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Empirical analysis of strategy selection for the technology leading and technology catch-up in the IT industry

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Abstract
R&D strategies of companies with low and high technological levels are discussed based on the concept of technology convergence and divergence. However, empirically detecting enterprise technology convergence in the distribution of enterprise technology (total productivity increase) over time and identifying key change factors are challenging. This study used a novel statistical indicator that captures the internal technology distribution change with a single number to clearly measure the technology distribution peak as a change in critical bandwidth for enterprise technology convergence and presented it as evidence of each technology convergence or divergence. Furthermore, this study applied the quantitative technology convergence identification method. Technology convergence appeared from the separation of total corporate productivity distribution of 69 IT companies in Korea in 2019–2020 rather than in 2015–2016. Results indicated that when the total technological level was separated from the technology leading and technology catch-up, IT companies were found to be pursuing R&D strategies for technology catch-up.

KEYWORDS
bootstrapping, club convergence, club divergence, IT industry, kernel distribution estimation, multiple peaks, technology catch-up, technology leading

1 | INTRODUCTION

Can companies with a low technology level catch-up with companies with a high technological level in terms of growth? The key question in industry and macroeconomics shows interesting corporate growth paths related to the corporate growth theory and the convergence between corporations. In the past few decades, the focus of studies on economic unit convergence has been shifting from the absolute convergence of the global GDP per capita to relative convergence, convergence group classification, and intraclub convergence analysis. This motivates and directs the insights of technology convergence research.

When the macroscopic data set is limited to a group of similar countries like OECD countries, research is far more likely to report β-convergence (negative relationship between the initial GDPs of different countries). The per-capita level and follow-up growth rate are σ-convergence (reduced changes in the per-capita log GDP), and the absolute convergence across the entire distributions appeared as a much more concentrated single

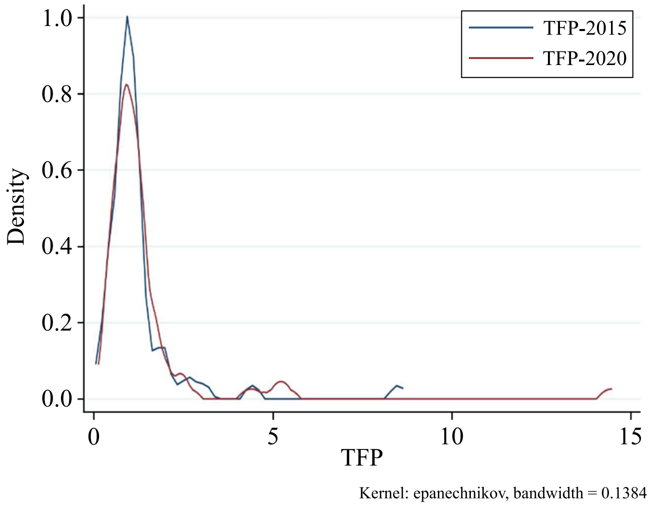

FIGURE 1 Changes in the total factor productivity of IT companies in 2020 versus 2015

peak around the peak of the distribution. However, looking at countries around the world, the per-capita GDP distribution has clearly shown multiple peaks, called the "Twin Peaks" by Quah [1], for decades. Only few studies have discussed about the convergence mentioned above based on company-level data.

In this study, the term club convergence, coined by Baumol [2] and explained by Quah [3], indicates the convergence of the per-capita GDP level of the countries in the same "club." The theoretical model, which explains the existence of several normal states, is primarily characterized by the heterogeneity of technology among countries (i.e., the OECD countries), human capital, and fertility [4] or the countries interacting with trade objects [3]. Moreover, it is unclear if the model works on the corporate level rather than the national level. This question provides important clues not only to the simple theory of corporate growth but also to the understanding of the industry and national growth theory.

