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RESEARCH ARTICLE

Technological Leadership in Industry 4.0: A Comparison Between Manufacturing and ICT Sectors Among Korean Firms

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ABSTRACT This paper examines the technological structures of the manufacturing and the ICT sectors in Korea to examine the potential shift of dominant technological sectors in the era of the Fourth Industrial Revolution (4IR). By using patent data of Korean firms from 1990 to 2021, we find that the manufacturing sector has been the dominant technological leader in Korea in terms of both the number of patents and the diversity of technologies, even in the era of 4IR. Although the ICT sector has shown an increasing focus on Industry 4.0 (I4) technologies after the 2000s, indicating the potential for a shift in dominance in the future, the gap between the two sectors is still significant. The study also reveals that the manufacturing sector tends to diversify technologies, while the ICT sector specializes in several target technologies. Our analysis also suggests that both sectors exhibit path-dependency, with the ICT sector exhibiting stronger characteristics, and firms in both sectors shows the tendency of intensive and extensive margin in their patenting activities, with the manufacturing sector exhibiting the stronger tendency.

INDEX TERMS Economic complexity, industry 4.0, network analysis, patent data, technological network, the fourth industrial revolution.

I. INTRODUCTION

Technological innovation is the primary driver of economic development and growth of a country [1]. However, as history has shown, innovation often happens in groups of significant breakthroughs, forming distinct changes that have the power to transform the socioeconomic system within a particular time and location. According to Perez [2], every technological revolution consists of a group of interconnected technological systems. Dosi [3] emphasized this aspect by introducing the term "technical paradigm," which refers to the implicit agreement among agents regarding what constitutes a valid search direction and what would be considered an improvement or superior version of a product, service, or technology, similar to the concept of a paradigm in Kuhn's theory. For instance, during the Second Industrial Revolution from the late nineteenth to the early twentieth century, the widespread adoption of mass production and its associated systems enabled economies to undergo significant structural changes. Similarly, the Third Industrial Revolution, which took place in the 1970s, was characterized by the emergence and diffusion of information technology. In the 2010s, we saw the rise of new tech companies in the US, such as Google, Amazon, and Meta, leading to significant changes

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in our daily lives, production systems, and socioeconomic structures. A number of scholars argue that we are currently experiencing a paradigm shift called the Fourth Industrial Revolution (4IR) [4], [5], [6], [7].

The 4IR is expected to be driven by emerging digital technologies, such as the Internet of Things (IoT), robotics, artificial intelligence, and self-driving cars, and is set to have a profound and pervasive impact on the economy across various sectors [5], [6]. These technologies are collectively referred to as Industry 4.0 (I4) technologies by scholars [8], [9], [10]. The 4IR is distinguished from previous industrial revolutions in that it involves the large-scale automation of entire groups of tasks, including both repetitive intellectual and non-routine tasks, rather than just physical work [11]. As the potential positive and negative impacts of I4 technologies are being assessed, the 4IR has emerged as a significant topic in the current industrial structure discourse [12], [13], [14], [15].

One interesting topic worth noting is the potential for a shift in the dominant actors of our economy, as technological revolutions throughout history have brought about changes in the primary sector of the economy. For instance, during the industrialization of the 20th century, the manufacturing sector surpassed other sectors in terms of productivity [16], [17], [18]. Kuznets [19] emphasized the importance of sectoral shifts in modern economic growth, particularly the shift from agriculture to non-agricultural activities, and later from industry to services. This view highlights the significance of the structural shift aspect in economic development.

In line with this, Saviotti and Pyka [20] examine the creation of new sectors as a driver of economic growth and development. They argue that the growth and development of new sectors are not merely a result of productivity growth within a sector, but a product of the emergence of new industries. Therefore, the key question regarding structural shift through technological revolutions is which sectors or agents hold the dominant power in a constant set of industries.

One reason why the dominant actor changes during a technological revolution is that the new sector that emerges often requires new capabilities and routines from firms to develop along the trajectory in the new sector. Dosi and Nelson [21] argue that a paradigm shift such as the 4IR generally implies a change in the direction of technological advances over time. These trajectories can shape a firm's routines [22], which are patterns of behavior that become established over time through repeated action and learning [23], [24], [25]. Routines also play a crucial role in shaping the trajectories of technological development within firms and industries. In other words, there are appropriate routines and capabilities for technological trajectories, and it is not easy to shape them differently because these trajectories are constrained by the limited rationality and capabilities of the companies involved [22], [26].

However, when a paradigm shifts, the emergence of a new sector in the economy can create new trajectories for firms and industries. For example, the emergence of the internet as a new sector in the 1990s created new trajectories for firms in the technology and communications industries [27]. Many firms in these industries developed new products and services that capitalized on the opportunities provided by the internet, such as e-commerce platforms, online advertising, and digital content [28], [29]. However, during the era of the internet, several companies struggled to adjust to the rapid changes, ultimately falling behind. The reason is that the routines embodied in the firm and the capabilities they have did not match the trajectories drawn by the new sectors. Taking into account what we've discussed, it can be said that a new sector that forms a new trajectory requires a new actor with a suitable routine and capability.

Then, can we expect a new sector to emerge as the dominant player in the economy with the arrival of the 4IR in the 2010s? To answer the question, we analyze Korean firms with comparing the manufacturing and the ICT sectors, rather than covering all countries. The reason why we focus on the case of Korea is that the socioeconomic context in which industries are situated can vary between countries, even when industries of different counties may produce similar products. Additionally, manufacturing is one of the dominant sectors of the Second Industrial Revolution and, as mentioned above, has been responsible for most of the productivity gains of the 20th century [16], [17], [18], [19]. On the other hands, as the 4IR is considered a revolutionary change that occurs when IT proliferates across all industries and is often referred to as the horizontal expansion of IT [7], the ICT sector is at the forefront of the 4IR and provides the foundational technologies and infrastructure needed for new technologies such as I4T to be integrated and optimized [5], [6], [7]. In particular, Korea is a country where both the manufacturing and the ICT industries are actively developed, and by analyzing the technological structure of the manufacturing and ICT sectors, it can be possible to identify the dominant players in the 4IR in a simple and clearer way.

Specifically, we analyze patent data associated with I4 technologies to determine which sector between the manufacturing and the ICT sectors dominates the 4IR era. Patents provide technical details of new inventions and protect the exclusive rights of inventors, making patent databases an excellent source of the latest technological information even before new technologies are commercialized [11].

To explore the technological dominance of the manufacturing and the ICT sectors in Korea, the research will adopt methodologies from network estimation and economic complexity research. To construct a network of technology, we first extract the applicant's (firm's) information and technical capability (e.g., a number of firm's patent applications related to a given technology) from the patent data. Using the firms and their technical capabilities, we construct two technological networks of the manufacturing and the ICT sectors. Motivated by the estimation of the gene regulatory network using the partial correlations in [30], we define an edge weight as Kendall's tau between two technologies, which measures a tendency for firms to have technical capabilities in both two technologies, and we identify the significant edges with the multiple testing procedure [31]. By comparing the connectivity and network characteristics of two technological networks, we can answer the question of which sector has better technological capabilities.

In addition, we use the relatedness measure to trace the different technological trajectories of innovation between the two sectors [32], [33], [34]. The metric of relatedness measure the overall affinity between a specific activity, such as producing products [32], [35], developing industries [36], [37], [38], [39], [40], or acquiring technologies [41], [42], [43], [44], and predicts the future trajectories of them. Since relatedness metrics explain path dependencies and help to predict which activities will grow and decline in countries, regions, or firms, we can explore the direction of technological trajectories and the level of path-dependencies of the two sectors.

We also use the economic complexity measures [34], [45]. The complexity measure originally was discovered by using world trade data, which is a country level. The economic complexity index of a country represents that the level of sophistication of countries' economy with conserving their structural characteristics and predicts the future economic growth. By using patent data, scholars try to predict the future technological growth of a region and a country as well [46], [47]. Similarly, this paper use the economic complexity measures to predict the future technological growth of two sectors at a firm level.

II. DATA

A. PATENT DATA

Our primary data set consists of patent data obtained from the Worldwide Patent Statistical Database (PATSTAT), which is provided by the European Patent Office (EPO) and updated biannually. Our data is the most recent version, updated in spring 2021. The PATSTAT database, which covers over 90% of the world's patent authorities, contains information on 100 million worldwide patents. To focus our analysis, we selected patent data from Korean firms from the United States Patent and Trademark Office (USPTO), the Korean Intellectual Property Office (KIPO), and the European Patent Office (EPO). The PATSTAT dataset includes comprehensive information on each patent, such as the applicants, inventors, citations, filing countries, and filing dates. Additionally, it provides Cooperative Patent Classification (CPC) codes, which represent the associated technologies of the patents.

In this study, we use the CPC code to identify the technologies associated with patents. The CPC code is an extension of the International Patent Classification (IPC) jointly developed by the EPO and the USPTO. It is composed of nine sections, A-H and Y (1-digit), which are further subdivided into classes, sub-classes (4-digit), groups, and sub-groups (6-digit), with approximately 250,000 classification entries. To identify the technologies of the 4IR, we examine the group level of the classification, and we explain how we define the 4IR technologies in Section II-C. We examine all the CPC codes of patents, not just the representative code, to capture all the associated technologies. For instance, if a firm has a patent application with three different CPC codes at time t, which it did not have before, we consider the firm to have developed the three technologies represented by the three CPC codes. We also consider family patents, such as when a firm applies the same patent, previously filed in one patent office, to another patent office with an additional CPC code. In such cases, we consider the patent to have all the CPC codes, including the one that was added.

The unique identifier in the patent data is the patent number, and the applicants or inventors do not have a unique identifier. Additionally, the written form of the applicant name on the patent may vary for various reasons such as typos and abbreviations. For example, while the International Business Machines Corporation is the same as IBM, they may be regarded as different applicant names in the patent data. To address this issue, scholars have developed methods for standardizing applicant names [48], [49], [50]. Kang et al. [51] used the OECD Harmonised Applicants Names (HAN) database, which includes unique applicant identifiers, to disambiguate applicants' names. In this study, we use HAN-IDs to identify unique applicants. As our focus is on Korean firms, we match the unique applicants' IDs to the unique IDs in the KisValue dataset (that will be explained in Section II-B), which provides financial information for Korean listed firms.

As a result, among 81,189,654 patents and 111,116,943 applicants in the PATSTAT database, we select 813,110 patents from Korean manufacturing sectors and 46,117 patents from Korean ICT sectors that are owned by 1,303 Korean manufacturing firms and 496 Korean ICT firms, covering from 1990 to 2021.

