdom	16548	Canada	United States
	552	United States	Germany	15991	United States	United Kingdom
	530	Taiwan	China	15410	United States	South Korea
00-04	1622	United States	United Kingdom	99614	Japan	United States
	1560	United States	Germany	88555	United States	Japan
	1547	United States	Japan	22764	Canada	United States
	1441	United States	Canada	20516	United Kingdom	United States
	1127	Taiwan	China	20055	United States	United Kingdom
05-09	2526	United States	Canada	63318	Japan	United States
	2254	United States	United Kingdom	50171	United States	Japan
	1965	United States	India	24136	United States	South Korea
	1892	United States	Germany	22289	Canada	United States
	1738	United States	Japan	21823	United States	Canada
10-14	3779	United States	India	67307	Japan	United States
	3670	United States	Canada	45108	Canada	United States
	2672	United States	China	36505	United States	Japan
	2614	United States	United Kingdom	35639	United States	Canada
	2190	United States	Germany	30755	South Korea	United States

There are also interesting findings in direction of knowledge flow in ICT. Until 1989, US had been the main source of ICT knowledge and it had flooded towards Japan mostly, however, the flow has been changed to the opposite direction since 1990, and Japan still plays a role of the main knowledge source in ICT sector. What is interesting in here is the emergence of South Korea. Even if South Korea has not been existed in collaboration scene during the whole periods, ICT knowledge suddenly flown to them in the 2004-2009, and finally they are now one of the main sources of ICT knowledge.

Figure 8 shows the trends in ranking of weighted degree, eigenvector, and betweenness centralities in ICT sector. We find a prominent increasing trend in weighted degree centrality of Canada, India, and China (see Figure 8-A) and eigenvector centrality of them (see Figure 8-C) in collaboration space. In knowledge flow, however, a prominent increasing trend is found in weighted degree and eigenvector centralities of Canada and South Korea (see Figure 8-B), and a prominent decreasing trend is found in France and Switzerland (see Figure 8-D).

