RESEARCH ARTICLE

Factors That Affect the Technological Transition of Firms Toward the Industry 4.0 Technologies

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ABSTRACT This research identifies factors that affect the technological transition of firms toward industry 4.0 (IT) technologies focusing on capabilities and policy impacts using relatedness and complexity measures. For the analysis, a unique dataset was used of Korean manufacturing firms' patents and their financial and market information. Following the Principle of Relatedness, which is a recently shaped empirical principle in the field of economic complexity, economic geography, and regional studies, a technology space is built, and each firm's footprint in the space is traced. Using the firms' technology space can identify those firms that successfully develop new I4 technologies and can examine whether their accumulated capabilities in their previous technology domains positively affect their technological diversification and which factors play a critical role in their transition towards I4. In addition, combining data on whether the firms received government support for R&D activities can help further analyze the role of government policy in supporting firms' knowledge activities in new I4 technologies. Firms with higher related technologies and more government support are more likely to engage in new I4 technologies. This research is expected to inform policymakers who intend to diversify firms' technological capabilities towards I4 technologies.

INDEX TERMS Industry 4.0, economic complexity, patent data, knowledge accumulation strategy, relatedness, I4 technologies.

I. INTRODUCTION

In the last half-century, South Korea's economy underwent a fast structural change from an agricultural society to an industrialized society. According to Wade [78], achieving industrialization is not an easy task. Only a few countries outside Europe and from among European offshoots (i.e., Australia, New Zealand, Canada, and the United States) have achieved industrialization by escaping the Malthusian trap. Excluding city-states such as Singapore and Hong Kong, very

few countries in the world, (e.g., Japan, Taiwan, South Korea) have achieved sustainable economic development capable of transforming their economies from a backward state to an advanced industrialized society [29]. This study focuses on Korea, especially the recent experience with the Fourth Industrial Revolution.

Scholars have argued that we are living in the era of the Fourth Industrial Revolution [52], [53], although scholarly debate exists over its discontinuity [62], [68]. Living in the Fourth Industrial Revolution implies that the windows of opportunity for economic development are now open for developing countries [64]. According to Perez [64],

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a technological revolution would provide the best opportunities for catching up with technical changes sufficient for initiating and advancing the development process. This is because every country is a beginner in the early stage of a new techno-economic paradigm and the probability of success by leap-frogging increases at that stage.

Perez [64] argued that each technological revolution is a cluster of technological systems. For example, during the Second Industrial Revolution around 1910, mass production and its successive systems allowed economies to achieve structural change, while the Third Industrial Revolution around the 1970s was associated with information technology. The most recent industrial revolution is industry 4.0 (I4) [52], [53], [67]. In fact, the term *industry 4.0* was introduced as part of a German industrial policy that aimed to improve the production system by combining the IT system with the current manufacturing system. However, industry 4.0 is often used interchangeably with the Fourth Industrial Revolution, since the new industries that emerged during it are yet to be defined. I4 technologies are expected to provide the domain knowledge that affects a wide range of economic sectors and can therefore be regarded as the core technologies in the Fourth Industrial Revolution.

Firms were the main actors that created new technologies and new sectors during earlier technological revolutions. It is true that the National Innovation System (NIS) should be considered when we examine the factors that determine the success of a revolution [24], [54]. Lundvall [54] argued that innovation at the country level depends on its NIS consisting of not only enterprises but also research institutes, universities, and government. From a broader perspective, innovation includes accumulated human capital, dynamics of the labor market, learning among enterprises, and sets of government policies. Kim et al. [46] also described how human capital formation, the inflow of foreign technologies, and various government policies provide the environment for firms' innovation activities. Within this environment, firms develop their strategies at the microeconomic level to sustain growth by acquiring technological capabilities. In the long run, these firms' innovation activities work as the main engine of economic development in a country by leading in the emergence of new sectors [71], [72]. This study, therefore, focuses on the main actor in innovation: the firm.

What are the characteristics of I4 technologies, and how do firms acquire the I4 technologies? What factors support firms in their technological diversification towards I4 technologies? Furthermore, do technology policies support firms in leveraging emerging technological opportunities to achieve economic development and make the economy more advanced in the era of the Fourth Industrial Revolution? This paper tries to identify the factors that affect the technological transition of firms toward advanced technologies, especially those associated with industry 4.0, by looking at the technological trajectories of Korean firms. The core questions are as follows. (i) What are the characteristics of I4 technologies, and how do these change in terms of complexity? (ii) Among the three factors of technological relatedness, complexity, and government policy, which ones play a critical role in firms' technological diversification, especially when firms enter the I4 technologies space? (iii) Which type of firm is more likely to succeed in entering a new technology that is associated with I4 technologies?

The target audiences of this research are businesses and business representatives and associations that aim to diversify their technological capabilities towards I4 technologies, plus researchers and policymakers who aim at designing and implementing innovation policies that support firms' industry diversification and transformation.

To explore these questions, the research adopts a methodology from the Principle of Relatedness. The principle indicates that firms, cities, regions, and countries are more likely to undertake new economic activities such as those related to new technologies, new products, and new industries when they already conduct related activities [34], [35]. In their seminal work, Hidalgo et al. [37] constructed a product space using world trade data and tracked the trajectories of industrial diversification by countries in the space. Following Hidalgo et al. [37], in this paper, the technology space of Korean firms was built and the footprints of technological diversification by those firms were followed, focusing on the transition toward industry 4.0 patent data. Using those data with data on firms' financial information and Korean government policy allowed an examination of the various factors that affect the technological diversification of firms.

II. LITERATURE REVIEW: TECHNOLOGICAL DIVERSIFICATION OF FIRMS

Diversification is one of the characteristics of modern enterprises [16], [17], [18]. Scholars have found various factors that affect the patterns and probability of success in diversification. For example, the firm's size [25] or age [38] can affect technological diversification. Furthermore, the quantitative aspect of R&D investment, such as the total amount [30], and the qualitative aspects of R&D investment, such as the persistence of the investment, also affect a firm's technological expansion. Factors associated with human capital, such as the CEO's expertise in technology and the collaborative environment among R&D labors, also affect technological diversification. In addition, firms' technological strategies (for example, either exploitation or exploration) can affect the pattern of diversification. Given those factors, firms expand their technological boundaries resulting from the interactions among them rather than a stochastic matter of a single factor [34], [79].

Teece [75] and Teece [76] explained firms' technological diversification by building a theory of multi-product firms (i.e., firms with a diversified portfolio of related products). He argued that when a firm develops a product requiring proprietary know-how and specialized physical assets, it tends to choose an efficient way to organize its economic activities, resulting in diversification. Given the fungible and tacit characteristics of organizational knowledge, profit-seeking

firms diversify in a way that avoids the high transaction costs associated with trading services and specialized assets in various markets. The direction of diversification, however, is not random but shows a path-dependent pattern. Analyzing US data from 1987, Teece et al. [79] showed that the most common way for a firm to diversify is by adding related activities.

Focusing on technological diversification in firms, Jaffe [39] introduced a measure of a firm's technological distance by examining its patents. To characterize the technological position, Jaffe [39] used the distribution of firms' patents by patent class and defined a cosine similarity index that represents the change in distribution over time. He found evidence that firms' patents, together with their profits and market value, are systematically related to the technological position of their research programs, and that movement in the technology space follows the pattern of contemporaneous profits according to different technological positions. Breschi et al. [15] also studied technological diversification in a firm by introducing technological relatedness, focusing on the development of its core technology. They calculated the cosine similarity index by examining the co-occurrence of International Patent Classification (IPC) codes in every patent and found that knowledge relatedness, measured using the cosine similarity index, is a critical factor in firms' technological diversification.