B. FINANCIAL INFORMATION OF A FIRM

To compare the technological performance of Korean firms in manufacturing and ICT sectors upon the 4IR, we use the KisValue data that allow us to figure out the sector the applicants belong to. Basically, the data provide the financial information of Korean listed firms on the stock markets. We look at the three stock markets: First, the Korea Composite Stock Price Index (KOSPI) is the major stock market mainly for large firms, second, the Korea Securities Dealers Automated Quotations (KOSDAQ) is the stock market for small and medium-sized enterprises or venture firms, and third, the Korea New Exchange (KONEX) is the stock market for smaller firms. By looking at those three stock markets, we can cover most Korean-listed firms.

KisValue data is compiled by the National Information & Credit Evaluation Inc. (NICE) for external audit. it contains various variables of firms including founding year, the number of employees, listing dates, income statement, statement of cash flow, etc. Our variables of interests, such as debt ratio and profit ratio, are calculated using the raw data.

Our KisValue data includes 4,431 and 1,497 firms in the manufacturing and ICT sectors, respectively. Among those listed firms, 1,303 and 496 firms in the manufacturing and ICT sectors own, at least, one patent.

C. INDUSTRY 4.0 TECHNOLOGIES

As the dominant technologies in the era of the 4IR, we choose the I4 technologies. However, I4 technologies can be defined in various ways without scholarly consensus on the formal classification of I4 activities [6], [52]. For example, Ménière et al. [11] argue that being different from the early days of digitization, we can observe the disruptive features of the technologies on 4IR and this distinctive nature of technologies originated from the combined usage of technologies between technologies associated with the digitization and highly effective connectivity, and technologies, such as cloud computing and artificial intelligence. According to Ménière et al. [11], those combined technologies allow the development of interconnected and autonomously operated smart objects, which shows the discontinuity of the technological paradigm. Ménière et al. [11] utilized the definition of the 4IR to identify inventions related to computing, connectivity, data exchange, and smart devices as the fundamental components of this revolution. The authors classified 4IR technologies into three categories: core technologies, enabling technologies, and application domains. Each of these categories is further subdivided into several technological fields. Core technologies include hardware, software, and connectivity. Enabling technologies comprise analytics, security, artificial intelligence, position determination, power supply, 3D systems, and user interfaces. Application domains encompass home, personal, enterprise, manufacturing, infrastructure, and vehicles.Using this cartography, they can extract 48,069 published and unpublished 4IR patent applications at the EPO from 1978 and 2016.

On the other hand, Ciffolilli and Muscio [53] analyzed data from the European region's collaborative research project supported by the 7th Framework Programme (FP7) to determine the relative and absolute technological advantages in enabling technologies of I4. They used expert peer review to select I4 technologies and focused on R&D activities. The authors identified eight I4 technology categories, which include advanced manufacturing solutions with interconnected and programmable collaborative robots; additive manufacturing, involving 3D printers linked to digital development software; augmented reality for production processes; simulation between interconnected machines to optimize processes; horizontal and vertical integration technologies that integrate information along the value chain, from suppliers to consumers; the industrial internet and cloud that enable multidirectional communication between production processes and products, and facilitate the management of big data on an open system; cybersecurity, ensuring security in network operations and open systems; and big data and analytics to optimize products and processes. They found 1,092 I4 projects financed by the FP7, based on this selection of I4 technologies.

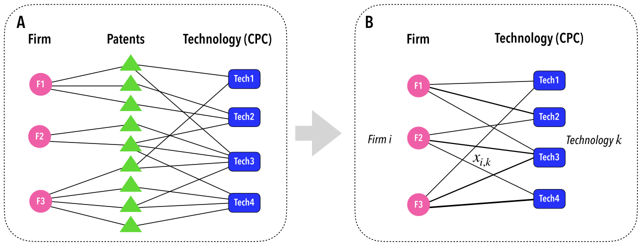


FIGURE 1. The structure of "firm-technology" bipartite network. The weight of link $x_{i,k}$ corresponds to the number of technology k that is owned by firm i.

While Ciffolilli and Muscio [53] focus on the input side of R&D, Balland and Boschma [52] focus on the output of R&D activities to select the I4 technologies. Balland and Boschma [52] analyzing patent data, they categorize I4 technologies into 10 categories: additive manufacturing, artificial intelligence, augmented reality, autonomous robots, autonomous vehicles, cloud computing, cybersecurity, quantum computers, machine tools, and system integration. Since there are approximately 250,000 classification entries in the CPC classification, they can elaborate on the I4 technologies by looking at the sub-group level (6-digit) of the CPC code. Considering that we aim to compare the technological performance of manufacturing and that of ICT sectors regarding the 4IR, we follow the Balland and Boschma's way of technological classification in [52], which has 66 CPC classifications in 6 digit.

III. METHODS

A. BUILDING A NETWORK OF TECHNOLOGY

To compare the network structure of technologies between the manufacturing and the ICT sectors, we first need to build a "firm-technologies" bipartite network. Again, technologies are represented by CPC codes. As depicted in Figure 1A, our patent data carries the information on the patent of certain firms, which has several CPC codes. By skipping the patent number, we can construct the bipartite network consisted with firm and technology, as you can see in Figure 1B. The weight of the network, $x_{i,k}$, is the number of CPC codes on technology k owned by a firm i.

From the firm-technologies bipartite networks of the manufacturing and the ICT sectors, we define two adjacency matrices whose elements are the weights of the bipartite network, where rows correspond to the firms and columns correspond to the CPC codes. Henceforth, we call these adjacency matrices "firm-CPC" matrices. To build a technological network, we consider the I4T-related CPC codes as nodes and define edges with Kendall's tau of two CPC codes based on the firm-CPC matrix. Specifically, we suppose that the firm-CPC matrix is given as follows.

	CPC_1	CPC_2	$\cdots$	CPC_n
Firm_1	$x_{1,1}$	$x_{1,2}$	$\cdots$	$x_{1,n}$
Firm_2	$x_{2,1}$	$x_{2,2}$	$\cdots$	$x_{2,n}$
$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$
Firm_m	$x_{m,1}$	$x_{m,2}$	$\cdots$	$x_{m,n}$

The Kendall's tau (τ_{kl}) of CPC_k and CPC_l is calculated by the equation:

$$\tau_{kl} = \frac{\sum_{i<j} a_{ij} b_{ij}}{\sqrt{(\sum_{i<j} a_{ij}^2)(\sum_{i<j} b_{ij}^2)}}, \tag{1}$$

where $a_{ij} = \mathrm{sign}(x_{i,k} - x_{j,k})$ and $b_{ij} = \mathrm{sign}(x_{i,l} - x_{j,l})$. Note that the firm-CPC matrix is usually very sparse (i.e., the matrix only has a few nonzero elements). Thus, we calculate Kendall's tau with the rows (i.e., firms) that do not have zero elements on both two target columns (i.e., two CPC codes) to exclude the effect from non-informative zeros. To identify the significantly related technologies, we conduct the independence tests with Kendall's tau and obtain the corresponding p-values. In this study, we consider the Benjamini-Hochberg's (BH) procedure [31] to control the false discovery rate (FDR) in the multiple testing, instead conducting each hypothesis test with a significance level of 0.05. Note that the number of simultaneous tests is $n(n-1)/2$ if we have n CPC codes, and the falsely rejected cases increase proportionally to the number of the simultaneous test if we only control the type-I error of the single hypothesis test. Among the identified dependent pairs of technologies, we focus on the positively correlated technologies, and hence we connect two CPC codes in the technology network if two CPC codes are significantly dependent with positive correlation when the FDR is controlled under 5%.

To compare the estimated two technological networks of the manufacturing and ICT sectors, we first compare two node sets and identify the CPC codes that are related to either the manufacturing sector or the ICT sector only. After comparing the node differences, we focus on the common CPC codes that are related to both the manufacturing and the ICT sectors. With the common CPC codes, we construct two sub-networks of the manufacturing and the ICT sectors. For these two sub-networks, we consider comparing overall network characteristics and edge differences. For the overall network characteristics, we compare the distribution of degrees and betweenness centrality measures. For the edge differences, we compare the structural difference (i.e., the existence of edges) and the magnitude difference on the common edges (i.e., Kendall's tau on the common edges). For the magnitude difference between the two common edges, we consider the permutation test to identify the edges that are significantly different between the two sectors. Specifically, let $x_k^{(M)} = (x_{1,k}^{(M)}, \ldots, x_{m,k}^{(M)})$ and $x_l^{(M)} = (x_{1,l}^{(M)}, \ldots, x_{m,l}^{(M)})$ be kth and lth columns of the firm-CPC matrix of the manufacturing sector, respectively. Similarly, $x_k^{(I)} = (x_{1,k}^{(I)}, \ldots, x_{m',k}^{(I)})$ and $x_l^{(I)} = (x_{1,l}^{(I)}, \ldots, x_{m',l}^{(I)})$ are defined for the ICT sector. From $(x_k^{(M)}, x_l^{(M)})$ and $(x_k^{(I)}, x_l^{(I)})$, we obtain Kendall's tau values $\tau_{kl}^{(M)}$ and $\tau_{kl}^{(I)}$ by the equation (1). To conduct the permutation test, we define the observed test statistic

$$D_{kl}^{obs} = \tau_{kl}^{(M)} - \tau_{kl}^{(I)}. \tag{2}$$

In the permutation test, the null distribution of the test statistic D_{kl} is estimated by the permutation of the combined sample under the null hypothesis H_0: $\tau_{kl}^{(M)} = \tau_{kl}^{(I)}$. In this study, we permute the rows of the combined firm-CPC matrix, where the combined firm-CPC matrix is obtained by merging two firm-CPC matrices along the row direction. Specifically, we first merge two firm-CPC matrices as follows.