Given the empirical relevance of club convergence, this concept of convergence remains somewhat ambiguous from the econometric point of view. There is a need for a clear formal definition of club convergence in the existing research literature or a distribution-oriented test for it. This paper has contributed to extending the universality of the methodology by applying this distribution-based test to the field of corporate convergence. For the purpose of this study, in the Korean IT company data comprising 69 enterprises, the total factor productivity of 2005–2016 was compared with that of 2019–2020. As shown in Figure 1, in different time periods, the distribution of the total factor productivity changed within the distribution for high-productivity companies and low-productivity companies. However, visually, the location and shape of the distribution in the productivity distribution do not accurately show that club convergence or divergence occurred in 2019–2020 due to R&D cost expenditures. In fact, if low corporate productivity and high corporate productivity converged to different points due to R&D activities, it is possible that the divergence of these two groups has become more distinct over time. If this is true, visual inspection of changes within a distribution can be tricky and potentially misleading. Due to corporate R&D activities, the overall increase in average productivity and distribution variance also complicates direct comparisons. And if one peak grows bigger and another peak becomes less prominent, what conclusion must be drawn about corporate club convergence?

To solve this problem, this study measures and analyzes how clear the single style of a distribution is due to a core change factor, and the correct index for club convergence over time. The new measurement method is based on the literature on the nonparametric multimodality test, which was proposed by Silverman [5] and implemented by Bianchi [6]. In particular, Krause [7] proposed the critical bandwidth (CB) calculation of the singularity and multiplicity for proving the existence of several peaks as a widely used test. In this study, to understand the change of convergence of Korean IT companies by applying these research studies, the technology change was decomposed, so the decomposed factors were dynamically examined and quantitatively measured.

This study applied the existing quantitative methodology for the technology convergence (divergence) phenomenon, provided a new empirical insight into the change factors of the distribution of the total productivity of 69 companies (separated into technology gap and technology catch-up) from 2015 to 2020, and evaluated corporate R&D strategies.* The peak was more salient in this period. Some low-productivity companies grew fast to catch-up with high-productivity companies, and a significant collective divergence phenomenon was observed. According to this analysis result, the R&D strategy of IT companies is rated as an effort for technology catch-up rather than technology leading.

This study is structured as follows: Section 2 briefly reviews existing literature on convergence, and the total productivity estimation method and separation. Section 2

*Generally, since IT-related industries start up and close up regularly, it is difficult to collect original data. The reason 69 companies were chosen out of 300 original data companies was because 69 companies had the entire required data during the analysis period. Another reason is that we considered the completeness of the variables. Because many companies omitted the variable to be evaluated (particularly patents), they were excluded from the analysis.

briefly describes how to construct the club convergence index according to changes in the CB. Section 3 presents the empirical evidence that shows the importance of corporate R&D strategy in corporate productivity club convergence as a result of empirical analysis. Section 4 presented the summary and implications.

2 | LITERATURE REVIEW AND ANALYSIS METHODOLOGY

2.1 | Literature review and decomposition of technology determinants

As corporate technology change is one of the most important explanations about the change of the techno economic paradigm [8], the focus is on the possibility of technology-based convergence and divergence. In addition, corporate technology change is recognized as the main driving force of corporate growth. In particular, according to the result of a recent study, it was disclosed that the main causes of technology change are closely intertwined with the construction strategy of the corporate R&D ecosystem and the technology performance co-evolution strategy of complementary technology [9].

As the technology convergence phenomenon reflects technology gap and technology catch-up activities as keys to corporate success, it is the most important in R&D [10]. Also, the corporate technology strategy generally has more influence on corporate growth than the product diversification strategy, which is a result of technology commercialization [11].

Corporate R&D activities are considered from two perspectives: economic transaction cost and corporate strategy [12]. The former is internalization of technical competency, and the latter originates from the resource-based theory [13]; that is, the resource-based theory is a point of view that focuses on the dynamic function of R&D [14], organizational learning, and knowledge dissemination [15].

The R&D strategy, that is, the main means of gaining access to new implicit technology, which cannot be obtained through a direct market mechanism, is growing fastest in the high-tech sector, particularly, ICT [16]. To verify the technology development success factors of ICT, several empirical studies are being conducted [17].