However, the methodology used in previous studies (e.g., using cosine similarity and defining relatedness centering on core activities) has room for improvement. First, the process of aggregating all technologies to obtain the technological relatedness of a whole industry and calculating firms' technological relatedness based on their core technology, does not reflect firms' heterogeneous characteristics. Similarly, applying industry-level technological relatedness to measure within-firm technological relatedness is rather vague because the level cannot consider the firm's accumulated technological infrastructure or path-dependent characteristics. Moreover, defining a firm's core technology as the highest proportion of the IPC could be an artificial interpretation of the analysis. Because the result combines several core technologies, it is hard to differentiate the unique core technology. Hence, it is necessary to develop a measure of relatedness involving a firm's idiosyncratically accumulated technological infrastructure.

To better capture firms' technological trajectories based on what technologies they already own, the methodology from the Principle of Relatedness was used. This empirical principle indicates that firms, cities, regions, and countries are more likely to enter new activities, such as new technologies, new products, and new industries, when they already have related activities in them [34], [35]. For example, by analyzing world trade data, Hidalgo et al. [37] calculated the density of every country's product and found that countries are more likely to diversify export products toward products with higher density. Similarly, Jun et al. [42] expanded the density measure into three relatedness measures and found that countries

are more likely to diversify their export products even in bilateral trade. This density measure is also used to explore the industrial diversification pattern of a region [59]. Using Swedish data on product portfolios in manufacturing plants, they showed that the density of related industries in a region affects the probability of success for entering a new industry.

The Principle of Relatedness holds in regions entering a new technology [48]. Using U.S. patent data, [48] found that cities are more likely to enter a new technology when the city has a higher density of the new technology. They also found that cities with a higher technology density tend to exhibit faster technological development showing their distinctive technological trajectories. The findings of Kogler et al. [48] and Rigby [69] showed that technological relatedness determines the path of knowledge accumulation at the city level. Although Kogler et al. [48] and Rigby [69] analyzed patent data, their unit of interest was not firms but geographic regions.

Kim et al. [47] examined the role of technological relatedness in firms' technological diversification at the firm level using Korean data. In the research stream of principal relatedness, Kim et al. [47] found that a firm is more likely to diversify into new technology when it already has related technologies. However, this research covered the entire range of technology owned by a manufacturing firm, instead of focusing on a certain type of technology such as I4 technologies. Moreover, Kim et al. [47] did not examine the role of government support in a firm's technological diversification. This research explores the effect of technological relatedness and government support on a firm's pattern of technological diversification at a firm level with focusing on I4 technologies.

Along with the relatedness measure, another measure (complexity) was used to capture the structural characteristics of technology, as well as the structural characteristics of a firm's technological capability. The complexity measure represents the competencies of the economic agents or the sophistication of their economic activity, conserving each characteristic of the activity or agent and by considering their interactions as well [36]. In their seminal work, Hidalgo and Hausmann [36] suggested two types of complexity: that of economic agents (countries, regions, or firms) and that of activity (production of goods, provision of services, knowledge creation, or patenting) by looking at the countries' export products. The complexity of a country represents that country's degree of diversification in export products, reflecting information about the complexity of each product. The more a country engages in diverse and complex activities, the more capable the country is. Similarly, the complexity in export products represents the sophistication of exporting products while preserving the complexity information of each country. The more an activity is engaged in by a large number of capable countries, the more sophisticated the activity is. Until now, work in complexity has proven its effects on various outcomes, including the future economic growth of countries [32], [36] for various types of economic activities,

such as services [74], employment [27], [77] technology [8], [9], [66] , and products [22], [32], [36]. This study explores the factors that affect the technological diversification of firms focusing on the effect of the technological relatedness, together with the effect from the complexity of technology.

In addition, the role of government policy in support of diversification is explored. Government support for the R&D agenda is justified based on the following argument: private sector R&D investments are suboptimal compared to the desired societal level. Since the output of firms' R&D activities shows the characteristics of public goods, the firms are likely to under-produce technological knowledge because of the appropriability issue [73]. Furthermore, considering the uncertainty and indivisibilities of R&D activities, firms are reluctant to engage in R&D that requires high costs and substantial resources [3]. From this aspect, the role of government in achieving the optimal social level of R&D for technological knowledge has been emphasized [73], and institutions such as patent or government subsidies that help achieve the optimal level of knowledge creation are often regarded as the prime engines of technological progress [20], [70] that further the economic development of countries [1], [61].

The role of government becomes more critical during the early stages of technological revolutions because the uncertainty of R&D activities tends to be higher than at other stages [64], and the demand for new products from new technologies often lags behind the speed of technological change [23]. Various technologies that initiated the new technological regimes have been seeded with government support. For example, technology related to packet switching funded by the Defense Advanced Research Project Agency (DARPA) resulted in Transmission Control Protocol/Internet Protocol (TCP/IP), which is the cornerstone of information and communication technologies (ICT). Mazzucato [57] introduced various examples of innovation and invention that were spearheaded by the state's visible hand.

Upon the emergence of a new technological paradigm during the Fourth Industrial Revolution, the marginal effect of government support again becomes bigger with high uncertainty in R&D. This is the reason for a positive and significant effect of government support (especially its direct support) on firms' I4 technologies development.

III. DATA
A. INDUSTRY 4.0 TECHNOLOGIES
There exist various definitions of I4 technologies, and there is no formal classification of them [7], [8]. For example, the World Bank (2020) defined digital industry 4.0 technologies as technologies that belong to the following three categories based on the underlying efficiency improvement caused by the technology group: (1) informational technologies, which leverage big data and analytics (e.g., cloud computing, big data analytics, and machine learning); (2) operational technologies, which replace labor by combining data with automation (e.g., Internet of Things (IoT), 3D printing, and smart drones); and (3) transactional technologies,

which match supply and demand such as in digital platforms and distributed ledger technologies.

Ciffolilli and Muscio [19] classified I4 technology into eight categories based on expert peer reviews, and they focused on the input of the R&D process for this classification. The categories include (1) advanced manufacturing solutions, (2) additive manufacturing, (3) augmented reality, (4) simulation between interconnected machines that optimize processes, (5) horizontal and vertical integration technologies that integrate information within the value chain, (6) the industrial internet and cloud that help multidirectional communication between production processes and products, (7) cyber-security that secures network operations; and (8) big data and analytics that optimize products and processes.

Balland and Boschma [7] focused on the output of R&D activities using patent data, and they categorized I4 technology into 10 categories. Based on the Cooperative Patent Classification (CPC) code of the OECD-REGPAT database, their categories are (1) additive manufacturing; (2) artificial intelligence; (3) augmented reality; (4) autonomous robots; (5) autonomous vehicles; (6) cloud computing; (7) cyber-security; (8) quantum computers; (9) machine tools; and (10) system integration. CPC provides one of the most precise technological classifications broken down into around 250,000 categories. To identify the patents of I4 technologies, they checked the CPC code of patents and reconstructed categories indirectly by combining sub-categories. Furthermore, they developed their own heuristics for some categories that are difficult to identify, and they analyzed the abstracts of patent data in case these categories did not allow them to identify the I4 technology. Considering that this research is interested in the output of firms' R&D activities, the definition and classification of Balland and Boschma [17] were followed.