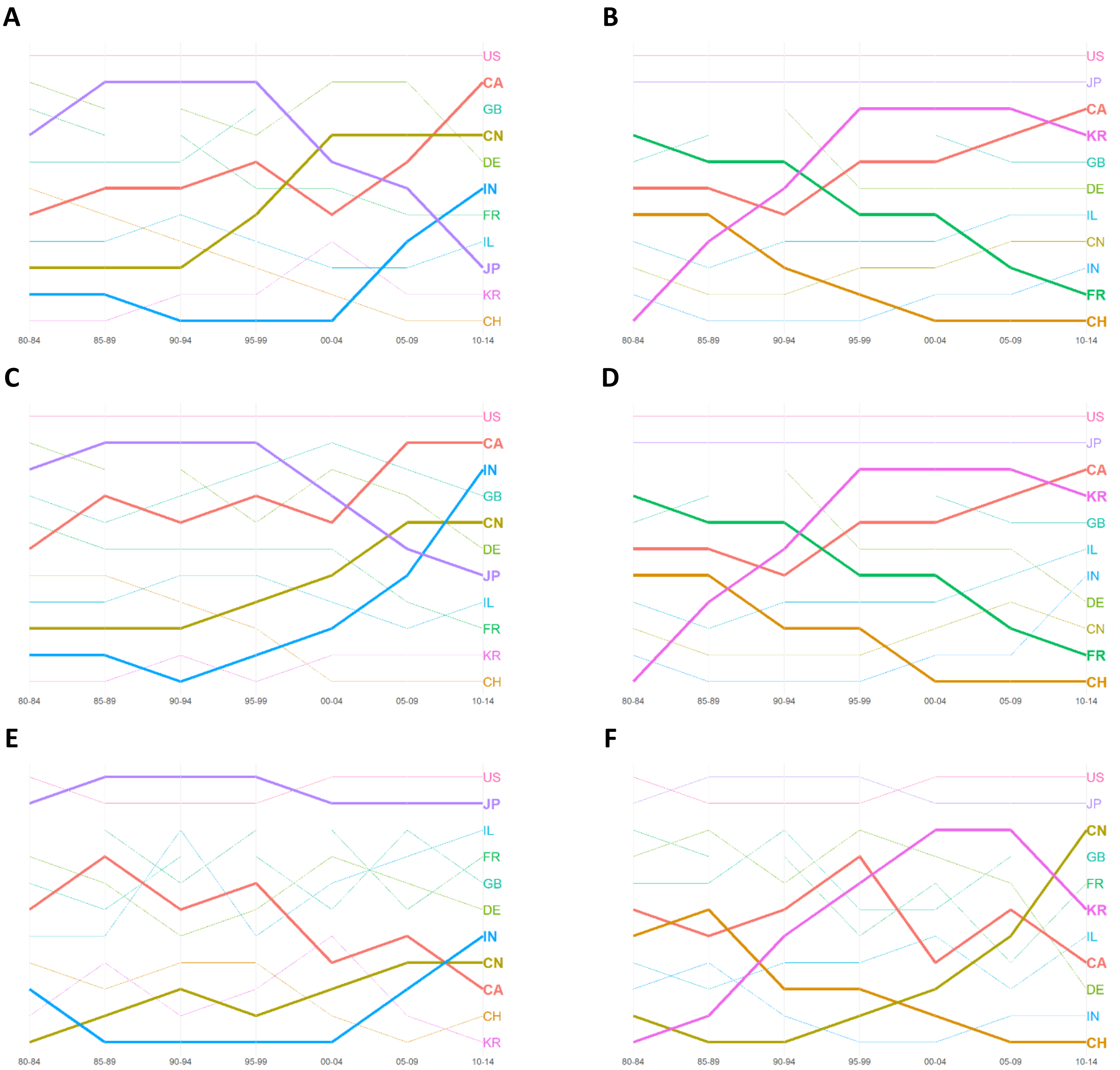


Fig 8. Ranking dynamics of centralities in ICT knowledge space and flow among countries

Note: Fig. 8 represents ranking dynamics of $C_{WD}(v)$ in knowledge space (**A**) and knowledge flow space (**B**), $C_{E}(v)$ in knowledge space (**C**) and knowledge flow space (**D**), and $C_{B}(v)$ in knowledge space (**E**) and knowledge flow space (**F**).

When it comes to the betweenness centrality, Japan keeps top tiered in both collaboration and knowledge flow (see Figure 8-E and -F). While, Canada is in decreasing trend even if they kept top tiered in weighted degree centrality and eigenvector centrality (see Figure 8-E). In knowledge flow, China made a rapid growth in betweenness and South Korea had made a significant growth until 2009, but stopped growing currently (see Figure 8-F). Even if South Korea has grown to an important knowledge source but current abrupt fall could lead them to a local hub, which has influential power only within the specific communities.

3.3. Capturing the relationship between countries by using network position matrix

To capture the positioning of the countries in collaboration and knowledge flow scenes, we apply the network position matrix. Figure 9 shows how each country has moved their position in collaboration and knowledge flow space. We find that, firstly, U.S. is the only country keeping the global hub position in the two spaces at the same time. Japan is a global hub in knowledge flow but has moved from a global hub to the bridge position in collaboration space. Canada was also one of the global hubs in the two spaces but has fallen into the local hub in both spaces. Switzerland is losing their influence (eigenvector centrality) and their gate-keeping role (betweenness centrality) in both spaces. South Korea is not a famous player in collaboration space, but in knowledge flow space they have been growing from periphery, through local hub, to the global hub. Currently, however, they stopped growing towards global hub, rather towards local hub. China was peripheral in both spaces, but they have grown to the local hub in collaboration space, and to bridge role in knowledge flow.