	CPC_1	CPC_2	$\cdots$	CPC_n
$\mathrm{Firm}_1^{(M)}$	$x_{1,1}^{(M)}$	$x_{1,2}^{(M)}$	$\cdots$	$x_{1,n}^{(M)}$
$\mathrm{Firm}_2^{(M)}$	$x_{2,1}^{(M)}$	$x_{2,2}^{(M)}$	$\cdots$	$x_{2,n}^{(M)}$
$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$
$\mathrm{Firm}_m^{(M)}$	$x_{m,1}^{(M)}$	$x_{m,2}^{(M)}$	$\cdots$	$x_{m,n}^{(M)}$
$\mathrm{Firm}_1^{(I)}$	$x_{1,1}^{(I)}$	$x_{1,2}^{(I)}$	$\cdots$	$x_{1,n}^{(I)}$
$\mathrm{Firm}_2^{(I)}$	$x_{2,1}^{(I)}$	$x_{2,2}^{(I)}$	$\cdots$	$x_{2,n}^{(I)}$
$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$
$\mathrm{Firm}_{m'}^{(I)}$	$x_{m',1}^{(I)}$	$x_{m',2}^{(I)}$	$\cdots$	$x_{m',n}^{(I)}$

Then, for a (k, l) pair, we define two combined vectors $z_k = (x_k^{(M)}, x_k^{(I)})$ and $z_l = (x_l^{(M)}, x_l^{(I)})$. For example, the combined vector z_k is represented as $z_k = (z_{k,1}, z_{k,2}, \ldots, z_{k,m}, z_{k,m+1}, \ldots, z_{k,m+m'})$, and z_l is similarly expressed. Let $\pi = (\pi_1, \ldots, \pi_{m+m'})$ be a permuted index vector of $(1, \ldots, m+m')$. Then, the permuted combined vectors $z_{k,\pi}$ and $z_{l,\pi}$ are defined as $z_{k,\pi} = (z_{k,\pi_1}, \ldots, z_{k,\pi_{m+m'}})$ and $z_{l,\pi} = (z_{l,\pi_1}, \ldots, z_{l,\pi_{m+m'}})$, respectively. With the permuted vectors $z_{k,\pi}$ and $z_{l,\pi}$, the permuted vectors $(x_k^{(M),\pi}, x_l^{(M),\pi})$ and $(x_k^{(I),\pi}, x_l^{(I),\pi})$ are defined as follows.

$$\begin{aligned} x_k^{(M),\pi} &= (z_{k,\pi_1}, \ldots, z_{k,\pi,m}), \\ x_k^{(I),\pi} &= (z_{k,\pi_{m+1}}, \ldots, z_{k,\pi_{m+m'}}), \\ x_l^{(M),\pi} &= (z_{l,\pi_1}, \ldots, z_{l,\pi,m}), \\ x_l^{(I),\pi} &= (z_{l,\pi_{m+1}}, \ldots, z_{l,\pi_{m+m'}}). \end{aligned} \tag{3}$$

With $(x_k^{(M),\pi}, x_l^{(M),\pi})$ and $(x_k^{(I),\pi}, x_l^{(I),\pi})$, we calculate Kendall's tau values $\tau_{kl}^{(M),\pi}$ and $\tau_{kl}^{(I),\pi}$ by the equation (1), and the permuted test statistic D_{kl}^{π} is defined as $D_{kl}^{\pi} = \tau_{kl}^{(M),\pi} - \tau_{kl}^{(I),\pi}$. We repeat the permutation B times and calculate the permuted statistics $D_{kl}^{\pi,(1)}, \ldots, D_{kl}^{\pi,(B)}$. The null distribution in the permutation test is estimated by the permuted statistics. The p-value p_{kl} of the permutation test is estimated by the following equation.

$$p_{kl} = \frac{1}{B} \sum_{i=1}^{B} I(|D_{kl}^{\pi,(i)}| > |D_{kl}^{obs}|), \tag{4}$$

where $I(\cdot)$ is the indicator function. Then, we identify the significantly different edges in terms of Kendall's tau if the p-value p_{kl} is less 0.05.

B. MEASURING DENSITY OF THE RELATED TECHNOLOGIES

Next, we also calculate the proximity among CPC codes by looking at the co-occurrence of CPC codes within the same applicants and the density of related technologies by using the firm-CPC matrix, following the method of Hidalgo et al. [32] and Proximity $\psi_{k,l}$ measures the minimum value of pairwise conditional probability that two CPC codes have a comparative advantage within the same firm:

$$\psi_{k,l} = min\{\Pr(RTA_k \mid RTA_l), \Pr(RTA_l \mid RTA_k)\} \tag{5}$$

where RTA represents the revealed technological advantage:

$$RTA_{i,k,t} = \frac{\frac{x_{i,k,t}}{\sum_k x_{i,k,t}}}{\frac{\sum_i x_{i,k,t}}{\sum_i \sum_k x_{i,k,t}}} \tag{6}$$

where $x_{i,k,t}$ is the number of CPC code k of firm i at time t [54]. $RTA_{i,k,t}$ represents the comparative advantage of firm i regarding the CPC code k representing a technology by measuring the share of the technology in the firm compared with the share of the technology in the entire market. We regard the firm i has the technological comparative advantage in the CPC code k as its value is greater than 1.

To examine the level of path-dependency of firms in their technological diversification [43], [44], we further calculate the density and check whether its effect is similar between the manufacturing and the ICT sectors by using the proximity $\psi_{k,l}$. The density of related technology of a firm at time t is given by

$$\omega_{i,k,t} = \frac{\sum_l \psi_{k,l,t} U_{i,l,t}}{\sum_l \psi_{k,l,t}} \tag{7}$$

where $\psi_{k,l,t}$ is the proximity between CPC code k and l and $U_{i,l,t}$ takes 1 if firm i has an RTA in technology l in year t and 0 otherwise.

C. MEASURING ECONOMIC COMPLEXITY OF FIRMS AND TECHNOLOGICAL COMPLEXITY OF TECHNOLOGIES

In order to compare the structural characteristics of technology and firms between the manufacturing and ICT sectors, we calculate the economic complexity index of a firm and the technological complexity index of technology, using the method developed by Hidalgo and Hausmann [55]. The authors constructed a "country-product" bipartite network based on world trade data, which revealed that countries producing complex products also engage in complex activities, and vice versa. They used an iterative approach to solve this observation as an eigenvalue problem, resulting in the development of two new indices: the economic complexity index for countries and the product complexity index for products. We apply these indices to capture the complexity of firms and technology in our study. They write their observation formally as following [55]:

$$K_{i,N} = \frac{1}{K_{i,0}} \sum_k M_{i,k} K_{k,N-1} \tag{8}$$

$$K_{k,N} = \frac{1}{K_{k,0}} \sum_f M_{i,k} K_{i,N-1} \tag{9}$$

for $N \geq 1$, where $M_{i,k}$ is the matrix composed of firms and CPC codes with RCA above 1, which is calculated from equation 6. With initial conditions given by the number of links of firms and technologies:

$$K_{i,0} = \sum_k M_{i,k} \tag{10}$$

$$K_{k,0} = \sum_i M_{i,k}, \tag{11}$$

$K_{i,0}$ and $K_{k,0}$ represent, respectively, the observed levels of technological diversification of a firm (the number of technologies owned by that firm) and the ubiquity of a technology (the number of firms possessing that technology). Over the iterative solving of Equation 8 and 9 with given initial conditions, we can get the value of "economic complexity of firm (ECI)" and "technological complexity of technology (TCI)" as iterative averages. Those metrics of complexity measures preserve the identity of the firm and the technology by using dimensionality reduction technique, being different from other methods, such as aggregation or distributions [34].

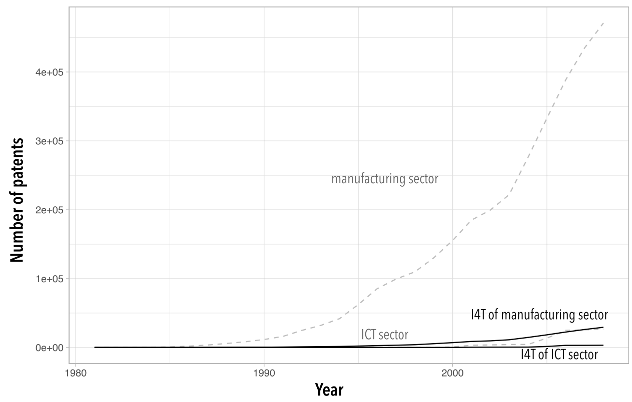


FIGURE 2. The cumulative number of patents (dotted lines) and that of I4 patents (lines) of the manufacturing and the ICT sectors.

IV. RESULTS

A. DESCRIPTIVE STATISTICS OF TECHNOLOGIES IN THE MANUFACTURING AND THE ICT SECTORS

To compare the technological performance of the Korean manufacturing and ICT sectors in the 4IR era, we begin by examining some simple quantitative facts about the two sectors. Figure 2 shows the cumulative number of patents for both sectors, with dotted lines representing the overall number of patents, and solid lines representing patents specifically related to I4 technologies. The graph reveals that, overall, the manufacturing sector has a greater number of patents for both

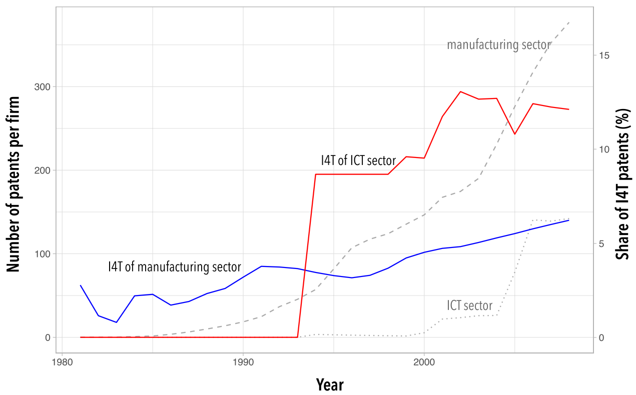


FIGURE 3. The cumulative number of patents per firm (dotted lines with y-axis on left side) and the share of I4 technologies among applied patents (blue and red lines with y-axis on right side) for the manufacturing and the ICT sectors.

types of technologies. However, this disparity may be partly attributed to the fact that there are more listed firms in the manufacturing sector (4,431) than in the ICT sector (1,497). Despite this, it is clear from Figure 2 that the manufacturing sector has consistently outperformed the ICT sector in terms of technological performance, including during the 4IR era.

To compare the technological performance of the Korean manufacturing and ICT sectors while controlling for their different sizes, we present Figure 3. The graph shows the cumulative number of patents per firm (dotted lines) and the share of I4 technologies among applied patents (blue and red lines) for both sectors over time. Despite the normalization for firm size, the manufacturing sector still demonstrates a higher number of patents per firm, which continues to grow over time. The ICT sector has also shown an increase in patents per firm, with a significant jump around 2004. However, it remains behind the manufacturing sector. We attribute this difference in part to the presence of large firms in the manufacturing sector, such as Samsung, LG, and Hyundai, which benefit from in-house R&D capabilities and greater financial resources for R&D.

As illustrated by the blue and red lines in Figure 3, the share of I4 technologies in the patents of the ICT sector was almost non-existent but experienced a sudden surge around the mid-1990s. In contrast, the manufacturing sector has demonstrated a consistent and slightly increasing trend in the share of I4 technologies. The higher share of I4 technologies in the ICT sector from the mid-1990s can be attributed to the IT boom during that time. From the late 1990s to the early 2000s, Korea experienced a surge in venture ICT companies. For instance, well-known firms such as NAVER and KAKAO were established in 1998 and 1995, respectively. Although the manufacturing sector outperforms the ICT sector in terms of the number of patents, the ICT sector has shown a higher share of I4 technologies in their patents since the IT boom era.