B. FINANCIAL INFORMATION OF A FIRM
This study focuses on Korean firms in the manufacturing sector where the share of GDP was above 25% of Korea's total GDP. From among them, the research boundaries were narrowed down to the firms listed in three stock markets; (i) the Korea Composite Stock Price Index (KOSPI), a major stock market that targets large companies, (ii) Korea Securities Dealers Automated Quotations (KOSDAQ), which targets promising small and medium-sized enterprises (SMEs) or venture companies, and (iii) the Korea New Exchange (KONEX), a stock market for SMEs with lower listing thresholds. Considering that only derivatives were excluded from all Korean capital markets, most of the firms listed in Korea are covered.

For firms' financial information, KisValue was used as the main dataset. This dataset from National Information & Credit Evaluation Inc. (NICE) provides a variety of information for external audit firms. The data include firms' general information (e.g., founding year, number of workers, listing or delisting dates) and financial information (e.g., income

statements, statements of cash flow, valuations). Key financial measures such as debt and profit ratios can be calculated based on the KisValue dataset.

C. TECHNOLOGY (PATENT) INFORMATION

The European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTATS) was used to obtain a technology dataset. PATSTATS was created by the EPO at the request of the OECD, and it is updated twice a year [43]. This study used the Spring 2021 edition to cover the years from 1984 to 2021. PATSTATS covers more than 90% of the world's patent authorities, including the Korean Intellectual Property Office (KIPO), the United States Patent and Trademark Office (USPTO), and the European Patent Office (EPO). The data contain comprehensive information on each patent, including applicants, inventors, publications, citations, filing country, filing date, registration status, and CPC codes. In this paper, the CPC code is used as a proxy for technology.

Using both patent and financial data, patents from PATSTATS were first matched based on applicant information. However, applicant information is not a unique identifier. Even for the same applicant, there could be variations in the written name due to spelling errors, abbreviations, use of a non-unified company name, and changes in company names. For this reason, matching a patent with its company owner is not always accurate. Accordingly, Hall et al. [31], Thoma et al. [77], Julius and De Rassenfosse [41], and He et al. [33] tried to standardize the names of applicants, with Kim et al. [45], Lee et al. [51], and Kang et al. [44] focusing on Korean firms. This study used the OECD Harmonised Applicant Names (HAN) database, which is based on text-matching algorithms such as the one presented by Kang et al. [44]. The HAN database provides a unique firm identifier called the HAN-ID that harmonizes the names of applicants in different countries. However, there are still mismatches and errors in the OECD HAN, and no changes in company name are considered [44]. This study, therefore, unified both mismatches in the HAN ID and errors in applicants' names to obtain the name of a representative applicant. Next, this representative applicant's name was matched with KisValue data that provide financial information. The result was a unique unbalanced panel dataset of listed Korean manufacturing companies. A total of 1,196 KisValue firms were matched with various applicant names within PATSTATS, and therewith, 388,454 patent applications from 2005 to 2018.

D. GOVERNMENT DIRECT SUPPORT

Data on whether firms involved in I4 technology knowledge activities received direct government support were used as well. In general, a government supports a firm's R&D activities in two ways. One is through direct support, including grants or matching grants to targeted firms. The other is by providing indirect support through R&D tax incentives and other means, which tend to generate incremental innovation. The data from the Korean Ministry of Science and ICT (MSIT) allows an investigation into the role of the government in firms' knowledge activity in new industry 4.0 technologies. This study only considered whether or not direct government support was allocated to firms without considering other information, such as the amount of support or the characteristics of government-funded projects. Outcomes were checked for each government-funded project at the National Science Technology Information Service (NTIS), which is managed by MSIT. Among various proxies that show the outcome of a project (success or failure of the project, journal publications, patents filed, etc.), information on applied or granted patents was chosen as the outcome of government-supported projects. Gathered were 696,293 patents applied for or granted from 99,482 government-funded projects between 2007 and 2018. Among them, 568,447 patents were selected. When there are multiple contributors to the outcome of a government project, each contributor claims and reports their share of the contribution. An organization was regarded as owning the patent when the report on the government-funded project claimed that the contribution of the organization was above 50%.

Next checked was the year a patent was granted, and that was regarded as the outcome of government support affecting technological development by the firm from the starting year of the project. In this way, a total of 34,947 cases were found where firms developed new technologies based on the CPC code from 2007 to 2018.

IV. METHOD
A. MEASURING TECHNOLOGICAL RELATEDNESS

A measure of relatedness is introduced to estimate the proportion of related technologies already existing in a firm [12], [28], [37], [42], [47], [48]. First, the CPC codes of each patent and firm are connected by building a CPC code–firm bipartite network in which the weight of the link is the number of CPC codes possessed by the firm. Every patent requires one or more CPC codes to classify its technology. All the CPC codes in one patent were examined, instead of using the representative CPC code. For example, if firm i applies for obtains a patent at time t, where the CPC codes are A, B, and C according to the KIPO, it was regarded as meaning the company developed all three technologies at time t. In a family of patents, although patents are identical, a new CPC code (e.g., technology D) could be added following the request of an examiner when filing the patent at another patent office (e.g., USPTO). After considering a patent granted by (for example) the KIPO or USPTO as one family patent, all non-overlapping technology areas (CPC codes A–D) are synthesized and regarded as the technology of the corresponding patent.

Next examined were co-occurrence of CPC codes within patents of the same firm, and then, the proximity between technologies α and β ($\varphi_{\alpha,\beta}$) was estimated by following the method of Hidalgo et al. [37]. Proximity $\varphi_{\alpha,\beta,t}$ indicates the minimum value of the pairwise conditional probability that two technologies have a comparative advantage together

within the same firm:

$$\varphi_{\alpha,\beta} = min\{Pr\left(RTA_{\alpha} \mid RTA_{\beta}\right), Pr(RTA_{\beta} \mid RTA_{\alpha})\} \quad (1)$$

where RTA stands for "revealed technological advantage":

$$RTA_{i,\alpha,t} = \frac{P_{i,\alpha,t}}{\sum_{\alpha} P_{i,\alpha,t}} \Bigg/ \frac{\sum_{i} P_{i,\alpha,t}}{\sum_{i}\sum_{\alpha} P_{i,\alpha,t}} \quad (2)$$

in which $P_{i,\alpha,t}$ is the number of patents related to technology α possessed by firm i at time t [6].

RTA indicates the comparative advantage of firm i in technology α by measuring whether it owns more than the average firm of technology α as a share of its total technologies. We say firm i develops a comparative advantage in technology α at time t when its $RTA_{i,\alpha,t}$ transitions from $RTA_{i,\alpha,t} < 1$ to $RTA_{i,\alpha,t} \geq 1$. Considering that previously developed technologies require some time (often more than three years) to affect the next generation of new related technologies, also examined were the three years before the development of a new technology. When defining a firm's development of technology α at time t, that technology's RTA value is below 1 at time $t - 1$, over 1 at time t, and it holds its value above 1 at $t + 1$ and $t + 2$, considering the forward condition [5].

Lastly, the proximity among technologies was used to aggregate the related technologies of a firm — termed the *density* of the related technology of firm i ($\omega_{i,\alpha,t}$) — which measures how a firm's existing technology portfolio is related to technology α from among all its technologies. Formally, the density of the related technology for technology α of firm i at time t is given by

$$\omega_{i,\alpha,t} = \frac{\sum_{\beta} \varphi_{\alpha,\beta,t} U_{i,\beta,t}}{\sum_{\beta} \varphi_{\alpha,\beta,t}} \quad (3)$$

where $\varphi_{\alpha,\beta,t}$ is the proximity between technologies α and β, and $U_{i,\beta,t}$ is 1 if firm i has an RTA in technology β in year t ($RTA_{i,\alpha,t} \geq 1$), but is 0 otherwise.