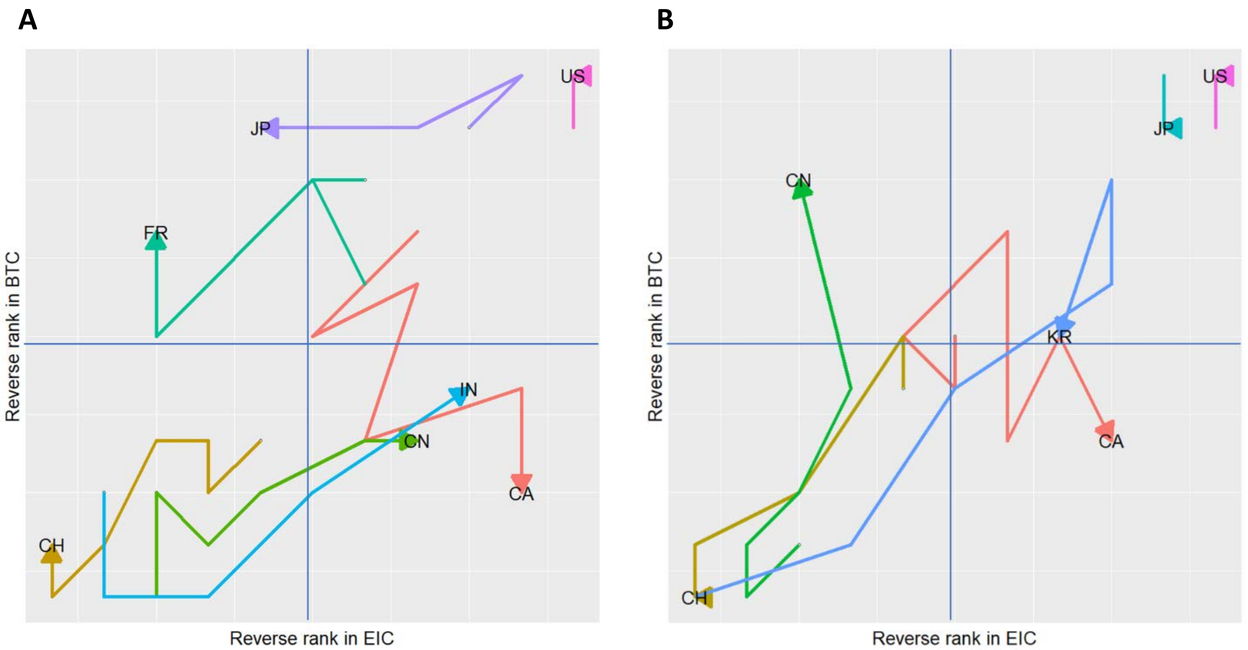


Fig 9. Trends of changing position in collaboration space and knowledge flow among countries

Note: **A** and **B** refer to positioning change in collaboration space and in knowledge flow space respectively.

3.4. *Capturing the information on knowledge source among technologies and countries*

Lastly, we use weighted out-degree ratio to figure out which technology (or country) become more source or foundation and which are more applied technologies (or which country is better in applying knowledge rather than creating new knowledge) in the knowledge flow spaces. Figure 10 shows the trends in weighted out-degree ratio, $\mathrm{ODR}(v)$, in ICT sector. Overall, it seems difficult to say that a macro trend can be detected, but there are some patterns we can capture. In Figure 10-A, *electronic measure* is observed in an increasing trend, indicating that electronic measuring technology has been changed from an applied to a source technology. In other words, it is no longer a trendy technology but could be a cash cow technology. A technology in a decreasing trend of ODR is *Large-capacity information analysis*, indicating that it has been changed from source to applied technology. It means that the big-data analysis could be a future technology largely created by the other source technologies. However, there also exists a risk of which these kinds of targeted technology could also be disappeared easily.