Based on Figures 2 and 3, we can observe that the manufacturing sector has consistently outperformed the ICT sector in terms of both overall patent numbers and I4 technologies until the 4IR era. However, after the IT boom of the mid-1990s, patents filed by ICT firms have been increasingly focused on I4 technologies compared to the manufacturing sector.

B. COMPARISON OF TECHNOLOGICAL NETWORKS

In this section, we depict the results of the independence tests with Kendall's tau from the firm-CPC matrices, which aim to compare two technological networks of the manufacturing and ICT sectors. Before constructing two networks, we first compare the two node sets of the manufacturing and the ICT sectors, where the elements of the node sets are defined as the I4T-related CPC codes. There are 65 and 38 I4T-related CPC codes in the manufacturing and ICT sectors, respectively. Among the 38 I4T-related CPC codes of the ICT sector, the 37 I4T-related CPC codes reported in Table 2 are also contained in the I4T-related CPC codes of the manufacturing sector, and the CPC code "B33Y 99: Additive manufacturing (subject matter not provided for in other groups of the subclass B33Y)" is only contained in the ICT sector. We also report the 28 I4T-related CPC codes contained only in the manufacturing sector in Table 1. Most of the 28 CPC codes in Table 1 are related to the machine tools or equipment for the manufacturing process rather than the computer program or algorithms. On the other hand, the 37 common CPC codes in Table 2 are more related to the communications, computer programs, and algorithms, including "B25J 9: Programme-controlled manipulators" and "G06T 7: Image analysis".

Here, we focus on the comparison of the two technological networks of the manufacturing and the ICT sectors on the 37 common nodes to identify the differences in the connectivity of the common technologies based on the relatedness of the technologies at the firm level. In Figure 4, we depict two technological networks of the manufacturing and ICT sectors with 37 common nodes, where the size of the node denotes the degree of a node and the thickness of an edge represents the magnitude of the connection (i.e., the magnitude of Kendall's tau). In the two technological networks, the 169 edges are connected to 35 nodes for the manufacturing sector and the 21 edges are connected to 12 nodes for the ICT sector, where the edges are identified by the independence tests with the BH procedure to control the FDR under 5%. To compare the network characteristics of the two networks, we also depict the distributions of the degree and the betweenness centrality measures in Figure 5. As shown in Figures 4 and 5, the technological network of the manufacturing sector has more nodes having a higher degree and betweenness centrality measures. These observations show that the technological network of the manufacturing sector has higher overall connectivity than that of the ICT sector on the common 37 technologies. This higher overall connectivity of the technologies of the manufacturing sector supports that the firms in the manufacturing sector tend to have a wider technological portfolio than the firms in the ICT sector.

TABLE 1. List of the CPC codes contained only the manufacturing sector.

No.	CPC	Description
1	B23Q 1	General build-up of a form of machine, particularly relatively large fixed members
2	B23Q 7	Arrangements for handling work
3	B23Q 9	Arrangements for supporting or guiding portable metal-working machines or apparatus
4	B23Q 11	Accessories fitted to machine tools for keeping tools or parts of the machine in good working condition or for cooling work
5	B23Q 15	Automatic control or regulation of feed movement, cutting velocity or position of tool or work
6	B23Q 16	Equipment for precise positioning of tool or work into particular locations
7	B23Q 23	Arrangements for compensating for irregularities or wear
8	B23Q 35	Control systems or devices for copying directly from a pattern or a master model
9	B23Q 37	Metal-working machines, or constructional combinations
10	B23Q2003	Devices holding, supporting, or positioning work or tools, of a kind normally removable from the machine
11	B23Q2005	Driving or feeding mechanisms; Control arrangements
12	B23Q2011	Accessories fitted to machine tools for keeping tools or parts of the machine in good working condition or for cooling work
13	B23Q2017	Arrangements for Measurement or correction of run-out or eccentricity indicating or measuring on machine tools
14	B23Q2039	Metal-working machines incorporating a plurality of sub-assemblies, each capable of performing a metal-working operation
15	B23Q2210	Machine tools incorporating a specific component
16	B23Q2220	Machine tool components
17	B23Q2230	Special operations in a machine tool
18	B23Q2240	Machine tools specially suited for a specific kind of workpiece
19	B23Q2701	Members which are comprised in the general build-up of a form of the machine
20	B23Q2707	Automatic supply or removal of metal workpieces
21	B23Q2716	Equipment for precise positioning of tool or work into particular locations
22	B23Q2717	Arrangements for indicating or measuring
23	B23Q2735	Control systems or devices for copying from a pattern or master model
24	B33Y 40	Auxiliary operations or equipment
25	B33Y 70	Materials specially adapted for additive manufacturing
26	B33Y 80	Products made by additive manufacturing
27	G05B 19	Programme-control systems
28	Y10T 82	Turning

TABLE 2. List of the CPC codes contained both the manufacturing and ICT sector.

No.	CPC	Description
1	B23Q 3	Devices holding, supporting, or positioning work or tools, of a kind normally removable from the machine
2	B23Q 5	Driving or feeding mechanisms
3	B23Q 17	Arrangements for Detection or prevention of collisions indicating or measuring on machine tools
4	B23Q 39	Metal-working machines incorporating a plurality of sub-assemblies
5	B23Q 41	Combinations or associations of metal-working machines
6	B23Q2703	Work clamping
7	B23Q2705	Driving working spindles or feeding members carrying tools or work
8	B25J 9	Programme-controlled manipulators
9	B29C 64	Additive manufacturing
10	B33Y 10	Processes of additive manufacturing
11	B33Y 30	Apparatus for additive manufacturing
12	B33Y 50	Data acquisition or data processing for additive manufacturing
13	B60T2201	Particular use of vehicle brake systems
14	B60W 30	Purposes of road vehicle drive control systems not related to the control of a particular sub-unit
15	G01S 17	Systems using the reflection or reradiation of electromagnetic waves other than radio waves
16	G05B2219	Program-control systems
17	G05D 1	Control of position, course or altitude of land, water, air, or space vehicles
18	G06F 9	Arrangements for program control
19	G06F 21	Security arrangements for protecting computers, components, programs against unauthorised activity
20	G06N 3	Computing arrangements based on biological models
21	G06N 5	Computing arrangements using knowledge-based models
22	G06N 7	Computing arrangements based on specific mathematical models
23	G06N 10	Quantum computing
24	G06N 99	Computing arrangements based on specific computational models (etc.)
25	G06T 7	" Image analysis"
26	G06T 19	Manipulating 3D models or images for computer graphics
27	H01L 27	Devices consisting of a plurality of semiconductor or other solid-state components
28	H04L 9	Cryptographic arrangements for secret or secure communications; Network security protocols
29	H04L 63	Network architectures or network communication protocols for network security
30	H04W 4	Services specially adapted for wireless communication networks
31	H04W 12	Security arrangements; Authentication; Protecting privacy or anonymity
32	Y02P 10	Technologies related to metal processing
33	Y04S 10	Systems supporting electrical power generation, transmission or distribution
34	Y04S 20	Management or operation of end-user stationary applications or the last stages of power distribution
35	Y04S 30	Systems supporting specific end-user applications in the sector of transportation
36	Y04S 40	Systems for electrical power generation, transmission, distribution or end-user application management
37	Y04S 50	Market activities related to the operation of systems integrating technologies

From the network centrality measures, we can also identify the main I4T-related technologies of the manufacturing and the ICT sectors among the 37 common technologies. We report the top-5 ranked technologies of the manufacturing

TABLE 3. List of the CPC codes having the top-5 degree rank in the technological networks of the manufacturing and the ICT sectors. The common technologies of two networks are highlighted in gray.

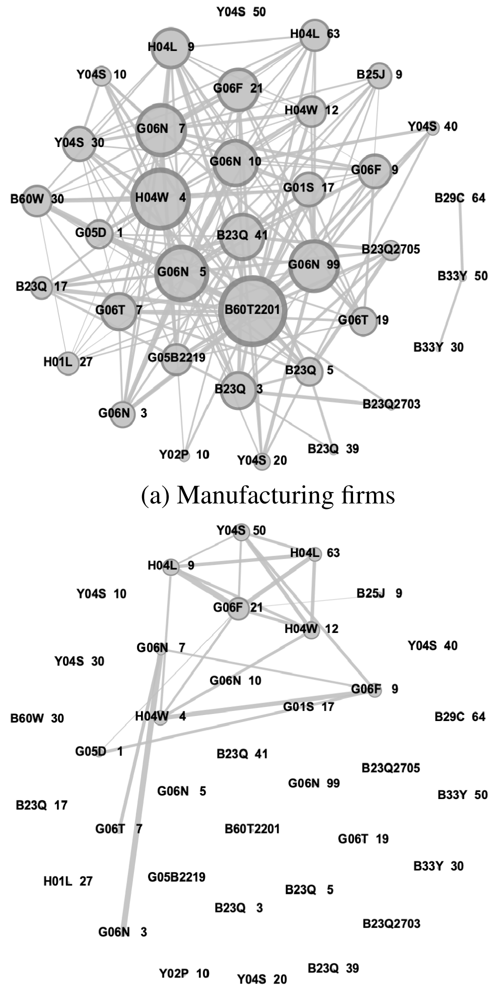
Rank	Manufacturing		ICT	
	CPC	Degree	CPC	Degree
1	B60T2201	23	G06F 21	7
2	H04W 4	20	H04L 9	5
			H04W 12	5
			Y04S 50	5
3	G06N 5	18	H04L 63	4
			G06F 9	4
			H04W 4	4
4	G06N 7	17	G06N 7	3
	G06N 99	17		
5	B23Q 41	15	G05D 1	2
	G06N 10	15		

TABLE 4. List of the CPC codes within the top 5 rank of the betweenness centrality in the technological networks of the manufacturing and the ICT sectors.

Rank	Manufacturing		ICT	
	CPC	Betweenness	CPC	Betweenness
1	B60T2201	89.02	G06F 9	25.25
2	B23Q 3	32.66	G06N 7	19.00
3	G06N 99	31.42	G06F 21	14.58
4	G06N 5	30.23	Y04S 50	10.67
5	H04W 4	29.15	H04W 4	6.67

and the ICT sectors in terms of the degree and the betweenness centrality measures in Tables 3 and 4, respectively. For the degree centrality, the two technologies "G06N 7: Computing arrangements based on computational models" and "H04W 4: Services specially adapted for wireless communication" have higher degrees in both the manufacturing and the ICT sectors, which means that the firms in the manufacturing and the ICT sectors tend to have these technologies in their technological portfolio. In addition, with the top-5 ranked betweenness centrality, we can identify the main technologies that bridge the other two technologies. For example, the technology "B60T2201: Particular use of vehicle brake systems" has the highest betweenness centrality, and it also has the highest degree centrality in the manufacturing sector. This shows that the technology "B60T2201" has its own technological importance and importance on the connectivity of the other technologies in the manufacturing sector. Moreover, we can see that the technologies related to the arrangements ("G06N 99", "G06N 5", "G06F 9", "G06N 7", "G06F 21") and the wireless communication network service ("H04W 4") play a central role to connect the other technologies in both the manufacturing and the ICT sectors.