B. MEASURING TECHNOLOGY COMPLEXITY

Along with the relatedness measure, *complexity* was used to capture the structural characteristics of a technology as well as that of a firm's technological capability. The concept of complexity was introduced by Hidalgo and Hausmann [36]. In their seminal work, they focused on the economic complexity of products and countries by looking at world trade data. Based on their observation that some countries export various kinds of products, and others export only a few kinds of products, they asked, "What are the distinguishing characteristics of these two different kinds of countries and their exported products" [36]. To answer this, they introduced a methodology called *Method of Reflection (MOR)*. From a bipartite network, this methodology can reduce the information of one dimension (for example, producing a sophisticated product) while preserving the rest of the information of the opposite dimension (for example, products that are produced by a country whose economy is sophisticated). As a result,

the MOR independently provides two types of symmetric information: (1) about actors (in the country, region, city, and firm, among others), and (2) about activities (industry, product, technology, and occupation, among others) which constitute a bipartite network.

First, the *Location Complexity Index (LCI)* represents the complex level of a location by measuring how much comparative advantage the location has in various economic activities, reflecting information on the complexity of economic activities. According to the work of Hidalgo and Hausmann [36], countries with diversified export product portfolios are highly correlated, reflecting a high *LCI* level. That is because countries that are more likely to export various products can produce more complicated products that cannot easily be manufactured by many countries. In countries with few kinds of export products, their *LCI* is low because they produce few products that are ubiquitous and that can be manufactured by many other countries. Second, the *Economic Complexity Index (ECI)* implies how frequently a certain activity is participated in at various locations while preserving the location's diversification information. We can intuitively understand that economic activities are more sophisticated when only a small number of countries can develop and possess them. Contrarily, if every country can participate in, and practice, a certain economic activity, that economic activity would have a low level of difficulty; in other words, it has little complexity.

By using *MOR*, we can reduce two different (but connected) pieces of information (location or economic activity) from the bipartite network to information of only one dimension by recursively calculating the average of diversification and ubiquity. The following equations are the general forms of *LCI* and *ECI*. Because we are interested in technology as an economic activity, and in firms for their locations, the technology expression was unified with subscript t and the expression for firms takes subscript f:

$$complexity\ of\ firm : K_{f,N} = \frac{1}{K_{f,0}} \sum_{t} M_{f,t} K_{t,N-1} \quad (4)$$

$$complexity\ of\ technology : K_{t,N} = TCI_{t,N}$$
$$= \frac{1}{K_{t,0}} \sum_{f} M_{f,t} K_{f,N-1} \quad (5)$$

where $M_{f,t}$ is a matrix composed of firms and technologies with an RCA above 1, which is calculated from equation (2). By using *MOR*, we can calculate the *Complexity of a firm* and the *Complexity of a technology* by averaging out previous characteristics levels in neighboring nodes that are iteratively positioned in the opposite dimension. When we set two different nodes as a starting point and a destination in the technology dimension, there exist numerous routes stopped by nodes of an opposite dimension (a space composed of firms).

The value of *Complexity* can have different meanings based on the iteration number, $N (\geq 0)$. N indicates how many times

it iterates through nodes of different dimensions to reach a destination. The initial condition of complexity, starting with $N = 0$, simply means the *degree* of a node in a network, and the number of links connecting it with other nodes within the opposite dimension.

$$Diversification\ of\ firm : K_{f,0} = \sum_t M_{f,t} \qquad (6)$$

$$Ubiquity\ of\ firm : K_{t,0} = \sum_f M_{f,t} \qquad (7)$$

$K_{f,0}$ and $K_{t,0}$, respectively, denote the technological diversification of a firm (the number of technologies developed by the firm) and the ubiquity of a technology (the number of firms that develop a certain technology). As N increases, we can average them out so that the values for *Complexity of a firm* and for *Complexity of a technology* converge. Because it iterates in increments of N until we cannot get additional information, interactions were stopped at the 20th run following the rule of thumb of this methodology.

V. RESULTS

Before moving to the empirical analysis that examines the factors that affect Korean firms' knowledge activities in I4 technologies, we visualize the technology space in detail.

A. UNDERSTANDING I4 TECHNOLOGY DIVERSIFICATION IN KOREAN FIRMS

Figure 1 (A) depicts the position of 10 different I4 technologies of Korean manufacturing firms in the technology space. The 10 I4 technologies are highlighted in green, and related technologies are in gray. The visualization of the technology space of Korea's manufacturing firms, in general, can be found in the Appendix. As seen in the figure, all 10 I4 technologies are located at the core or in a coherent cluster at the upper-left corner of the technology space. The size of the node is proportional to the number of patents, and among the 10 I4 technologies, quantum computers, cloud computing, and cybersecurity seem to be the major patents for Korean manufacturing firms. (See the Appendix for the technology space covering all CPC codes.)

Figures 1 (B) and (C) explore the relationships among I4 technologies. Proximity between technologies is represented by the thickness of the edge in Figure 1 (B), and by colors of the heat map in Figure 1 (C). We can see there is a high level of proximity between cloud computing and cybersecurity. The second-highest level can be found among augmented reality, system integration, and autonomous robots. This indicates that technologies in cloud computing and cybersecurity are likely to share common technological capabilities of Korean firms, resulting in patenting in tandem. Likewise, high proximity among technologies in augmented reality, system integration, and autonomous robots implies they require similar technological capabilities. In addition, the machine tools have a high level of average proximity with all other technologies, meaning that machine tool technologies are widely used with other I4 technologies.
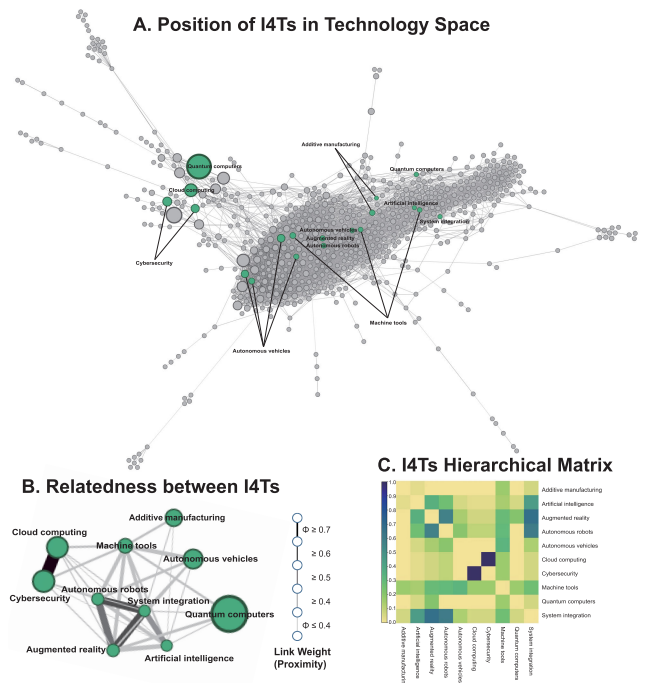