In this study, corporate technology convergence and divergence are regarded as the strategic actions of corporate R&D in the industrial environment [18]. In the IT industry, the possibility of technology convergence and divergence depends on the degree of participation in R&D of the company along the industrial value chain for the industry, including upstream and downstream alliances and horizontal alliances, in which companies participating in the new product development process form R&D alliances.

Various examples of technology convergence occurring at the corporate level indicate that companies reach upstream of the product development process and approach universal technology or new research areas. Companies can cooperate horizontally with other technology opportunities to combine resources and technology. Alternatively, through downstream alliance, companies can access manufacturing, distribution, or marketing knowledge and commercialize various realizable technologies into marketable products. As each alliance type has a different type of related partner and type of delivered knowledge, they require different alliance management functions [19].

Among the methods of measuring and identifying the temporal changes of technology convergence (or divergence), the Malmquist Productivity Index (MPI) can decompose total technological change into technology gap factors and technology catch-up changes through data envelope analysis (DEA) like a nonparametric approach that measures changes in corporate technological productivity with temporal changes. To ensure that corporate productivity is measured with technology change factors and decomposed into technology catch-up and technology leading, concurrent versions of data and temporal transformation of technology should be used in the target period. MPI can use the observation values of time t and $t+1$, x (input variable), and y (output variable) and express them in the following (1) and (2) with the distance function (E).

$$\mathrm{MPI}^{t}=\frac{E^{t}(x^{t+1},y^{t+1})}{E^{t}(x^{t},y^{t})}, \tag{1}$$

$$\mathrm{MPI}^{t+1}=\frac{E^{t+1}(x^{t+1},y^{t+1})}{E^{t+1}(x^{t},\ y^{t})}.\mathrm{MPI}^{t+1}=\frac{E^{t+1}(x^{t+1},y^{t+1})}{E^{t+1}(x^{t},y^{t})}. \tag{2}$$

The geometric mean of (1) and (2) is as follows:

$$\mathrm{MPI}^{G}=\left[\mathrm{MPI}^{t}.\mathrm{MPI}^{t+1}\right]^{\frac{1}{2}} \tag{3}$$

The above formula is divided into the technology catch-up factor (catch-up) and the technology leading factor (technology expansion) as follows:

$$\mathrm{MPI}^{G}=[\mathrm{EFFCH.\ TECHCH}]=\left[\left(\frac{E^{t+1}(x^{t+1},y^{t+1})}{E^{t}(x^{t},y^{t})}\right)\right].\left[\left(\frac{E^{t}(x^{t},y^{t})}{E^{t+1}(x^{t+1},y^{t+1})}\right)\left(\frac{E^{t}(x^{t+1},y^{t+1})}{E^{t}(x^{t},y^{t})}\right)\right]^{\frac{1}{2}}. \tag{4}$$

The first and second terms of the above formula indicate the technology leading (technology change) and the technology catch-up (change in technology efficiency and size), respectively. That is, the total technology change can be defined by using a method of measuring the distance function like DEA. The components of MPI are derived from estimation of the distance function defined in the leading technology. Fare and others [20] provided formal derivation of MPI, and it is the most popular among the various methods developed to estimate production technology [21].

The degree to which a change in firm-level technical efficiency contributes to the change in productivity between two periods is measured by the change in technological efficiency (i.e., change in scale efficiency and change in pure technological efficiency). Technological change refers to the degree of change in skill level between the two periods (i.e., the degree to which the change in the effective frontier contributed to the change in productivity). Therefore, EFFCH means the catch-up, and TECHCH indicates the technology leading.