To distinguish the differences between the two technological networks, we categorize the difference into the structural difference between the two networks and the magnitude difference on the common edges of two networks. First, we depict the difference in the connectivity of two networks in Figure 6 (a), where the edges connected only in either the manufacturing or the ICT sector are highlighted in blue or red, respectively. Overall, the number of edges only connected in the manufacturing sector (156 edges) is quite larger than the



(a) Manufacturing firms

(b) ICT firms

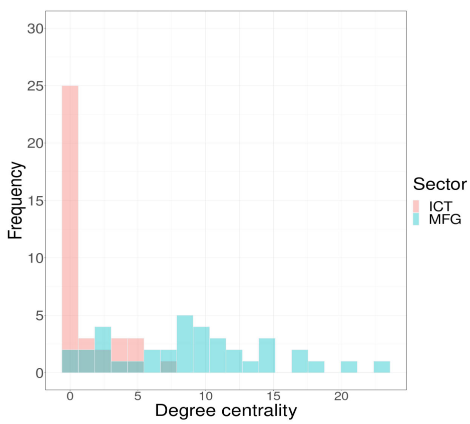
FIGURE 4. Technological networks of the manufacturing and ICT firms with the partial CPC codes.

number of edges only connected in the ICT sector (8 edges). This observation also supports that the technologies of the manufacturing firms have been diversified and ICT firms tend to specialize in several technologies, including computing arrangements and communication network services. In addition, the technology of the market activities related to the operation of systems integrating technologies ("Y04S 50") has five edges among eight edges only in the technological network of the ICT sector while the technology "Y04S 50" does not have any edges in the technological network of the manufacturing sector.

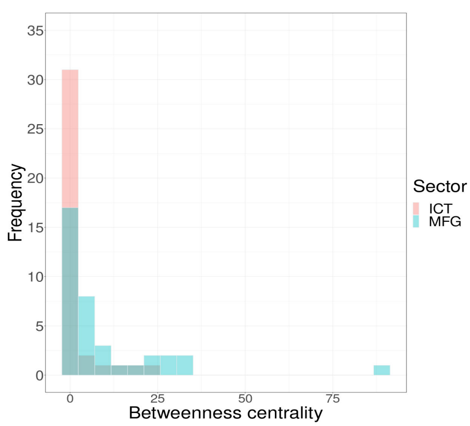
To compare the common edges between two technological networks depicted in Figure 6, we first calculate the difference between Kendall's tau values of 13 common edges. We report the 13 common edges and corresponding Kendall's tau values of the two technological networks in Table 5. As described in Section III-A, we apply the permutation test procedure to identify the significantly different edges in terms of the magnitude at the significance level of 0.05.

TABLE 5. Summary of the permutation tests for the common edges of the technological networks of the manufacturing and the ICT sectors. The significantly different edge by the permutation test is highlighted in gray.

Edge No.	Edge A	Edge B	$\tau^{(M)}$	$\tau^{(I)}$	$\tau^{(M)} - \tau^{(I)}$	Perm. p-value
1	H04L 9	H04L 63	0.2872	0.3862	-0.0990	0.3241
2	H04L 9	G06F 21	0.2763	0.4837	-0.2074	0.0733
3	H04L 9	H04W 12	0.2352	0.3588	-0.1236	0.2970
4	H04L 9	H04W 4	0.3480	0.3347	0.0132	0.9251
5	H04L 63	G06F 21	0.2121	0.4219	-0.2098	0.1306
6	H04L 63	H04W 12	0.1966	0.3898	-0.1932	0.0898
7	G06F 21	H04W 12	0.1698	0.3655	-0.1957	0.2820
8	G06F 21	H04W 4	0.2924	0.3382	-0.0458	0.5977
9	G06F 9	G06N 7	0.4276	0.3290	0.0987	0.7801
10	G06F 9	H04W 4	0.2487	0.4289	-0.1802	0.0763
11	G06T 7	G06N 7	0.3324	0.3863	-0.0539	0.8503
12	H04W 12	H04W 4	0.3468	0.3578	-0.0110	0.9332
13	G06N 7	G06N 3	0.3516	0.4927	-0.1411	0.6784

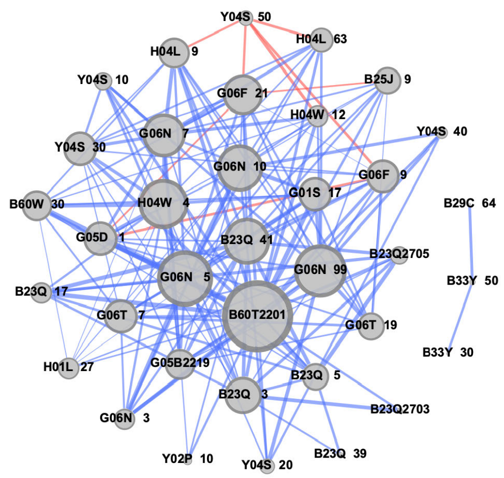


(a) MFG

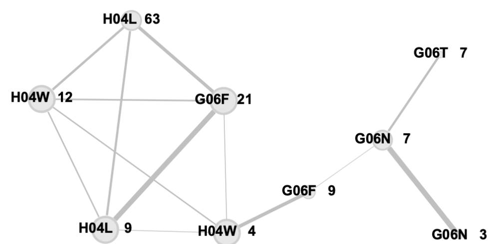


(b) ICT

FIGURE 5. Distributions of the degree and betweenness centralities of the technological networks of the manufacturing (MFG) and the ICT sectors.



(a) Different edges



(b) Common edges

FIGURE 6. Common and different edges between the technological networks of the manufacturing and the ICT sectors. In (a), the blue edges and red edges denote the edges only in the MFG and the ICT, respectively.

We consider the number of permutations B as 100,000 to estimate the null distribution of the test statistic D_{kl} defined in the equation (2). To describe the estimated null distributions by the permutation, we depict the estimated null distributions for the six common edges among the 13 common edges in Figure 7. With the estimated null distribution, we calculate the p-values of the permutation test by the equation (4) and report the p-value in the last column of Table 5. From Table 5, there is no significantly different edge if we consider a significant level as 0.05. Although there is no significant difference between the common edges of the manufacturing and the ICT sectors, the signs of the difference show a pattern that the magnitudes of the common edges of the ICT sector tend to be larger than those of the manufacturing sector. To test this pattern, we apply the sign test with the null hypothesis H_0 : Median$(\tau^{(M)} - \tau^{(I)}) = 0$, where the sign test is one of the non-parametric hypothesis tests, and the null

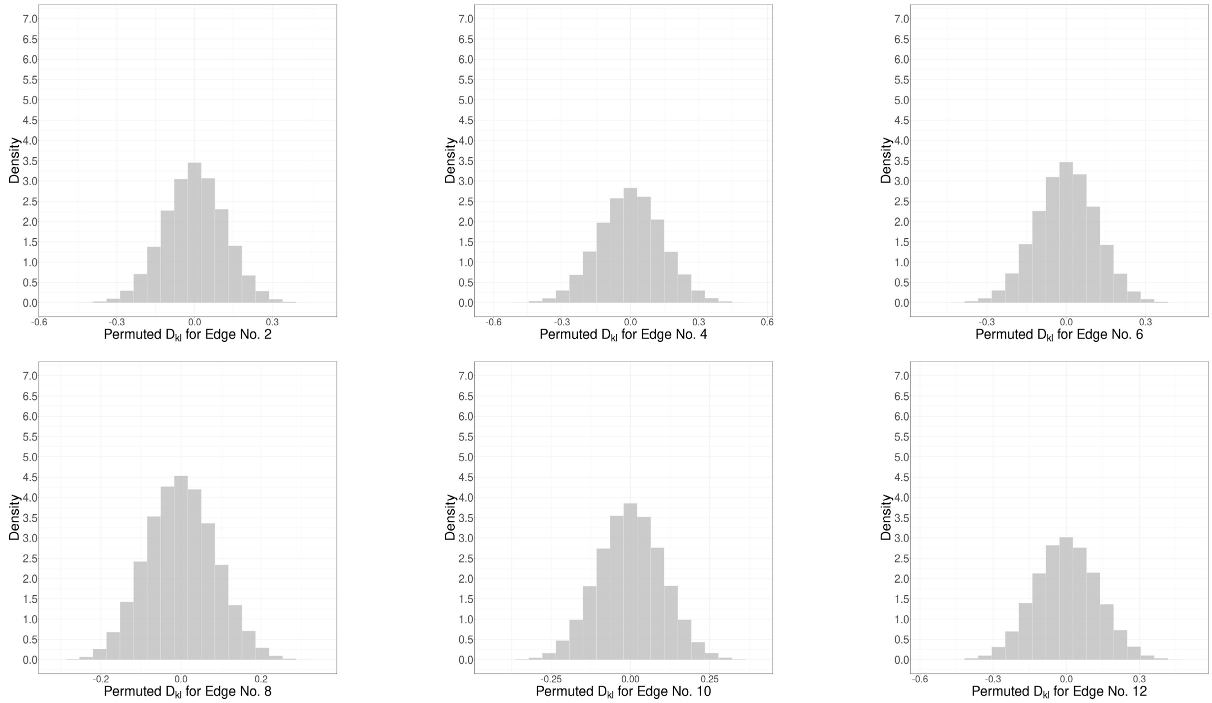


FIGURE 7. Estimated null distributions of D_{kl} by the permutation for 6 common edges (Edge No. 2, 4, 6, 8, 10, 12) among 13 common edges of the technological networks of the manufacturing and the ICT sectors.

distribution of the sign test follows the binomial distribution regardless of the distribution of the observation. As a result, the possibility that two negative values are observed among 13 binary random samples of $\{-1, +1\}$ is significantly rare if the positive and negative values have the same probability. Thus, the magnitudes of the common edges of the ICT sector tend to be stronger than that of the manufacturing sector. This result weakly supports that the firms of the ICT sector take a strategy to specialize in several target technologies rather than the diversification of the technologies.