FIGURE 1. (A) Highlighting 10 different kinds of I4 technologies in the technology space of the manufacturing industries of Korea from 2010 to 2019. Green denotes CPC codes related to I4 technologies, and each radius is proportional to the number of patents belonging to each CPC code. (B) A more detailed technology space composed of only 10 I4 technologies. The thickness of the links indicates the proximity between pairs of technologies (an alternate expression of the hierarchical matrix). (C) This hierarchical matrix shows the proximity of technology relatedness. The color intensity indicates the level of relatedness between pairs of technologies.
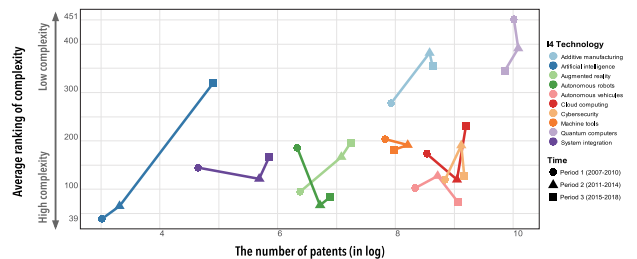

FIGURE 2. Ranking complexity and numbers of patents for I4 technologies. The x-axis is the total number of patents (in log form) and the y-axis is average rankings for complexity of CPCs within each I4 technology. A large value on the y-axis means the complexity of the I4 technology was rather low (i.e., it was ubiquitous). The different types of I4 technologies are divided into 10 colors and the shapes of nodes represent changes in their coordinate values in the three periods.

Next, to study the sophistication of an I4 technology, patents for the 12 years from 2007 to 2018 were aggregated and explored to rank technology complexity using equation (5). Figure 2 shows the complexity ranking of I4 technologies and how they evolved over the 12 years. Patents of every CPC within each I4 technology were aggregated and positioned on the x-axis after log transformation. If multiple CPCs were assigned within one I4 technology, the complexity ranking of every CPC within each I4 technology was ranked and plotted on the y-axis. How complexity ranking and the

TABLE 1. Top three companies in terms of numbers of patents in i4 technologies.

Artificial intelligence	Additive manufacturing	Autonomous robots	Cybersecurity	Cloud computing
1. LG Electronics Inc.	1. LG Chem. Ltd.	1. LG Electronics Inc.	1. LG Electronics Inc.	1. LG Electronics Inc.
2. SK Hynix	2. POSCO	2. Samsung Heavy Industries	2. Pantech	2. SK Hynix
3. Hyundai Motor Company	3. LG Electronics Inc.	3. Hyundai Mobis, 3. Daewoo Heavy Industries Ltd., 3. Korea Shipbuilding & Offshore Engineering, 3. Sewon Corp	3. SK Hynix	3. LG Display
Machine tools	**Augmented reality**	**Autonomous vehicles**	**Quantum computers**	**System integration**
1. Hyundai Motor Company	1. LG Electronics Inc.	1. Hyundai Motor Company	1. SK Hynix	1. LG Electronics Inc.
2. Doosan Infracore	2. Hanwha Aerospace	2. Mando Corporation	2. LG Display	2. LS ELECTRIC Co., Ltd
3. LG Electronics Inc.	3. Hyundai Motor Company	3. Hyundai Mobis	3. Samsung SDI	3. Hyundai Motor Company

number of the patents evolved over the period was checked based on three phases: period 1 (2007-2010), period 2 (2011-2014), and period 3 (2015-2018). The financial crisis happened in period 1. Period 2 was the recovery from the crisis. In period 3, a seminal paper in AI was introduced (LeCun et al., 2015) and the phenomena associated with the Fourth Industrial Revolution started to be vividly observed.

A large value on the y-axis means the technology was ubiquitous, with many other firms already having developed it. For example, from period 1 to period 3, artificial intelligence became more ubiquitous, although the total number of patents was still low. Total applied patents for nine I4 technologies increased from period 1 to period 3, except for quantum computers, where total numbers of patents remained invariant. In the first period (2007-2010), the I4 technology most commonly possessed by Korean manufacturing firms was quantum computers, and least common was artificial intelligence. A small number of patents in artificial intelligence were owned by a relatively small number of firms, while relatively more patents in quantum computing were developed by a larger number of firms. The least ubiquitous technology in period 3 was autonomous vehicles because this field was nascent at the time, with only a few firms successfully developing technologies related to autonomous vehicles.

Table 1 shows the names of the top three companies for each of the I4 technologies based on the number of patents. Well-known Korean conglomerates such as LG Electronics, SK Hynix, and Hyundai Motor Company were found to be key players in the I4 technologies space. Interestingly, Samsung Electronics, one of the companies with the most patents in Korea, did not have a lot of patents in I4 technologies compared to other big firms.

Also checked were the ages of firms that owned I4 technologies. From 2008 to 2014, there were 851 firms with at least one patent in I4 technologies from among all 1,113

firms. When only looking at 2014, 645 firms had at least one patent in I4 technologies from among all 908 firms. Looking at 2008, the average age of I4 technology firms was 20.7 years, while that of all firms was 21.82. For 2014, the average age of I4 technology firms was 25.45 years, while that of all firms that owned any kind of patent was 26.68 years. This indicates that firms that developed I4 technologies were slightly younger than the rest. The p-value from a t-test that asked whether the average age of firms with I4 technologies was less than that of all firms was 0.017 at the 95% confidence interval, which implies that firms that developed I4 technologies were significantly younger than the rest.

The size of firms was measured by the number of employees. From 2008 to 2014, the average number of employees in firms that owned I4 technologies was 740, whereas that of all firms was 630 employees. When we only look at 2008, the average number of employees of firms with I4 technologies was 966, whereas that of all firms in the sample was 714.5. In 2014, the average number of employees in I4 technology firms was 1,114, while that of all firms in the sample was 899. The p-value of the t-test that asked if the average size of firms with I4 technologies was greater than that of all firms was 0.1645 at the 95% confidence interval. This tells us we cannot say that firms with I4 technologies were significantly larger.

B. THE EMPIRICAL MODEL
To examine the factors that affect the development of new I4 technologies in a firm, the following multivariate probit model was constructed:

$$U_{i,\alpha,t+2} = \beta_0 + \beta_1 \omega_{i,\alpha,t} + \beta_2 TCI_{\alpha,t} + \beta_3 Gov_{i,\alpha,t}$$
$$+ \beta_4 \textbf{\textit{Firm}}_{i,t} + \beta_5 \textbf{\textit{Technology}}_{\alpha,t} + \theta_t + \mu_i + \varepsilon_{i,\alpha,t}$$
$$(8)$$

$U_{i,\alpha,t+2}$ is 1 when firm i successfully enters new technology α at time $t+2$; otherwise, it is 0. The main explanatory variable, $\omega_{i,\alpha,t}$, and $TCI_{\alpha,t}$ represent the density of related technologies and the technological complexity at time t, respectively. $Gov_{i,\alpha,t}$ indicates whether firm i received government R&D support for developing technology α.

The second line of equation (8) consists of control variables: $\textbf{\textit{Firm}}_{i,t}$ includes (i) $Age_{i,t}$ (the tenure of firm i since its inception), $num\_employee_{i,t}$, which controls for the size effect of the firm, and $Profit\_ratio_{i,t}$ and $Debt\_ratio_{i,t}$, which are profit-to-sales and total liabilities to total assets in year t, respectively. $Profit\_ratio_{i,t}$ and $Debt\_ratio_{i,t}$ control for the quantitative aspects of the firm (representing a capital structure that can capture its value and expected growth). Lastly, $numberof RTA_{i,t}$ represents all technologies that offer an advantage within firm i. This value reflects the quantitative aspect of a technological capability, rather than the qualitative aspect. The other vector, $\textbf{\textit{Technology}}_{\alpha,t}$, includes the number of competitors ($num\_competitor_{\alpha,t}$) in order to examine the firm's technological environment. This variable is the number

TABLE 2. Summary statistics after all variables undergo Box-Cox transformation by year and are pooled.