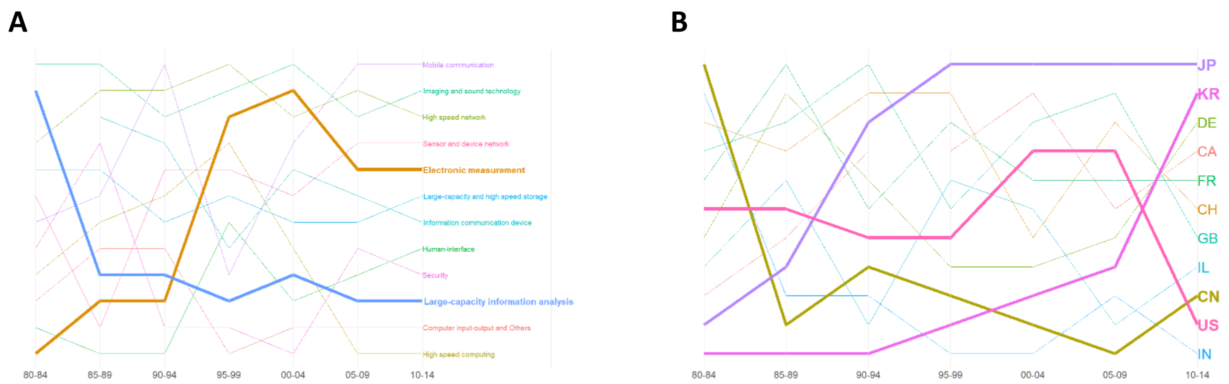


Fig 10. Ranking dynamics of weighted out-degree ratio in knowledge space and flow among ICT technologies and countries

Note: **A** and **B** refer to ranking dynamics of $\mathrm{ODR}(v)$ among technologies and countries.

Figure 10-B shows ranking dynamics of ODR in knowledge flow space among countries. Japan was a first rising star in this scene and has maintained their position of the country pertaining source technologies. South Korea is a second rising star growing in relatively recent periods as being a country owned source technologies. However, as South Korea is only actively participating in the knowledge flow scene and not trying to join the collaborative space, their growth could be limited compared to Japan participating in both collaboration and knowledge flow spaces strongly. US has been always a defending champion in both collaboration and knowledge spaces, their ODR has been dropped, thus US is no longer a strong technology sourcing country at least in ICT sector.

4. Discussion and Concluding Remarks

Insights into the multiple dimensions that shape the evolutionary pathways of ICT technology advancements highlight the factors that shape the knowledge structure and network properties in what is a rapidly changing environment. In parallel, they also raise the awareness of the dynamic capabilities and significant factors that should be considered by organizations and entities when developing strategies and policies geared towards maximising their future growth potential. The present investigation identified 4 specific dimensions that are of relevance in this context. Technology convergence measures based on the knowledge space methodology developed by Kogler et al. (2013), provide an understanding of how proximate technological sub-class are to each other, which in turn can be interpreted as an indicator of re-combination potential, i.e. technologies close to each other in the knowledge space have a much higher potential to be recombined than those that are not. This has important implications for development strategies, where a dense knowledge space might lead itself to approaches that are geared towards increased patterns of specialization while a rather distributed space might offer opportunities for diversification (Boschma, 2017; Kogler, 2017). Globalization, advancements in transportation and communication are all processes that reinforce the notion of a globalized knowledge economy, and the growing numbers of international inventor collaborations certainly confirm this. Thus, patterns of international collaboration in knowledge production, here measured by the development of novel products and processes of economic value, i.e. inventions, are yet another important dimension to consider in the present context. The knowledge and collaboration space are measures based on co-occurrence indicate a symmetrical relationship between the respective units of interest, which provides important insights of the overall structural properties of the technology under investigation. However, knowledge exchange is not necessarily unidirectional, but some organization units or spatial configurations might be in a more favourable position to source knowledge from parts in the system than others. To account for this fact two further dimensions were considered in the present investigation, i.e. knowledge flows among technology sub-classes, and similar countries, within the global ICT sector as indicated by patent citation knowledge flow patterns. The competitive position of an organization is directly linked to its levels of dynamic capabilities, understanding the evolutionary trajectories concerning technology convergence, international collaborative relationships, and knowledge flows among technologies and countries is an important building block in this regard. In summary, all 4 dimensions should provide a rounded picture of technology evolution in an international context, something that is not only relevant for practitioners and policy makers, but also for a number of scientific disciplines, incl. strategy and management, innovation studies, and evolutionary economic geography.