2.2 | Exploring technology convergence (divergence)

2.2.1 | The kernel function and optimal bandwidth

Recently, researchers have been using the nonparametric method of kernel density estimation to estimate the distribution of national per-capita income without making a potential restrictive assumption about the formed distribution form. It is purely based on data, so when this method is used, the advantage is that it is possible to analyze the distribution that has characteristics that cannot be captured by bias, multiple peaks or parametric methods.[†]

The kernel density function $f(x)$ is as follows:

$$f(x)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{x-x_i}{h}\right).$$

Here, K is the kernel function, and h is the bandwidth.

A general Gauss kernel is as follows:

$$K\left(\frac{x-x_i}{h}\right)=\frac{1}{\sqrt{2\pi}}\exp\frac{1}{2}\left(\frac{x-x_i}{h}\right)^2.$$

[†]For introduction, see Silverman [5] and Bowman and Azzalini [22].

In kernel density estimation, the bandwidth h is important parameter because it determines the shape and mode of the distribution by adjusting the amount of smoothing applied to the kernel around the data point.

As the high bandwidth induces substantial smoothing, only the most distinct peaks are visible. When the bandwidth is gradually reduced, additional peaks appear; thus, relatively more peaks appear in the low bandwidth than that in high bandwidth. Thus, the bandwidth and the number of peaks are inversely proportional.

It is possible to draw a conclusion about corporate technology convergence (divergence) by applying the proposed method. The key application of this study is that to make an inference about technology convergence, it is necessary to observe changes in the technological level distribution across time and particularly monitor whether technology distribution peaks become more salient. However, visual comparison of distribution functions may be complicated and potentially misleading, particularly given the overall increase of variance. This problem can be solved by examining changes in the CB. Here, the purpose of analysis is to capture the changes in the internal technology distribution, which is the foundation of club convergence or divergence.

2.2.2 | Convergence (divergence) and CB

The core idea of this analysis method is to measure how the shape of the distribution changed using CB changes. In addition, since the distribution of MPI has multiple peaks, it is necessary to estimate the CB value. If the two peaks of the bimodal distribution become more salient, the CB for the single peak increases. Let us examine the problems of dynamic settings rather than static settings. The CB based on raw data is sensitive to changes that affect the entire distribution. This is important in light of the widely known increase in overall variability. The indicator of club convergence must reflect how distinct the peaks are compared with other parts in the distribution, and it must be invariant to changes in the overall distribution's variance. This can be achieved by working with a standardized density that has the same shape as the original [7].

> **Proposition 1.** If $f(x)$ is the kernel density function, and if it is standardized in the support $[x_L : x_U]$ and bandwidth h with $y_i = (x_i - \mu)/\sigma$, $h_y = \sigma^{-1}h_x$, $f(y)$ will have the same shape as the original $f(x)$.

Next, let us examine the relationship between the CB and convergence (divergence). It is described in Definition 1.

Definition 1. When $f(y)$ is the standardized probability density function, there is a critical bandwidth CB_1, CB_2, and it will be defined as follows:

Club convergence: $CB_2 \rangle CB_1$.
Club divergence: $CB_2 \langle CB_1$.

Intuitively, if the two peaks become more distinct, the CB of a single peak *CB* will increase. To change the shape of the bimodal distribution to a unimodal shape, a greater level of smoothing (h) must be applied.

The great advantage of Definition 1 is that it provides the convergence (divergence) index that captures the result of the changes in the potentially complicated distributions with a single number using *CB* repeatedly. For example, club convergence may occur due to the increased separation between clusters and the increased concentration within the cluster, or the combination of the two. All these changes are reflected in the increase of *CB*.

In this study, as shown in Figure 2, the number of employees of the company and research expenditure are input variables, and the sales and number of patents are output variables, and the total corporate productivity is measured using DEA. Using this method, the measured corporate technology level is divided into technology leading and technology catch-up, that is, the two determinants and the R&D strategies of the IT companies during the analysis (2015–2020) are identified.

3 | EMPIRICAL ANALYSIS

3.1 | Basic statistics

Data collected by the Electronics and Telecommunications Research Institute in 2021 [23] were used to analyze the economic convergence and divergence of IT companies. The data came from 300 companies, and the output variables were the sales and the number of research patents, and the input variables were the research expenditures and the number of employees. As most companies have data from 2015 through 2020, the years are the beginning and ending year of the sample period.