Statistic	N	Mean	St.Dev.	Min	Max
$U_{i,\alpha,t+2}$	5,410,717	0.002	0.050	0	1.000
$\omega_{i,\alpha,t}$	5,410,717	0.006	1.869	-6.758	5.909
$TCI_{\alpha,t}$	5,410,717	3.987	0.527	2.01	4.615
$Gov_{i,\alpha,t}$	5,410,717	0.004	0.062	0	1.000
$Age_{i,t}$	5,410,717	-0.0005	1.280	-4.668	4.136
$num\_employee_{i,t}$	5,410,717	0.000	0.626	-4.142	2.754
$num\_competitor_{\alpha,t}$	5,410,717	0.009	2.208	-5.019	5.376
$num\_RTA_{i,t}$	5,410,717	0.000	0.804	-1.553	2.176
$Profit\_ratio_{i,t}$	5,410,717	0.196	3.044	-47.861	43.226
$Debt\_ratio_{i,t}$	5,410,717	-0.000	0.005	-0.013	0.038

TABLE 3. Correlation table.

	$U_{i,\alpha,t+2}$	$\omega_{i,\alpha,t}$	$TCI_{\alpha,t}$	$Gov_{i,\alpha,t}$	$Age_{i,t}$	$num\_employee_{i,t}$	$num\_competitor_{\alpha,t}$	$num\_RTA_{i,t}$	$Profit\_ratio_{i,t}$	$Debt\_ratio_{i,t}$
$U_{i,\alpha,t+2}$	1									
$\omega_{i,\alpha,t}$	0.061	1								
$TCI_{\alpha,t}$	0.005	0.001	1							
$Gov_{i,\alpha,t}$	0.022	0.090	-0.011	1						
$Age_{i,t}$	0.021	0.191	-0.00004	0.028	1					
$num\_employee_{i,t}$	0.032	0.232	-0.009	0.017	0.000	1				
$num\_competitor_{\alpha,t}$	0.051	0.870	0.00001	0.081	0.206	0.000	1			
$num\_RTA_{i,t}$	0.035	0.343	0.0004	0.055	0.462	0.000	0.352	1		
$Profit\_ratio_{i,t}$	-0.002	-0.022	0.0711	-0.001	-0.075	-0.0001	-0.005	-0.050	1	
$Debt\_ratio_{i,t}$	0.004	0.031	-0.0004	0.003	-0.044	0.000	0.024	0.003	-0.130	1

of firms that have a comparative advantage in technology α in the industry to which the firm belongs. These variable captures two aspects: how many learning opportunities exist in the industry, and how many competitors for that technology exist in the industry. Also checked were other factors of the firms. Finally, year-fixed effects (θ_t) and industry-fixed effects (μ_i) were added to control for nationwide time trends and time-invariant characteristics of industries, respectively. $\varepsilon_{i,\alpha,t}$ is the error term.

C. TECHNOLOGICAL RELATEDNESS, COMPLEXITY, AND DIVERSIFICATION

We now explore the factors affecting a firm's technological diversification. To estimate the effect of technological relatedness and complexity described in equation (8), Box-Cox transformation was applied to all variables (except for the binary variables) and to $TCI_{\alpha,t}$ based on the year. $TCI_{\alpha,t}$ was rescaled to 0-1 and log transformed. Table 2 shows summary statistics of the variables.

Table 3 is the correlation table for all the variables. We can see that $\omega_{i,\alpha,t}$ is heterogeneous among firms and is highly correlated with the number of other kinds of a firm's technologies. Interestingly, $\omega_{i,\alpha,t}$ was not highly correlated with a firm's basic characteristics, such as age ($Age_{i,t}$), size ($num\_employee_{i,t}$), or financial structure ($Profit\_ratio_{i,t}$ and $Debt\_ratio_{i,t}$), but was highly correlated with the number of technologies that revealed a technological advantage ($num\_RTA_{i,t}$). To avoid the multicollinearity problem among independent variables, the variance inflation factor (VIF) was measured, and the value was not very high (1.219). Also tested was the VIF for $Age_{i,t}$ and $num\_employee_{i,t}$, and the result was 1.055, which implies that all the variables can be simultaneously considered in the regression model.

Table 4 shows the results for the entire sample covering all technologies. In columns (1) and (2), only the main variables of interest are considered. The results show that $\omega_{i,\alpha,t}$,

TABLE 4. Results covering all technologies and firms' technological diversification from 2005 to 2016.

	Dependent variable: $U_{i,\alpha,t+2}$				
	(1)	(2)	(3)	(4)	(5)
$\omega_{i,\alpha,t}$	0.001518***	0.001479***		0.001159***	0.001035***
	(0.000010)	(0.000010)		(0.000026)	(0.000028)
$TCI_{\alpha,t}$		0.000559***		0.000526***	-0.000093
		(0.000036)		(0.000041)	(0.000188)
$Gov_{i,\alpha,t}$		0.013267***		0.012644***	0.011948***
		(0.000313)		(0.000343)	(0.000344)
$Age_{i,t}$			0.000160***	0.000172***	0.000208***
			(0.000018)	(0.000019)	(0.000023)
$num\_employee_{i,t}$			0.001414***	0.001222***	0.001028***
			(0.000040)	(0.000040)	(0.000046)
$num\_competitor_{\alpha,t}$			0.000729***	0.000497***	0.000520***
			(0.000009)	(0.000011)	(0.000011)
$num\_RTA_{i,t}$			0.002734***	0.000360***	0.000490***
			(0.000028)	(0.000060)	(0.000063)
$Profit\_ratio_{i,t}$			-0.000000	0.000003	0.000003
			(0.000007)	(0.000007)	(0.000007)
$Debt\_ratio_{i,t}$			0.02615***	0.022604***	0.011956**
			(0.00939)	(0.003929)	(0.004176)
Industry fixed effect	No	No	No	No	Yes
Time fixed effect	No	No	No	No	Yes
Costant	0.002321***	0.000052	0.002479***	0.000329***	
	(0.000019)	(0.000146)	(0.000021)	(0.000163)	
Observations	6,299,159	6,299,159	5,410,717	5,410,717	5,410,717
Adjusted R2	0.003	0.004	0.004	0.004	0.005
Residual Std. Error	0.048	0.048	0.050	0.049	0.049

*p < 0.1; **p < 0.05; ***p < 0.01

$TCI_{\alpha,t}$, and $Gov_{i,\alpha,t}$ had a positive and significant effect on a firm's technological diversification. This implies that firms are more likely to develop technologies that are related to the technologies they already have. This tendency gets stronger when a technology is more complex.

As shown in columns (4) and (5), the positive and significant effects hold even with control variables. Column (4) shows that an increase in technological relatedness, $\omega_{i,\alpha,t}$, by 1 unit results in a 0.11% increase in the odds of developing technology α, provided other variables remain fixed. Likewise, with an increase of 1 unit in technological complexity and government support, $Gov_{i,\alpha,t}$ enhances the odds of technological development by 0.05% and 1.272%, respectively.