In summary, we construct two technological networks of the manufacturing and the ICT sectors based on the firm-CPC matrices. From the estimated networks, the comparison results support that the firms in the manufacturing sector tend to diversify the technologies and the firms in the ICT sector tend to specialize in several target technologies. Note that we only use the firm-technology bipartite network information to construct the networks. Thus, this comparison shows that the overall tendency of the firms in two sectors for the technologies. To investigate the effect of the time-dependent variables, including the financial variables of the firms and other factors, we consider the regression analysis in the following sections.

C. PATH-DEPENDENT EMERGENCE OF NEW TECHNOLOGY IN THE MANUFACTURING AND THE ICT SECTORS

In this section, we compare the two sectors focusing on the technological and the financial factors of a firm that affect the emergence of new I4 technologies in the firm. To examine the different effect of factors, we construct the following model:

$$\begin{aligned} Jump_{i,k,t+2} = \beta_0 + \beta_1 \omega_{i,k,t} + \beta_2 ECI_{i,t} + \beta_3 TCI_{k,t} \\ + \beta_4 Patent_{k,t} + \beta_5 tenure_{i,t} + \beta_6 debt_{i,t} \\ + \beta_7 labor_{i,t} + \beta_8 profit_{i,t} \\ + \theta_t + \mu_k + \epsilon_{i,k,t} \end{aligned} \tag{12}$$

where i denotes a firm, k indicates a technology, and t means time. The dependent variable, $Jump_{i,k,t+2}$, is 1, when a firm i successfully develops a new technology k at time $t+2$, and 0, otherwise. Since $Jump_{i,k,t+2}$ is a binary variable, we estimate the effects on the emergence of new technology with a logistic model. Our main explanatory variables that are associated with the technological structure are $\omega_{i,k,t}$, $ECI_{i,t}$, and $TCI_{k,t}$. The first variable covering the technological structure of a firm's technology, $\omega_{i,k,t}$, is the density of the related technologies of a firm i's technology k at time t, indicating the level of path-dependency in the firm's technological diversification. Second, $ECI_{i,t}$ is the economic complexity index of a firm i at time t, and, last, $TCI_{i,t}$ is the technology complexity index of a technology k at time t.

We also include $Patent_{k,t}$, which represents the number of firms that possess technology k at time t. This variable captures both the competitiveness of the market and the pervasiveness of the technology. Additionally, we incorporate other firm-level information, such as the number of employees, which reflects the size of the firm; the debt ratio, which is the total liabilities to total assets; the profit ratio, which

TABLE 6. The effects of relatedness, firm complexity, and technological complexity on the emergence of new I4 technologies in the manufacturing and the ICT sector.

	$Jump_{i,k,t+2}$	
	(1) $Manufacturing$	(2) ICT
$\omega_{i,k,t}$	0.279***	11.042***
	(0.006)	(2.331)
$ECI_{i,t}$	1.004***	15.278***
	(0.068)	(3.792)
$TCI_{k,t}$	−0.208***	−3.186***
	(0.022)	(0.801)
$patent_{k,t}$	0.545***	0.936***
	(0.021)	(0.330)
$tenure_{i,t}$	0.341***	0.613
	(0.019)	(0.618)
$debt_i$	0.068***	2.714
	(0.011)	(5.162)
$labor_i$	0.019***	0.129
	(0.005)	(1.124)
$profit_i$	−0.109**	−0.274
	(0.049)	(0.506)
Technology fixed effect	*Yes*	*Yes*
Time fixed effect	*Yes*	*Yes*
Observations	765,034	5,594
McFadden R^2	0.149	0.545
Log Likelihood	−16,690.390	−67.972
Note:	*p<0.1; **p<0.05; ***p<0.01	

TABLE 7. Summary of descriptive statistics of exploratory variables.

Statistic	N	Mean	St. Dev.	Min	Max
$\omega_{i,k,t}$	1,209,964	0.000	1.000	−0.265	23.870
$ECI_{i,t}$	908,282	0.000	1.000	−5.744	0.742
$TCI_{k,t}$	1,209,964	0.000	1.000	−1.607	2.284
$patent_{i,t}$	1,209,964	0.000	1.000	−0.745	4.260
$patent_{k,t}$	1,209,964	0.000	1.000	−0.096	44.573
$cpc_{i,k,t}$	1,209,964	0.000	1.000	−0.015	409.668
$tenure_{i,t}$	1,197,403	0.000	1.000	−2.855	5.009
$debt_{i,t}$	1,064,812	0.000	1.000	−0.152	118.748
$labor_{i,t}$	1,038,306	0.000	1.000	−0.217	30.503
$profit_{i,t}$	1,060,299	0.000	1.000	−116.829	1.739

is the share of profit to sales; and the tenure of the firm i at time t since its establishment. In cases where a firm's patent application was filed before its listing year, the tenure variable may be negative. Finally, we include time-fixed effects (θ_t) and technology-fixed effects (μ_k) to account for the national time trend and time-invariant characteristics of technology within large classifications.[1]

Table 6 shows our results of econometric models. Column (1) and (2) depict the results of the logistic model, which estimate the effect of structural factors of technology on the emergence of new I4 technology in a firm and ask whether there exists a difference in the effects between the manufacturing and the ICT sector. Our analysis confirms the findings of Kim et al. [43], [44] that the density of related technologies, $w_{i,k}$, has a positive and significant effect on the firm's probability of success in entering a new I4 technology. Moreover, we find that this effect is stronger in the ICT sector than in the manufacturing sector. This suggests that firms in the ICT sector have a higher probability of success in entering a new I4 technology when they already possess related technologies, compared to manufacturing firms. On the other hand, the results indicate that path-dependency plays a more significant role in the ICT sector when it comes to entering a new I4 technology. While the coefficient of manufacturing firms' $omega_{i,k,t}$ remains positive, indicating the presence of path-dependent characteristics, interestingly, the accumulated knowledge on I4 technologies benefits ICT firms more. This could be because established manufacturing firms have access to other resources for technological diversification compared to ICT firms.

Second, regarding the effect of ECI of a firm on the emergence of new I4 technology, we can see the significant and positive effect consistently in column (1) and (2). Again, the effect of the ECI in ICT sector is larger than that of the manufacturing sector. We implies that complex firms with respect to their technological portfolio is more likely to enter a new I4 technologies. Since the ECI value can be bigger either their portfolio is more diverse or their technologies are rarer, this result implies that ICT firms jumping into the new I4 technology tend to have a rare technology.

When examining the effect of TCI on the emergence of new I4 technology, we observe significant and negative effects of TCI on firms' ability to enter a new I4 technology. This result suggests that the probability of successfully entering a new I4 technology is lower for firms that aim to acquire a complex technology. The negative effect is stronger for the ICT firms.

The number of firms that possess a technological advantage in the same technology k also increases the probability of a firm's success in entering a new technology, indicating that $patent_k$ serves as a learning opportunity for firms rather than a source of competition. Another interesting finding is that older firms are more likely to enter I4T technologies in the manufacturing sector, while the age of the firm has no effect in the ICT sector. Furthermore, larger firms are more likely to enter a new I4 technology, while the size of the firm has no effect in the ICT sector.

D. INTENSIVE AND EXTENSIVE MARGIN OF FIRM's TECHNOLOGY IN MANUFACTURING AND ICT FIRMS

Next, we examine the effect of a firm's factors on both the intensive and extensive margins of its technology. For the factors that represent a firm's technological structure, we only consider the effect of $ECI_{i,t}$ since other variables, such as $\omega_{i,k,t}$ and $TCI_{k,t}$, have larger and different dimensions compared to the dependent variable, $ECI_{i,t}$. We calculate $ECI_{i,t}$ by

[1]The summary statistics of variable is in Table 7 and the correlation of among variable is in Table 8. All the explanatory variables are normalized.

TABLE 8. Correlation matrix of the exploratory variables.

	$\omega_{i,k,t}$	$ECI_{i,t}$	$TCI_{k,t}$	$patent_{i,t}$	$patent_{k,t}$	$cpc_{i,t}$	$tenure_{i,t}$	$debt_{i,t}$	$labor_{i,t}$	$profit_{i,t}$
$\omega_{i,k,t}$	1									
$ECI_{i,t}$	0.075	1								
$TCI_{k,t}$	0.023	0.002	1							
$patent_{i,t}$	0.768	0.035	0.024	1						
$patent_{k,t}$	-0.038	-0.008	-0.389	-0.038	1					
$cpc_{i,t}$	0.045	0.005	-0.001	0.041	0.039	1				
$tenure_{i,t}$	0.210	-0.064	0.003	0.111	0.034	0.012	1			
$debt_{i,t}$	0.015	0.012	0.001	0.001	-0.015	0.0003	0.0005	1		
$labor_{i,t}$	0.691	0.026	0.021	0.648	-0.042	0.030	0.212	0.014	1	
$profit_{i,t}$	-0.032	-0.271	-0.0002	-0.005	-0.001	-0.001	-0.122	-0.048	-0.013	1

examining the accumulated technologies of a firm at time t, and the complexity only increases when a firm adds a technology that is above its current average [34]. While the economic complexity index at the country or regional level has been explored as a factor of economic growth [55], [56], [57], [58], [59], [60], income inequality [61], and sustainability [62], [63], [64] of a country or region, it has rarely been explored at the firm level. Therefore, this paper aims to explore the factors that affect technological performance and compare the manufacturing and ICT sectors. We examine the effect of ECI on the technological performance, which includes both the intensive and extensive margins of a firm's technology. Factors on the firm's capital structure, $profit_{i,t}$ and $debt_{i,t}$, and the age of the firm, $tenure_{i,t}$, are also explored. Therefore, the empirical specification is following:

$$\begin{aligned} patent_{i,t+2} = {} & \beta_1 ECI_{i,t} + \beta_2 ECI_{i,t} \cdot ICT \\ & + \beta_3 patent_{i,t} + \beta_3 patent_{i,t} \cdot ICT \\ & + \beta_4 tenure_{i,t} + \beta_4 tenure_{i,t} \cdot ICT \\ & + \beta_5 debt_{i,t} + \beta_5 debt_{i,t} \cdot ICT \\ & + \beta_6 labor_{i,t} + \beta_6 labor_{i,t} \cdot ICT \\ & + \beta_7 profit_{i,t} + \beta_7 profit_{i,t} \cdot ICT + \theta_t + \epsilon_{i,k,t} \end{aligned} \tag{13}$$

$$\begin{aligned} cpc_{i,t+2} = {} & \beta_1 cpc_{i,t} + \beta_2 patent_{i,t} \cdot ICT \\ & + \beta_3 ECI_{i,t} + \beta_4 ECI_{i,t} \cdot ICT \\ & + \beta_5 tenure_{i,t} + \beta_6 tenure_{i,t} \cdot ICT \\ & + \beta_7 debt_{i,t} + \beta_8 debt_{i,t} \cdot ICT \\ & + \beta_9 labor_{i,t} + \beta_1 0 labor_{i,t} \cdot ICT \\ & + \beta_1 1 profit_{i,t} + \beta_1 2 profit_{i,t} \cdot ICT + \theta_t + \epsilon_{i,k,t} \end{aligned} \tag{14}$$

where $patent_{i,t+2}$ is the number of applied patent of a firm i at time $t+2$ and $cpc_{i,t+2}$ is the number of cpc that are added to a firm i at time $t+2$, indicating the intensive margin and extensive margin of the firm's technology, respectively. Also, we control for the $patent_{i,t}$ and $cpc_{i,t}$, which are the number of newly applied patent and cpc code in a firm i at time t. The interaction terms are added to capture the difference between the manufacturing and the ICT sector.