To analyze changes in the distribution over time, it is important to balance the data set so that the distribution comprises exactly the same companies over a number of years. Accordingly, those companies without data during the entire period were deleted. Many companies had insufficient data, so this study used data from only 69 companies from 2015 to 2020.

Table 1 shows the basic statistics about the corporate productivity of target companies in 2015 versus 2020. Looking at the descriptive statistics in Table 1, first, overall technology changes improved more in 2019–2020 than 2015–2016. Second, the increase of technology change is attributed to technology catch-up rather than technology gap. Third, it is impossible to draw a clear conclusion that the focus of the R&D strategies of IT companies was on technology catch-up rather than on technology gap. The reason is that the standard deviation and kurtosis of technology changes based on simple descriptive statistics increased and the skewness increased or decreased. To draw a correct conclusion, a definitive quantitative technique is necessary.

Figure 1 illustrates the evolution of the descriptive statistics of the technology changes of the analysis data over time. The mean and median of corporate technology changes increased in the past 5 years, and despite the global financial crisis in 2018–2019, the technology increase of IT companies from 2015 to 2020 went up from 1.203 to 1.415, reflecting $(\mu^{2015}/\mu^{2020})^{1/5} - 1 \approx 3.29\%$ an average annual growth rate of about 3% per year. The fact that median is higher than the mean in technology catch-up reflects the negative skewness value of the distribution.

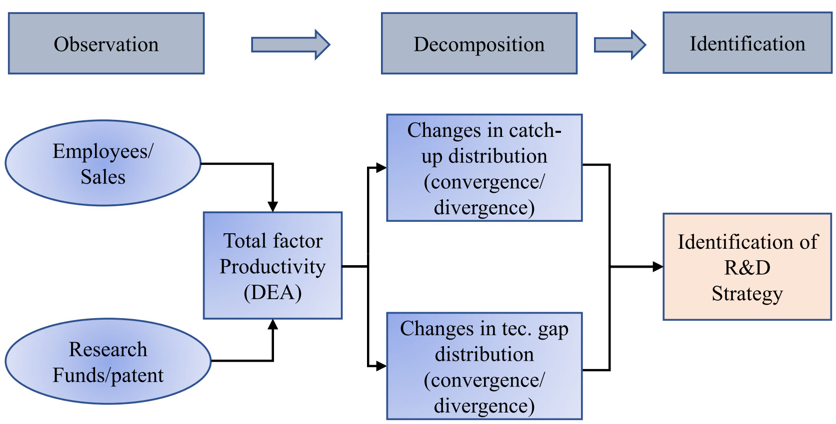

FIGURE 2 Structure of this study and analysis procedure

TABLE 1 Comparison of the basic statistics about corporate productivity in 2015–2016 versus 2019–2020

Statistics	2015–2016			2019–2020		
	Technology change	Technology leading	Technology catch-up	Technology change	Technology leading	Technology catch-up
Average	1.203797	1.465857	0.991587	1.415425	1.02292	1.618526
Median	0.9722	1.0881	0.8173	1.0785	0.6421	1.6508
Standard deviation	1.119629	1.565836	0.417014	1.846523	1.264702	0.625224
Variance	1.253569	2.451842	0.173901	3.409646	1.599471	0.390905
Kurtosis	27.04216	12.87332	0.43091	37.56692	15.89747	−1.01041
Skewness	4.601815	3.417082	1.213696	5.637784	3.700299	−0.22973
Minimum	0.1944	0.1011	0.3635	0.1317	0.1317	0.3709
Maximum	8.4882	8.6252	2.1181	14.4581	8.0657	2.5342