Since the advent of smartphones, ICT has become a very dynamic market, driven by fierce “ecosystem competition” (Lee, Lee, & Hwang, 2015; Lee, Park, & Lee, 2016; Lee, Park, & Lee, 2018) where it is about capabilities to re-combine knowledge embedded in technologies, rather than one that’s dominated by competition for a single technology (Basole, Park, & Barnett, 2015; Fransman, 2010; Lee, Kim, & Lee, 2017). Therefore, units that are competent in very few technology sub-classes should look towards a road-map for diversification into a more, albeit related to their current expertise as well as locally and internationally embedded, technology base. (Kim & Lee, 2017). Needless to say, this is a difficult task at hand because one would have to anticipate future technology trajectories in order to develop strategies and policies that would be most favorable for an entity going forward. The proposed approach based on technology class and citation flow information from USPTO patent documents, combined with the suggested methodological tools that produce a number of basic indicators in network analysis, and network positioning matrix measures, should provide essential insights for such planning purposes.

Results show that *mobile communication* and *large-capacity information analysis* are the fastest growing technologies in both spaces in terms of both weighted degree centrality and eigenvector centrality. On the other hand, *information and communication devices* indicate a tendency to decrease in both spaces. Therefore, when determining a strategy or policy that aims for expansion in the ICT technology sector, a company or country should consider these trends.

However, even if a particular company or country tries to expand the scope of technologies in its portfolio, it is certainly not possible to be competitive across the whole spectrum due to resource restrictions. To circumvent such restrictions, utilizing collaboration networks with other companies or other countries in a framework of open innovation have been recommended (Kim, Lee, & Kim, 2016). In this context it is of course more favorable for a company or country to engage with an advanced and influential partner rather than one that is a laggard in the respective sector as this would provide the opportunity to take advantage of significant knowledge inputs. In the present investigation the evolutional paths of the collaboration space are analyzed by considering location of inventors at the time of invention. The results indicate that the U.S. is the only country that maintains a global hub position in both analyzed spaces. Further, in the case of South Korea no significant influence on the collaboration space was found, but the country exhibits a rapid growth in the knowledge flow space. Contrary, it is observed that Switzerland has lost its influence in both spaces over time.

Although the present study examines technology-specific as well as country-specific trends, one limitation that remains is the omission of technology-specific trends by country or country-specific trends by technology. This leaves important questions that should be investigated in follow-up studies, e.g. what technologies have played a major role in maintaining the position notes as global hub, or what have been the technological drivers that enable certain countries to grow in terms of knowledge flow position? Also, an enrichment of the present analysis with further data sources, such as financial data on ICT related revenues and ICT import/export data, would further enhance our understanding of evolutionary trajectories in technology advancement and how this potentially linked to economic performance, growth and change.

Acknowledgments

Dieter F. Kogler and Changjun Lee would like to acknowledge funding from the European Research Council under the European Union's Horizon 2020 research and innovation programme (grant agreement No 715631, TechEvo). This research was also supported by the MIST (Ministry of Science and ICT), Korea, under the National Program for Excellence in SW supervised by the IITP (Institute for Information & communications Technology Promotion) (2015-0-00914), and by the Ministry of Education of the Republic of Korea, the National Research Foundation of Korea (NRF-2017R1C1B5017518).

References

Abbas, A., Zhang, L., & Khan, S. U. (2014). A literature review on the state-of-the-art in patent analysis. *World Patent Information, 37*, 3-13.