Table 9 reports the results of our firm level analysis. Column (1) and (2) is the results on the intensive margin, while column (3) and (4) shows the results on the extensive margin of the firm's technology. Also, column (1) and (3) shows the results of all the firms and column (2) and (4) shows the results of firms that possess I4 technologies. According to our results, the firm's technological performance at time t is the

TABLE 9. Summary of the firm level analysis for intensive and extensive margin of firm's technology.

	Dependent variable:			
	Intensive margin $patent_{i,t+2}$		*Extensive margin* $cpc_{i,t+2}$	
	(1) *All*	(2) *I4T*	(3) *All*	(4) *I4T*
$patent_{i,t}$	0.958*** (0.002)	1.021*** (0.003)		
$patent_{i,t} \cdot ICT$	−0.369*** (0.024)	−0.443*** (0.034)		
$cpc_{i,t}$			0.996*** (0.002)	1.065*** (0.003)
$cpc_{i,t} \cdot ICT$			−0.406*** (0.030)	−0.487*** (0.043)
$ECI_{i,t}$	0.0002 (0.004)	0.005 (0.005)	−0.150 (3.423)	0.804 (2.220)
$ECI_{i,t} \cdot ICT$	0.029 (0.083)	0.001 (0.024)	24.729 (80.035)	1.028 (11.025)
$tenure_{i,t}$	0.004 (0.004)	0.0003 (0.001)	3.173 (3.952)	0.022 (0.568)
$tenure_{i,t} \cdot ICT$	−0.002 (0.024)	−0.002 (0.006)	1.682 (23.336)	−0.608 (2.997)
$debt_{i,t}$	0.044*** (0.013)	0.0001 (0.003)	28.299** (12.495)	−0.456 (1.518)
$debt_{i,t} \cdot ICT$	−0.096 (0.212)	−0.015 (0.062)	−48.952 (203.365)	−3.470 (28.663)
$labor_{i,t}$	0.031*** (0.004)	0.009*** (0.001)	58.087*** (3.909)	4.722*** (0.459)
$labor_{i,t} \cdot ICT$	−0.017 (0.020)	−0.004 (0.005)	−49.135*** (18.958)	−2.827 (2.418)
$profit_{i,t}$	0.002 (0.004)	0.00005 (0.001)	1.902 (3.655)	−0.038 (0.425)
$profit_{i,t} \cdot ICT$	−0.0001 (0.022)	0.0001 (0.006)	0.071 (21.034)	−0.020 (2.613)
Time fixed effect	*Yes*	*Yes*	*Yes*	*Yes*
Observations	29,229	9,730	29,229	9,730
Adjusted R^2	0.919	0.944	0.935	0.950
Note:				*p<0.1; **p<0.05; ***p<0.01

most critical for the intensive and extensive margin of firm's technology at time $t+2$, indicating a firm that performs well at time t is likely perform well again at time $t+2$. This implies that the creating of new technologies are not just one time event, but something that is affected by embedded capabilities of the firm. Interestingly, although ICT sector still shows the positive and significant effects of $patent_{i,t}$ and $cpc_{i,t}$, as seen in the interaction terms, $patent_{i,t} \cdot ICT$ and $cpc_{i,t} \cdot ICT$, the effects become smaller that those of the manufacturing sector for all technologies, as we can notice from its negative sign.

Firm's economic complexity, age, and profit ratio do not affect the firm's technological intensive and extensive margin and we cannot observe the significant difference between the two sectors. On the other hands, debt ratio of firms in the manufacturing sector gives a positive and significant effect on the intensive and extensive margin of their technology and there is no difference between the two sectors. Regarding the number of employees, which indicates the size of the firm, has a positive and significant effect on the intensive and extensive margin and the effect on the extensive margin becomes smaller for the ICT firms as shown in column (3).

V. CONCLUSION

Our analysis suggests that the manufacturing sector has been the dominant technological leader in Korea in terms of both the number of patents filed and the diversity of technologies pursued even in the era of 4IR. Although, the ICT sector has shown an increasing focus on I4 technologies after the 2000s, indicating the potential for a shift in dominance in the future, the gap between the two sectors is still significant.

Additionally, our network estimation and relatedness analysis reveal that the manufacturing sector tends to diversify technologies while the ICT sector specializes in several target technologies. Moreover, our analysis found that both sectors exhibit path-dependency in their technological diversification, with the ICT sector exhibiting stronger path-dependent characteristics. Finally, we found that firms in both sectors exhibit the tendency of intensive and extensive margin in their patenting activities, but this tendency is stronger for firms in the manufacturing sector.

Upon initiating this study, we initially expected a rapid catch-up by the ICT sector in Korea, in light of the emergence of new tech companies in the US. However, the study's findings reveal the continued dominance of the manufacturing sector in the I4 technologies, and the gap between the two sectors remains significant. One possible explanation for this disparity could be attributed to the differing financial institutions that support the growth of ICT firms in the US versus Korea. While the US has a well-developed venture capital industry that supports ICT firms, Korea's financial market for these firms is still in its nascent stages compared to that of the US, limiting their access to financial resources. In contrast, manufacturing firms in Korea, often represented by *chaebols*, large industrial conglomerates, are not as constrained in their financial availability.

Another possible explanation for our results is the differing product characteristics between the two sectors. The manufacturing sector's primary product is typically physically tangible, while that of the ICT sector tends to be intangible services. As a result, manufacturing firms can embed their technologies in their products, pushing them to apply for more patents than the ICT sector. Furthermore, the geographically limited market for ICT services can constrain their growth and development, whereas Korean manufacturing firms have a broader reach, resulting in their dominance in patenting performance in Korea.

Although our study compared the technological structures of two sectors, it is limited in capturing other aspects of technological dominance, such as the quality of IT services or the market share of online platforms. For example, online platforms are another type of capital associated with technological dominance that patent data cannot capture.

Despite these limitations, our research sheds light on the potential shift in dominant technological sectors in the 4IR era and emphasizes the importance of ongoing monitoring of technological trends in Korea. While the increasing focus of the ICT sector on I4 technologies suggests the possibility of its emergence as the dominant sector in the future, our analysis demonstrates that there is still a significant quantitative gap between the two sectors.

REFERENCES

[1] J. A. Schumpeter, *The Theory of Economic Development: An Inquiry Into Profits, Capital, Credit, Interest, and the Business Cycle*. Cambridge, MA, USA: Harvard Univ. Press, 1934.

[2] C. Perez, *Technological Revolutions and Financial Capital*. Cheltenham, U.K.: Edward Elgar, 2003.

[3] G. Dosi, "Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change," *Res. Policy*, vol. 11, no. 3, pp. 147–162, 1982.

[4] K. Schwab, *The Fourth Industrial Revolution*. Cologny, Switzerland: World Economic Forum, 2016.

[5] Y. Lu, "Industry 4.0: A survey on technologies, applications and open research issues," *J. Ind. Inf. Integr.*, vol. 6, pp. 1–10, Jun. 2017.

[6] Y. Liao, F. Deschamps, E. D. F. R. Loures, and L. F. P. Ramos, "Past, present and future of industry 4.0—A systematic literature review and research agenda proposal," *Int. J. Prod. Res.*, vol. 55, no. 12, pp. 3609–3629, Jun. 2017.

[7] M. Lee, J. Yun, A. Pyka, D. Won, F. Kodama, G. Schiuma, H. Park, J. Jeon, K. Park, K. Jung, M.-R. Yan, S. Lee, and X. Zhao, "How to respond to the fourth industrial revolution, or the second information technology revolution? Dynamic new combinations between technology, market, and society through open innovation," *J. Open Innov., Technol., Market, Complex.*, vol. 4, no. 3, p. 21, Jun. 2018.

[8] M. Ghobakhloo, "The future of manufacturing industry: A strategic roadmap toward industry 4.0," *J. Manuf. Technol. Manage.*, vol. 29, no. 6, pp. 910–936, 2018.

[9] H. Kagermann, "Recommendations for implementing the strategic initiative industrie 4.0: Final report of the industrie 4.0 working group," Forschungsunion, Berlin, Germany, Tech. Rep., 2013.

[10] F. Shrouf, J. Ordieres, and G. Miragliotta, "Smart factories in industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage.*, Dec. 2014, pp. 697–701.

[11] Y. Ménière, I. Rudyk, and J. Valdes, *Patents and the Fourth Industrial Revolution: The Inventions Behind Digital Transformation*. Munich, Germany: European Patent Office, 2017.

[12] D. Horváth and R. Z. Szabó, ''Driving forces and barriers of industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?'' *Technol. Forecasting Social Change*, vol. 146, pp. 119–132, Sep. 2019.

[13] J. Vacek, ''On the road: From industry 4.0 to society 4.0,'' *Trends Bus.*, vol. 7, no. 4, pp. 43–49, 2017.

[14] M. Brettel, N. Friederichsen, M. Keller, and M. Rosenberg, ''How virtualization, decentralization and network building change the manufacturing landscape: An industry 4.0 perspective,'' *Int. J. Mech. Ind. Sci. Eng.*, vol. 8, no. 1, pp. 37–44, 2014.

[15] J. Basl, ''Pilot study of readiness of Czech companies to implement the principles of industry 4.0,'' *Manage. Prod. Eng. Rev.*, vol. 8, no. 2, pp. 3–8, Jun. 2017.

[16] A. G. B. Fisher, ''Production, primary, secondary and tertiary,'' *Econ. Rec.*, vol. 15, no. 1, pp. 24–38, Jun. 1939.

[17] S. Fabricant, *The Output of Manufacturing Industries, 1899-1937*. Cambridge, MA, USA: NBER, 1940.

[18] C. Clark, *The Conditions of Economic Progress*. New York, NY, USA: Macmillan, 1940.

[19] S. Kuznets, ''Modern economic growth: Findings and reflections,'' *Amer. Econ. Rev.*, vol. 63, no. 3, pp. 247–258, 1973.