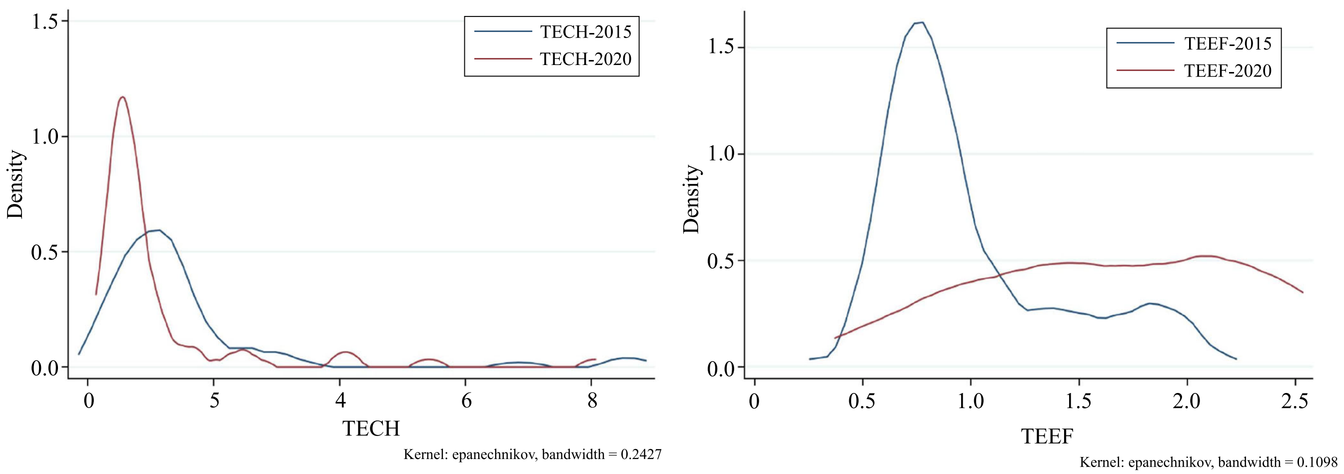

FIGURE 3 Comparison of the technology leading distribution and the technology catch-up distribution of 2015 versus 2020

In Figure 3, the first figure indicates the technology catch-up distribution and the second figure shows the technology leading distribution, respectively. In Figure 3, according to the evidence on corporate convergence, the mean increased. However, the standard deviation of technology changes also increased over time, 1.11 in 2015–2016 to 1.84 in 2019–2020 (Table 1). One may wonder if the increase in the standard deviation of technology changes is caused by some outliers at the top and bottom of the distribution. Furthermore, it is unclear if technology gap or technology catch-up is important analysis target. Visual testing can be done by examining the factors of technology changes in Figure 3. As shown in the two distributions, the visual difference can be seen particularly in the technology catch-up distribution, but there are limitations in drawing a correct conclusion based on a clear corporate convergence (divergence) hypothesis.

3.2 | Analysis result

In the IT industry, a clear quantitative conclusion about corporate technology convergence can be drawn by clearly comparing the index changes of the transformed density function, *CB*, including between-distribution changes and within-distribution changes. These changes of *CB* are calculated based on the standardized density and correctly filter the changes in variance. Tables 2 through 4 show a few characteristics of the *CB* density after standardized transformation.

The relatively high peaks of Korean IT companies include most of the population during the sample period, and the peak of the corporate technological level evolves over a number of years. The peak of the corporate technological level is more apparent in 2019–2020 than in 2015–2016. As discussed above, the conclusion about the technology change convergence, based on the visual

TABLE 2 Unimodal analysis of the distribution of changes in corporate technology in 2015–2016 versus 2019–2020

Numbers	2015–2016	2019–2020
CB	0.2237 (0.5780)	0.2493 (0.5020)

Note: The *p*-value of the single peak is in parentheses.

TABLE 3 The unimodal analysis of the corporate technology leading distribution in 2015–2016 versus 2019–2020

Numbers	2015–2016	2019–2020
CB	0.2286 (0.5500)	0.2603 (0.4920)

Note: The *p*-value of the single peak is in parentheses.