Column (3) shows the results considering the effect of control variables only. The results show that older and larger firms are more likely to develop new technologies. This might be because older firms have already accumulated technological capabilities, and larger firms can utilize more R&D resources, such as personnel. The probability of knowledge spillover is high when a firm has various technology pools. Lastly, firms with a higher debt ratio are more likely to diversify their technologies. The profit ratio did not have a significant effect on technological diversification.

To investigate when technological complexity can have a significant effect on diversification, two samples were selected based on the level of technological relatedness ($\omega_{i,\alpha,t}$). One group consisted of firms with top 10% relatedness, and the other group was in the bottom 10%. Comparing column (4) with column (5), the significant and positive effect

TABLE 5. The effects of technological complexity on the technological diversification of firms based on different levels of technological relatedness.

	Dependent variable: $U_{i,\alpha,t+2}$					
	(1) High relatedness	(2) Low relatedness	(3) High relatedness	(4) Low relatedness	(5) High relatedness	(6) Low relatedness
$TCI_{\alpha,t}$	0.001243***	0.000061*	0.003377***	0.000037	0.004252***	-0.000318**
	(0.000266)	(0.000034)	(0.000319)	(0.000040)	(0.001294)	(0.000136)
$Gov_{i,\alpha,t}$	0.004064***	0.013657***	0.000004	0.010705***	-0.000609	0.010679***
	(0.0009411)	(0.000822)	(0.001039)	(0.000886)	(0.001042)	(0.000886)
$Age_{i,t}$			0.001398***	-0.000002	0.001874***	0.000002
			(0.000160)	(0.000016)	(0.000264)	(0.000021)
$num\_employee_{i,t}$			0.001416***	0.000190***	0.000100	0.000145***
			(0.000263)	(0.000041)	(0.000447)	(0.000046)
$num\_competitor_{\alpha,t}$			0.002430***	0.000107***	0.002528***	0.000107***
			(0.000071)	(0.000011)	(0.000071)	(0.000011)
$num\_RTA_{i,t}$			0.010300***	0.000050	0.009348***	0.000006
			(0.000694)	(0.000050)	(0.000971)	(0.000058)
$Profit\_ratio_{i,t}$			-0.000212***	0.000007	-0.000183***	0.000009
			(0.000057)	(0.000005)	(0.000063)	(0.000006)
$Debt\_ratio_{i,t}$			-0.087554***	-0.002306	-0.179470***	-0.001508
			(0.030818)	(0.003389)	(0.038829)	(0.003744)
Industry fixed effect	*No*	*No*	*No*	*No*	Yes	Yes
Time fixed effect	*No*	*No*	*No*	*No*	Yes	Yes
Costant	0.007021***	-0.000058	-0.018360***	0.000294		
	(0.001084)	(0.000138)	(0.001832)	(0.000188)		
Observations	629,916	629,915	541,072	541,072	541,072	5,471,072
Adjusted R2	0.000059	0.000440	0.002975	0.000520	0.005262	0.000749
Residual Std. Error	0.109506	0.013969	0.112709	0.014637	0.112579	0.014635

*p < 0.1; **p < 0.05; ***p < 0.01

of technological complexity, $TCI_{\alpha,t}$, disappears with fixed effects for industry and time.

Table 5 shows the effects of technological complexity ($TCI_{\alpha,t}$) on technological diversification based on different relatedness. Column (1) of table 5 indicates that technological complexity plays a greater role in developing new diversified technologies when firms already have a high level of technological relatedness. This implies that for firms to develop more complex and non-ubiquitous technologies, they need to accumulate related technologies first. Balland et al. [8] explained it as a *diversification dilemma*, meaning that a firm cannot develop a more difficult technology even though it is more attractive.

Interestingly, the effect of government support disappeared for firms that have already accumulated related technologies, but the effect was significant for firms with low technological relatedness. This result implies that government support is more crucial for firms that have not yet accumulated enough technological capabilities. The positive and significant effects of government support in columns (2), (4), and (6) imply that governments, which all have limited budgets, should focus their support on firms that have low levels of technological relatedness so they can jump into unrelated technology

spaces. Therewith, more complex technologies and firms need to exploit government R&D support to diversify their technologies towards unrelated, less ubiquitous, and more complex technologies.

D. FACTORS THAT AFFECT FIRMS' I4 TECHNOLOGY DIVERSIFICATION

To examine the factors that determine I4 technology diversification, 10 I4 technologies were selected and examined for the effects of relatedness and other variables. The effect of technological complexity ($TCI_{\alpha,t}$) was not seen here because the sample consisted of only I4 technologies where complexity was similar.

Table 6 shows the results. Column (1) describes the effects of relatedness and government support, while column (2) shows the results from all control variables. Industry- and time-fixed effects were controlled for in all columns. The results in tables 4 and 5 hold for I4 technologies as well. Firms are likely to enter a new I4 technology when they have a more related technology base, more government support, and more competitors with the same technologies. A firm's age did not matter for I4 technology diversification. However, the total number of technologies in the firm, $Num\_RTA_{i,t}$,

TABLE 6. The effect of relatedness and government support on firms' technological diversification toward I4 technologies.

	(1) All firms with I4T	(2) All firms with I4T	(3) Large technology stock (4th quantile)	(4) Medium-high technology stock (3rd quantile)	(5) Medium-low technology stock (2nd quantile)	(6) Small technology stock (1st quantile)	(7) High density	(8) Low density
				Dependent variable: $U_{i,\alpha,t+2}$				
$\omega_{i,\alpha,t}$	0.002103***	0.007726***	0.004188	0.009228***	0.005570**	0.001408		
	(0.000382)	(0.001608)	(0.003924)	(0.003184)	(0.002701)	(0.001225)		
$Gov_{i,\alpha,t}$	0.005079***	0.006425***	0.006622*	0.012449***	-0.000484	0.006034**	0.005579	0.005067**
	(0.001597)	(0.001765)	(0.003812)	(0.004225)	(0.003173)	(0.003021)	(0.004055)	(0.002117)
$Age_{i,t}$		-0.000015	-0.001853	0.002467	-0.000860	-0.000182	0.001016	0.000498
		(0.000630)	(0.002487)	(0.001759)	(0.001125)	(0.000888)	(0.002493)	(0.000640)
$num\_employee_{it}$		-0.001069	-0.001872	-0.010433*	0.001448	0.001395	-0.006180	0.000481
		(0.001772)	(0.006286)	(0.005391)	(0.003333)	(0.002459)	(0.006742)	(0.001777)
$num\_competitor_{\alpha,t}$		0.000856**	-0.000807	0.001724**	0.001202*	0.002176***	-0.000739	0.001499***
		(0.000366)	(0.000903)	(0.000833)	(0.000627)	(0.000509)	(0.000968)	(0.000381)
$num\_RTA_{i,t}$		-0.006490***					-0.005868	-0.001690
		(0.001772)					(0.005271)	(0.001065)
$Profit\_ratio_{it}$		-0.000066	-0.000817	-0.000149	0.000039	0.000229	-0.000818	0.000256
		(0.000245)	(0.000726)	(0.000607)	(0.000375)	(0.000337)	(0.000810)	(0.000239)
$Debt\_ratio_{it}$		-0.196468	-0.422719	-0.336622	0.212875	-0.128772	-0.870960*	-0.140125
		(0.121861)	(0.446120)	(0.292333)	(0.212587)	(0.168643)	(0.499131)	(0.120451)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,744	19,133	4,781	4,782	4,784	4,786	4,781	4,786
Adjusted R2	0.000743	0.002909	0.006557	0.016856	0.003055	0.001871	0.005628	0.005067
Residual Std. Error	0.077942	0.079807	0.100397	0.086889	0.064628	0.059443	0.110101	0.043218

*p < 0.1; **p < 0.05; ***p < 0.01

negatively affected diversification, implying that firms with a smaller stock of technologies were better diversified toward I4 technologies.