[20] P. P. Saviotti and A. Pyka, ''Economic development by the creation of new sectors,'' *J. Evol. Econ.*, vol. 14, no. 1, pp. 1–35, Jan. 2004.

[21] G. Dosi and R. R. Nelson, ''Technical change and industrial dynamics as evolutionary processes,'' *Handbook Econ. Innov.*, vol. 1, pp. 51–127, Jan. 2010.

[22] R. R. Nelson and S. G. Winter, ''In search of a useful theory of innovation,'' in *Innovation, Economic Change and Technology Policies: Proceedings of a Seminar on Technological Innovation Held in Bonn*, Berlin, Germany: Springer, Apr. 1977, pp. 215–245.

[23] J. G. March, ''Exploration and exploitation in organizational learning,'' *Org. Sci.*, vol. 2, no. 1, pp. 71–87, 1991.

[24] I. Nonaka, ''A dynamic theory of organizational knowledge creation,'' *Organ. Sci.*, vol. 5, no. 1, pp. 14–37, 1994.

[25] D. J. Teece, ''Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance,'' *Strategic Manage. J.*, vol. 28, no. 13, pp. 1319–1350, Dec. 2007.

[26] B. J. Loasby, ''The organisation of capabilities,'' *J. Econ. Behav. Org.*, vol. 35, no. 2, pp. 139–160, 1998.

[27] E. Brynjolfsson and B. Kahin, *Understanding the Digital Economy: Data, Tools, and Research*. Cambridge, MA, USA: MIT Press, 2002.

[28] H. R. Varian, J. Farrell, and C. Shapiro, *The Economics of Information Technology: An Introduction*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[29] S. S. Srinivasan, R. Anderson, and K. Ponnavolu, ''Customer loyalty in e-commerce: An exploration of its antecedents and consequences,'' *J. Retailing*, vol. 78, no. 1, pp. 41–50, Mar. 2002.

[30] J. Schäfer and K. Strimmer, ''An empirical Bayes approach to inferring large-scale gene association networks,'' *Bioinformatics*, vol. 21, no. 6, pp. 754–764, 2005, doi: 10.1093/bioinformatics/bti062.

[31] Y. Benjamini and Y. Hochberg, ''Controlling the false discovery rate: A practical and powerful approach to multiple testing,'' *J. Roy. Stat. Soc., B Methodol.*, vol. 57, no. 1, pp. 289–300, 2019.

[32] C. A. Hidalgo, B. Klinger, A.-L. Barabási, and R. Hausmann, ''The product space conditions the development of nations,'' *Science*, vol. 317, no. 5837, pp. 482–487, Jul. 2007. [Online]. Available: https://science.sciencemag.org/content/317/5837/482

[33] C. A. Hidalgo, P.-A. Balland, R. Boschma, M. Delgado, M. Feldman, K. Frenken, E. Glaeser, C. He, D. F. Kogler, A. Morrison, F. Neffke, D. Rigby, S. Stern, S. Zheng, and S. Zhu, ''The principle of relatedness,'' in *Unifying Themes in Complex Systems IX*, A. J. Morales, C. Gershenson, D. Braha, A. A. Minai, and Y. Bar-Yam, Eds. Cham, Switzerland: Springer, 2018, pp. 451–457.

[34] C. A. Hidalgo, ''Economic complexity theory and applications,'' *Nature Rev. Phys.*, vol. 3, pp. 92–113, Jan. 2021, doi: 10.1038/s42254-020-00275-1.

[35] B. Jun, A. Alshamsi, J. Gao, and C. A. Hidalgo, ''Bilateral relatedness: Knowledge diffusion and the evolution of bilateral trade,'' *J. Evol. Econ.*, vol. 30, no. 2, pp. 247–277, 2020.

[36] J. Gao, B. Jun, A. S. Pentland, T. Zhou, and C. A. Hidalgo, ''Spillovers across industries and regions in China's regional economic diversification,'' *Regional Stud.*, vol. 55, no. 7, pp. 1311–1326, Jul. 2021.

[37] R. Boschma and S. Iammarino, ''Related variety, trade linkages, and regional growth in Italy,'' *Econ. Geography*, vol. 85, no. 3, pp. 289–311, Apr. 2009.

[38] F. Neffke, M. Henning, and R. Boschma, ''How do regions diversify over time? Industry relatedness and the development of new growth paths in regions,'' *Econ. Geography*, vol. 87, no. 3, pp. 237–265, Jul. 2011. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1111/j.1944-8287.2011.01121.x

[39] Q. Guo and C. He, ''Production space and regional industrial evolution in China,'' *GeoJournal*, vol. 82, no. 2, pp. 379–396, Apr. 2017.

[40] C. He, S. Zhu, X. Hu, and Y. Li, ''Proximity matters: Inter-regional knowledge spillovers and regional industrial diversification in China,'' *Tijdschrift Voor Economische Sociale Geografie*, vol. 110, no. 2, pp. 173–190, Apr. 2019.

[41] P.-A. Balland, R. Boschma, J. Crespo, and D. L. Rigby, ''Smart specialization policy in the European union: Relatedness, knowledge complexity and regional diversification,'' *Regional Stud.*, vol. 53, no. 9, pp. 1252–1268, Sep. 2019, doi: 10.1080/00343404.2018.1437900.

[42] D. F. Kogler, D. L. Rigby, and I. Tucker, ''Mapping knowledge space and technological relatedness in US cities,'' *Eur. Planning Stud.*, vol. 21, no. 9, pp. 1374–1391, Sep. 2013, doi: 10.1080/09654313.2012.755832.

[43] S. H. Kim, B. Jun, and J.-D. Lee, ''Technological relatedness: How do firms diversify their technology?'' SocArXiv 47ank, Center Open Sci., 2021.

[44] S. H. Kim, J. H. Jeon, A. Aridi, and B. Jun, ''Factors that affect the technological transition of firms toward the industry 4.0 technologies,'' *IEEE Access*, vol. 11, pp. 1694–1707, 2023.

[45] R. Hausmann, C. A. Hidalgo, S. Bustos, M. Coscia, and A. Simoes, *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. Cambridge, MA, USA: MIT Press, 2014.

[46] P.-A. Balland and D. Rigby, ''The geography of complex knowledge,'' *Econ. Geography*, vol. 93, no. 1, pp. 1–23, Jan. 2017.

[47] S. Petralia, P.-A. Balland, and A. Morrison, ''Climbing the ladder of technological development,'' *Res. Policy*, vol. 46, no. 5, pp. 956–969, Jun. 2017.

[48] B. H. Hall, A. B. Jaffe, and M. Trajtenberg, ''The NBER patent citation data file: Lessons, insights and methodological tools,'' Nat. Bureau Econ. Res., Cambridge, MA, USA, Working Paper no. 8498, Oct. 2001. [Online]. Available: http://www.nber.org/papers/w8498

[49] G. Thoma and S. Torrisi, *Creating Powerful Indicators for Innovation Studies With Approximate Matching Algorithms: A Test Based on PATSTAT and Amadeus Databases*. Milan, Italy: Università commerciale Luigi Bocconi, 2007.

[50] T. Julius and G. De Rassenfosse, ''Harmonising and matching IPR holders at ip Australia,'' Melbourne Inst., Melbourne, VIC, Australia, Work. Paper 15/14, 2014.

[51] T. Kang, C. Baek, and J.-D. Lee, ''Effects of knowledge accumulation strategies through experience and experimentation on firm growth,'' *Technol. Forecasting Social Change*, vol. 144, pp. 169–181, Jul. 2019.

[52] P.-A. Balland and R. Boschma, ''Mapping the potentials of regions in Europe to contribute to new knowledge production in industry 4.0 technologies,'' *Regional Stud.*, vol. 55, nos. 10–11, pp. 1652–1666, Nov. 2021.

[53] A. Ciffolilli and A. Muscio, ''Industry 4.0: National and regional comparative advantages in key enabling technologies,'' *Eur. Planning Stud.*, vol. 26, no. 12, pp. 2323–2343, Dec. 2018.

[54] B. Balassa, ''Trade liberalisation and 'revealed' comparative advantage,'' *Manchester School*, vol. 33, no. 2, pp. 99–123, 1965.

[55] C. A. Hidalgo and R. Hausmann, ''The building blocks of economic complexity,'' *Proc. Nat. Acad. Sci. USA*, vol. 106, no. 26, pp. 10570–10575, Jun. 2009.

[56] V. Stojkoski, Z. Utkovski, and L. Kocarev, ''The impact of services on economic complexity: Service sophistication as route for economic growth,'' *PLoS ONE*, vol. 11, no. 8, Aug. 2016, Art. no. e0161633.

[57] A. Tacchella, D. Mazzilli, and L. Pietronero, ''A dynamical systems approach to gross domestic product forecasting,'' *Nature Phys.*, vol. 14, no. 8, pp. 861–865, Aug. 2018.

[58] J. C. Chávez, M. T. Mosqueda, and M. Gómez-Zaldívar, ''Economic complexity and regional growth performance: Evidence from the Mexican economy,'' *Rev. Regional Stud.*, vol. 47, no. 2, pp. 201–219, Jun. 2017.

[59] M. Cristelli, A. Tacchella, and L. Pietronero, "The heterogeneous dynamics of economic complexity," *PLoS ONE*, vol. 10, no. 2, Feb. 2015, Art. no. e0117174.

[60] S. J. P. Balsalobre, C. L. Verduras, and J. D. Lanchas, "Measuring the economic complexity at the sub-national level using international and interregional trade," in *Proc. 19th Annu. Conf. Eur. Trade Study Group*, 2017, pp. 1–36.

[61] D. Hartmann, M. R. Guevara, C. Jara-Figueroa, M. Aristarán, and C. A. Hidalgo, "Linking economic complexity, institutions, and income inequality," *World Develop.*, vol. 93, pp. 75–93, May 2017.

[62] O. Neagu and M. Teodoru, "The relationship between economic complexity, energy consumption structure and greenhouse gas emission: Heterogeneous panel evidence from the EU countries," *Sustainability*, vol. 11, no. 2, p. 497, Jan. 2019.

[63] M. Can and G. Gozgor, "The impact of economic complexity on carbon emissions: Evidence from France," *Environ. Sci. Pollut. Res.*, vol. 24, no. 19, pp. 16364–16370, Jul. 2017.

[64] J. P. Romero and C. Gramkow, "Economic complexity and greenhouse gas emissions," *World Develop.*, vol. 139, Mar. 2021, Art. no. 105317.

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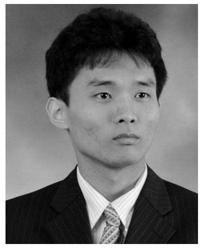

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