TABLE 4 Unimodal analysis of the corporate technology catch-up distribution in 2015–2016 versus 2019–2020

Numbers	2015–2016	2019–2020
CB	0.4840 (0.2240)	0.4123 (0.3700)

Note: The *p*-value of the single peak is in parentheses.

inspection of distribution changes, the occurrence of corporate technology convergence due to a particular factor, may be misleading, so changes in *CB* over time must be examined quantitatively.

Examining the patterns of the distribution and changes over time, *CB*, it can be seen that the change tracking method has an advantage. However, one disadvantage of this pure data-based method is the sensitivity to outliers. If multimodal testing is based only on changes in the first derivative of density, companies with a higher, not lower, standard deviation than the mean in 2015–2016 form individual peaks. Empirically, the multimodal literature has two simple approaches for handling these isolated peaks. That is, those countries with outliers will be immediately removed from the sample, or the critical value will be included in testing the peak that needs to exceed the density value to be classified as a peak.[‡]

If individual outliers and peaks are ignored in the bootstrap multimodal test of Silverman [5], the density is processed with up to one peak (Tables 2–4). If 1000 bootstrap copies are used to conduct (static) multimodal tests every year, the unimodal null hypothesis cannot be rejected early until 2020.

[‡]In this study, the second possibility was selected, and for the standardized density, bigger clusters were appropriately classified in all critical values and used to remove the peaks of individual peaks of companies.

Therefore, *CB* value increases in 2020 compared with 2015; the single-peak shape means that technology convergence clearly occurred in IT companies. Further, the evolution of *CB* and the CB shows a rather large difference in the technology leading and technology catch-up distribution (Tables 2–4). In changes in the technology gap distribution, the *CB* of the technology catch-up (*CB*) is smaller in 2015–2020. That is, companies with high and low corporate productivity convergence have a single peak after 2015, reflecting no significant change. In the two technology change factor distributions, after 2015, there is clearly no significant change in the single-peak shape. However, an important characteristic is that the *CB* value is absolutely greater in the technology catch-up distribution than in the technology gap distribution. It causes the technology catch-up factors to clearly converge on the corporate technology changes in the IT industry and greatly affects technology changes. The result of this empirical analysis shows that the purpose of the R&D activities of companies in the IT industry is technology catch-up rather than technology leading.

In summarizing the analysis results, first, technology changes of IT companies show technology convergence. Second, the main factor of corporate technology convergence can be found in technology catch-up factors rather than technology leading factors. The above two results show that from 2015 to 2020, the major R&D activities of IT companies were the major R&D strategy for catching up with the technologies of leading companies rather than for technology leading.

3.3 | Relationships with existing studies and robustness

Results indicate that the total productivity of IT companies converged from 2015 to 2020, and the primary factor for convergence is technological catch-up rather than technological leadership, that is, catching up with other productivity leaders. However, the implicit assumption that the initial conditions of the IT firm have no effect on the long-run distribution of the firm's total productivity is the basis for the existence of a single stable state of the firm in which the marginal output of the production factor is decreasing. However, firms with constant or increasing revenues, however, may have stable steady-state diversity or none. In light of this, the most suitable analytical model for economic and corporate convergence studies must be determined for statistical testing using the null hypothesis of nonconvergence and the alternative hypothesis of convergence.

With classical criticism that the existing method for studying economic convergence considered only a few

TABLE 5 Unconditional convergence tests results

Technology	Estimate	STd. error	*t* value	*p* (>|*t*|)
Changes				
Intercept	79.78983	68.03526	0.731824	0.517262
Time	−0.02435	−0.03371	0.722228	0.522361
Leading				
Intercept	−53.2382	80.33451	−0.66271	0.554886
Time	0.026536	0.039809	0.666582	0.552722
Catch-up				
Intercept	37.40623	68.85927	0.543227	0.624738
Time	−0.01819	−0.03412	0.533164	0.63089