Basole, R. C., Park, H., & Barnett, B. C. (2015). Coopetition and convergence in the ICT ecosystem. *Telecommunications Policy, 39*(7), 537-552.

Boschma, R. (2017). Relatedness as driver of regional diversification: A research agenda. *Regional Studies*, *51*(3), 351-364.

Bonino, D., Ciaramella, A., & Corno, F. (2010). Review of the state-of-the-art in patent information and forthcoming evolutions in intelligent patent informatics. *World Patent Information, 32*(1), 30-38.

Chen, H., Zhang, G., Zhu, D., & Lu, J. (2017). Topic-based technological forecasting based on patent data: A case study of Australian patents from 2000 to 2014. *Technological Forecasting and Social Change, 119*, 39-52.

Codina-Filbà, J., Bouayad-Agha, N., Burga, A., Casamayor, G., Mille, S., Müller, A., ... & Wanner, L. (2017). Using genre-specific features for patent summaries. *Information Processing & Management*, *53*(1), 151-174.

Daim, T. U., Rueda, G., Martin, H., & Gerdsri, P. (2006). Forecasting emerging technologies: Use of bibliometrics and patent analysis. *Technological Forecasting and Social Change, 73*(8), 981-1012.

Dosi, G., & Nelson, R. R. (1994). An introduction to evolutionary theories in economics. *Journal of evolutionary economics*, *4*(3), 153-172.

Fransman, M. (2010). *The new ICT ecosystem: Implications for policy and regulation*: Cambridge University Press.

Griliches, Z. (1998). Patent statistics as economic indicators: a survey. In *R&D and productivity: the econometric evidence* (pp. 287-343). University of Chicago Press.

Guan, J., & Chen, Z. (2012). Patent collaboration and international knowledge flow. *Information Processing & Management*, *48*(1), 170-181.

Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science, 317*(5837), 482-487.

Hird, M. D., & Pfotenhauer, S. M. (2017). How complex international partnerships shape domestic research clusters: Difference-in-difference network formation and research re-orientation in the MIT Portugal Program. *Research Policy, 46*(3), 557-572.

Inaba, T., & Squicciarini, M. (2017). ICT: A new taxonomy based on the international patent classification. *OECD Science, Technology and Industry Working Papers*.

Jaffe, A. B. (1986). Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. *The American Economic Review*, 984-1001.

Jaffe, A. B., & Trajtenberg, M. (2002). *Patents, citations, and innovations: A window on the knowledge economy*: MIT press.

Jiang, J., Shi, P., An, B., Yu, J., & Wang, C. (2017). Measuring the social influences of scientist groups based on multiple types of collaboration relations. *Information Processing & Management*, *53*(1), 1-20.

Joung, J., & Kim, K. (2017). Monitoring emerging technologies for technology planning using technical keyword based analysis from patent data. *Technological Forecasting and Social Change, 114*, 281-292.

Khasseh, A. A., Soheili, F., Moghaddam, H. S., & Chelak, A. M. (2017). Intellectual structure of knowledge in iMetrics: A co-word analysis. *Information Processing & Management*, *53*(3), 705-720.

Kim, E., Lee, D., & Kim, J. (2016). How collaboration networks affect innovation in Korea's ICT industry in the era of Internet of Things. Asian Journal of Technology Innovation, 24(2), 202-221.

Kim, G., & Bae, J. (2017). A novel approach to forecast promising technology through patent analysis. *Technological Forecasting and Social Change, 117*, 228-237.

Kim, H., & Park, Y. (2009). Structural effects of R&D collaboration network on knowledge diffusion performance. *Expert systems with applications, 36*(5), 8986-8992.

Kim, J., & Lee, S. (2017). Forecasting and identifying multi-technology convergence based on patent data: the case of IT and BT industries in 2020. *Scientometrics*, *111*(1), 47-65.

Kim, Y. G., Suh, J. H., & Park, S. C. (2008). Visualization of patent analysis for emerging technology. *Expert systems with applications, 34*(3), 1804-1812.