Intrigued by the results in column (2), columns (3) to (6) split the sample based on the level of technology stock, which is measured by the total number of competitive technologies in the firm, and we see the results focusing on the density of technologies and on government support. Regarding the effect of density, only firms with medium-high and medium-low technology stock exhibited a significant effect from density on I4 technology diversification. Since firms with a small amount of technology stock, by definition, lacked the related technology for diversification, the effect of related technology seems insignificant. In firms with a large amount of technology stock, because they already occupied a vast territory in the technology space, their marginal technology expansion might be difficult, so the density effect turned out to be insignificant.

Interestingly, the effect of government support was strongest for firms with a medium-high level of technology stock. Its impact seemed to be meaningful for firms with small and large amounts of technology stock. For firms with a smaller technology stock level, related technologies seemed to compensate for capabilities associated with the number of technologies, while the efficiency of government support seemed to be greatest for firms with a medium-high technology stock level.

To check the effectiveness of government support, the sample was split based on different density levels in I4 technologies for columns (7) and (8). The effects of I4 technologies density and government support were only significant for firms with low density. This result indicates that support from the government can help firms that do not have related technology yet still want to jump into I4 technologies.

VI. CONCLUSION

This research analyzed factors that affect Korean manufacturing firms' technological diversification toward I4 technologies by using data on patents, financial information, and government-funded projects. In terms of the absolute number of patents owned by Korean manufacturing firms, dominant I4 technologies were quantum computers, cloud computing, and cybersecurity. Relationships among I4 technologies were checked by constructing a technology space, which showed cloud computing and cybersecurity technologies had the closest relationship, implying those two technologies share common capabilities. Moreover, augmented reality, system integration, and autonomous robots showed high proximity to each other. Technology for autonomous vehicles did not turn out to be relatively ubiquitous, although relatively speaking a lot of patents were filed and obtained for such technology. This implies that only a few companies can develop technologies related to autonomous vehicles, and they occupied a monopolistic status in this technology space. Looking at the names of the firms that published patents in I4 technologies, mostly large, well-known firms developed those technologies in Korea.

Our empirical analysis found that firms with related technologies were more likely to enter new I4 technologies. This means that when a firm intends to enter a technology, having other related technologies can increase the probability of success in entering that technology. Results suggest that when firms aim for complex and non-ubiquitous technology, they need to accumulate related technologies to develop them.

In general, direct government support increased the probability of a firm successfully entering the technology space. Government support turned out to be more significant for firms that possessed low technological relatedness and for firms that possessed a medium-high or a small level of technology stock when entering I4 technologies. The results show that firms that receive government R&D support can diversify toward unrelated, less ubiquitous, and more complex technologies.

Interestingly, the role of government support diminished as firms accumulated more related technologies. This implies that firms that have already accumulated related technologies (i.e., technological capabilities for the new technologies) do not depend on government support to enter a new technology. It seems that the role of government support is more of an instigator or a nudge for firms that are relatively less competitive and with a low number of accumulated technologies. Government can maximize resources by supporting firms with low relatedness and small amounts of technology stock so they can jump into unrelated and more complex technologies. The role of government support in firms' diversifying toward I4 technologies can be to nudge those firms so they can be better equipped to climb the technology ladder by themselves, rather than to hand the ladder over.

The fact that big firms are more likely to enter such technologies indicates that entering I4 technologies is not an easy task for smaller firms with limited R&D resources. Therefore, policies should be designed and implemented considering the context of each country's existing firms and markets. At the same time, government support needs to be oriented towards supporting a firm's technology accumulation in general, rather than helping them leapfrog into I4 technologies. This is because the positive effect of government support disappears when a firm becomes large.

While technological relatedness and direct government support affected technological diversification, this research was limited to capturing other factors that affect technological diversification, such as R&D investment in certain types of technologies, foreign ownership, local infrastructure, data policies, etc. Because of data availability, only variables of interest could be considered, but omitted factors need to be considered in future research. In addition, for a similar reason, only the direct effect of government support could be examined, without considering indirect government support for firms' patents. However, even if there is selection bias in only looking at direct government support, bigger firms preferred indirect R&D support, and results are limited to showing the effect of government R&D support on diversification.
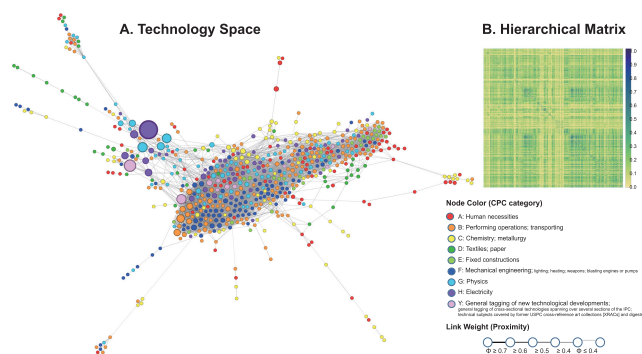

FIGURE 3. (A) The technology space of manufacturing industries in Korea from 2010 to 2019. The color of a node classifies it by one-digit CPC code, and its radius is proportional to the number of patents belonging to each CPC code. (B) Hierarchical matrix for the proximity of technology relatedness *Source:* Kim et al. [47].

Furthermore, the micro-mechanism of relatedness among different technologies was not shown, and the source of relatedness was not empirically examined. Recent literature on multi-product firms hints at the source of relatedness in technologies. According to Boehm et al. [10], input capabilities determine the evolution of multi-product firms' product spaces. By analyzing India's manufacturing data, they showed that input capabilities affected firms' core competencies, and in turn, core competencies determined product diversification in multi-product firms. This finding suggests that input capabilities, which can stem from human capital, institutions, and tacit knowledge already within firms for developing technologies, will decide the pattern of technological diversification. However, this micro-mechanism of technological relatedness is outside the scope of this paper.

Despite the limitations, this research will help policymakers who aim to diversify technology and gain competitiveness in industry 4.0 technologies. One caveat is that this paper is solely based on the Korean manufacturing sector. Big manufacturing firms are the main players that drive the technological transition toward I4 technologies in Korea. This should be understood in the context of Korea's history of economic and industrial development.

APPENDIX

Figure 3 is the technology space of Korea, based on patent data from 2010 to 2019. Each node represents a technological category expressed with a CPC code, while links represent the proximity between technologies. The radius of a node can be viewed as broadly indicative of the total number of patents in that CPC code. The technology space for Korea exhibits a core/periphery structure such that the subcategories of physics and mechanical engineering, lighting, heating, and weapons are likely located at the center, while those of human necessities, textiles, and paper are at the periphery. Simultaneously, we see a coherent cluster in the upper left-hand corner that consists of subcategories for electricity, physics, mechanical engineering, lighting, heating, and weapons. This cluster is from Samsung, which owns 31% of all Korean patents and specializes as an electronics and chip maker.

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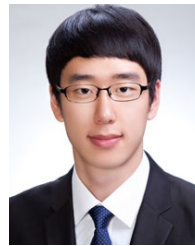
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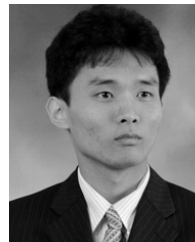
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