TABLE 6 Conditional convergence tests results

Technology	Estimate	STd. error	*t* value	*p* (>|*t*|)
Changes				
Alpha	0.000541	0.01985	0.02725	9.78E-01
Beta	−0.2399	0.025586	−9.37636	9.38E-14
Leading				
Alpha	0.081053	0.015206	5.330407	1.24E-06
Beta	−0.31774	0.049531	−6.41499	1.66E-08
Catch-up				
Alpha	−0.08475	0.022813	−3.71519	0.000416
Beta	−0.22882	0.028418	−8.05193	1.94E-11

instances of the distribution of output per capita, Quah [1,2] introduced the "distribution dynamics" approach to investigate the role of nonlinear convergence in economic growth. This research method is fundamentally a dynamic distribution approach. Quah's study showed "twin peaks" in income distributions across countries in the long-run. The two peaks represent two attractive states during growth. Henderson, Parmeter, and Russell [24] identified multiple peaks in the cross-country distribution of output per capita using various concepts and statistical tests. Recent studies have suggested the existence of two or more attractive states [25]. Pittau, Roverto, and Johnson [25] estimate a finite mixture model of income distribution between countries and argue that multiple peaks are neither necessary nor sufficient for the converging clubs. They found three constituent peaks in the income distribution. Krause [7], who provided the basis for our methodology, proposed the calculation of CBs of specificity and diversity to prove the existence of multiple peaks as a widely used validation.

σ-convergence and β-convergence are the traditional analysis methods closely related to convergence using the distribution dynamics discussed above. In this study, σ-convergence and β-convergence were examined for the total productivity data of an IT company. As shown in the Table 5, we see that the technology leading factor acts as a factor narrowing the effect of expanding the target company to catch-up with the technology. These results are consistent with our key analysis results. Furthermore, the regression analysis results of the β-convergence show mixed results (Table 6). Technology leaders and technology catch-up companies support the convergence phenomena; however, the degree of influence on their convergence is contradictory with the results of this study.[§]

[§]A reviewer of this paper pointed out the essential problem of the nonparametric verification method and questioned the robustness of the results of this study. The difference between the opposite values of CB in Tables 3 and 4 indicates when the CB value increases (convergence) and when the CB value decreases (divergence). However, although the CB value has decreased over time, the technology catch-up factor Table 3 is larger than the technology lead factor Table 4, and the overall IT company convergence phenomenon Table 2 is attributed to the technology catch-up.

4 | SUMMARY AND IMPLICATIONS

This study empirically analyzed the estimation of optimal kernel density regarding the decomposition method for the two technologically changing factors using the novel corporate technology convergence (divergence) metric. Various within-distribution changes like separation between enterprises and increase or decrease in within-cluster density were summarized and calculated as a single metric and empirically analyzed. An increase/decrease in the CB regarding the singularity of the corporate technology distribution indicates a clear technology convergence/divergence.

Looking at the results of empirical analysis, after 2015, the technology convergence of low-productivity IT companies on high-productivity IT companies is observed. In other words, after 2015, the technology distribution peaks tend to clearly converge to one peak. Furthermore, if corporate technology changes are divided into factors, this corporate convergence phenomenon shows that the R&D purpose of enterprises is in technology catch-up rather than in technology leading. Comparing the IT club convergence indexes of Korea, the technology convergence phenomenon, similar to those described in existing studies, was clarified, but they are important in that they clearly track changes in the shapes of the technology distribution and causal factors.

As for technology policy implications, R&D strategies adopted by individual enterprises to occupy a good position in the given technology distribution must be analyzed rigorously. The desirable direction of the technology policies of enterprises is to induce technology leading based on the development of new technologies rather than technology catch-up based on copying leading technologies. Accordingly, it establishing a technology policy that will continuously induce the development of advanced technologies for the development of the IT industry is essential. Moreover, a technological policy should be incorporated to strengthen the technological level of leading companies and build a mutual cooperative ecosystem for improving the technology of catch-up enterprises.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest.

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