Kodama, F. (1992). Technology Fusion and the New R&D. Harvard Business Review, July-August: 70-78.

Kogler, D. F. (2017). Relatedness as driver of regional diversification: a research agenda–a commentary. *Regional Studies*, *51*(3), 365-369.

Kogler, D. F., Essletzbichler, J., & Rigby, D. L. (2017). The evolution of specialization in the EU15 knowledge space. *Journal of Economic Geography, 17*(2), 345-373.

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *European Planning Studies, 21*(9), 1374-1391.

Kyebambe, M. N., Cheng, G., Huang, Y., He, C., & Zhang, Z. (2017). Forecasting emerging technologies: A supervised learning approach through patent analysis. *Technological Forecasting and Social Change, 125*, 236-244.

Lee, C., Lee, D., & Hwang, J. (2015). Platform openness and the productivity of content providers: A meta-frontier analysis. *Telecommunications Policy*, *39*(7), 553-562.

Lee, C., & Kim, H. (2018). The evolutionary trajectory of an ICT ecosystem: A network analysis based on media users' data. *Information & Management*.

Lee, C., Kim, J. H., & Lee, D. (2017). Intra-industry innovation, spillovers, and industry evolution: Evidence from the Korean ICT industry. *Telematics and Informatics, 34*(8), 1503-1513.

Lee, J., Kim, C., & Shin, J. (2017). Technology opportunity discovery to R&D planning: Key technological performance analysis. *Technological Forecasting and Social Change, 119*, 53-63.

Lee, K. (2013). *Schumpeterian analysis of economic catch-up: Knowledge, path-creation, and the middle-income trap*: Cambridge University Press.

Lee, K., Park, Y., & Lee, D. (2016). Effect of the ICT ecosystem structure on the sustainable growth of ICT firms: A metafrontier analysis on China, South Korea, the United States, and Japan. *Sustainability*, *8*(5), 469.

Lee, K., Park, Y., & Lee, D. (2018). Measuring efficiency and ICT ecosystem impact: Hardware vs. software industry. *Telecommunications Policy*, *42*(2), 107-115.

Liu, S.-H., Liao, H.-L., Pi, S.-M., & Hu, J.-W. (2011). Development of a Patent Retrieval and Analysis Platform–A hybrid approach. *Expert systems with applications, 38*(6), 7864-7868.

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography, 87*(3), 237-265.

Newman, M. E. (2008). The mathematics of networks. *The new palgrave encyclopedia of economics, 2*(2008), 1-12.

Patel, P., & Pavitt, K. (1997). The technological competencies of the world's largest firms: complex and path-dependent, but not much variety. *Research Policy, 26*(2), 141- 156.

Rycroft, R. W., & Kash, D. E. (2004). Self-organizing innovation networks: implications for globalization. *Technovation, 24*(3), 187-197.

Teece, D. J. (1998). Capturing value from knowledge assets: The new economy, markets for know-how, and intangible assets. *California management review*, *40*(3), 55-79.

Wagner, C. S., & Leydesdorff, L. (2005). Network structure, self-organization, and the growth of international collaboration in science. *Research Policy, 34*(10), 1608-1618.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*(5827), 1036-1039.

Yoon, B., & Park, Y. (2004). A text-mining-based patent network: Analytical tool for high-technology trend. *The Journal of High Technology Management Research, 15*(1), 37-50.

Yoon, B., & Park, Y. (2005). A systematic approach for identifying technology opportunities: Keyword-based morphology analysis. *Technological Forecasting and Social Change, 72*(2), 145-160.

Yu, X., & Zhang, B. (2017). Obtaining advantages from technology revolution: A patent roadmap for competition analysis and strategy planning. *Technological Forecasting and Social Change*.

Zhang, J. (2017). Uncovering mechanisms of co-authorship evolution by multirelations-based link prediction. *Information Processing & Management*, 53(1), 42-51.