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Analysis of R&D Efficiency Change in IT Sector using Cumulative Malmquist Index

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Abstract: *This study analyzes the changes in the efficiency of Korean R&D projects in the IT sector from 2010 to 2018. The data envelopment analysis (DEA) and Cumulative Malmquist index were used to measure the change in R&D efficiency. The results were as follows. First, the Korean IT sector has developed around hardware, applied research, development research, and private enterprises rather than software, basic research, universities, and public research institutes. Second, short-term efficiency improvement is possible in the government's R&D projects in which large-scale investments are executed. Third, in Korea, it is more urgent to improve efficiency in the public sector than in the private sector. The results provide insights into policy implications required to enhance national competitiveness in the era of the 4th industrial revolution and digital transformation.*

Keywords: IT; National R&D; R&D Efficiency; Data Envelopment Analysis; Malmquist Index

1. Introduction

As the 4th industrial revolution and digital transformation are accelerating, information and telecommunication (IT) technology competency is emerging as important national competitiveness beyond companies. Developed countries are boldly increasing their investment in Research and Development (R&D) to respond to these environmental changes and take the lead in promising industries in the future [1].

The Korean government also greatly expanded the size of national R&D investment in future growth areas, reaching 20.5 trillion Korea won (KRW) in 2019, exceeding 20 trillion KRW for the first time ever, and 24.2 trillion KRW in 2020 and 27.4 trillion KRW in 2021, showing a double-digit growth rate for two consecutive years. In the R&D investment strategy, the Korean government is also trying to move away from the fast-follower strategy in which the goal of technology development was clear, and shift to a challenging first-mover strategy. Specifically, high-risk and innovative R&D projects are being expanded, and the budget for basic research centered on researchers is greatly increased to maximize the creativity and autonomy of researchers while creating a stable research environment for researchers and expanding research opportunities for new researchers.

Although R&D is investment intensive, the results are uncertain, and the payback period is long [2]. Therefore, since a company must secure future profitability through R&D to maximize profits, it is an important decision to determine how much R&D investment can achieve expected results. Accordingly, some companies actively invest in R&D depending on the circumstances of the company or the characteristics of managers, but some companies tend to avoid investing in R&D with high uncertainty and long-term effects. Therefore, government-led R&D needs to be boldly invested in creative and challenging R&D projects from a long-term perspective rather than being absorbed in short-term results to create innovative research results. And although basic research has high economic and social ripple effects, the possibility of short-term commercialization is low, and the private sector's investment capacity is insufficient, so long-term R&D investment is required by the government.

The Korean government is recently starting to discuss the efficiency of R&D investment. Korea's R&D investment is the second largest in the world, and the ratio of government R&D investment to gross domestic product (GDP) is the highest in the world. However, as the success rate of technology commercialization and the ranking of science and technology competitiveness did not improve, the importance of efficiently using the limited national budget emerged. In addition, as the scale of R&D investment has steadily increased due to the promotion of large-scale R&D projects such as the Digital New Deal, the importance of investment in fields that can contribute to improving national competitiveness in the future is being mentioned. In other words, the increase in government R&D investment raises the interest in resource allocation for government R&D policies, which requires understanding of R&D efficiency [3, 4]. Efficiency is usually measured as the ratio of input to output, which is a narrow definition of technical efficiency. In other words, if an organization achieves its goal with minimal input resources, it can be recognized as an organization that has achieved technical efficiency. A method using this concept is Data Envelopment Analysis (DEA), and the target of R&D efficiency analysis is very diverse, such as countries, companies, government research institutes, government-sponsored programs, and projects.

First, research on R&D efficiency at the national level is as follows. Rousseau and Rousseau [5] analyzed the R&D efficiency of 14 European countries using the DEA methodology. This study used GDP, R&D expenditure, and active population as inputs, and the number of patents and publications as outputs. Lee and Park [6] measured the R&D efficiency of 27 Asian countries using DEA. They found that Singapore was relatively efficient, while Taiwan, Korea, and China were relatively inefficient. Wang and Huang [4] compared the R&D efficiency of 30 countries using 3stage-DEA, and more than half were found to be inefficient. In particular, they proposed for the first time a 3stage-DEA method that can consider the effects of factors affecting the slack of inputs. Sharma and Thomas [7] compared the R&D efficiency of 22 developed and developing countries. As a result of the study, the efficiency of Korea, China, and Japan was high in the constant returns to scale model. On the other hand, in the variable returns to scale model, in addition to Korea, China, and Japan, India, Hungary, and Slovenia were also found to be effective.

The following studies investigated the R&D efficiency of companies and government research institutes. Hashimoto and Haneda [8] analyzed the R&D efficiency of 10 Japanese pharmaceutical companies from 1983 to 1992 using DEA and Malmquist index. The study found that the efficiency of Japanese pharmaceutical companies continued to decline. Lee and Lee [9] analyzed the R&D efficiency of 10 government research institutes in Korea and suggested effective performance evaluation methods to contribute to the establishment of government R&D policies. Jang, et al. [10] investigated the change in efficiency of 49 major R&D companies from 2007 to 2013 using DEA and Malmquist index. As a result of the analysis, companies found that overall R&D efficiency decreased slightly. Han, et al. [11] investigated the change in R&D efficiency of China's high-tech industry from 1998 to 2009. During this period, R&D investment cost increased, but efficiency did not increase. They pointed out that the inefficiency of the technology commercialization process could be the cause.

As mentioned above, research on R&D efficiency has been conducted in various fields from the national level to the individual project level. However, for a long time, studies on national R&D efficiency analysis for specific research fields are very limited. Therefore, this study intends to analyze the change in the efficiency of R&D projects in IT sector sponsored by the Korean government from 2010 to 2018. In particular, analyzing changes in the efficiency by technologies, R&D stages, and R&D players can contribute to drawing political implications that can enhance national competitiveness in the era of the 4th industrial revolution and digital transformation.

This study can contribute to the expansion of the literature on R&D efficiency academically, and in practice, it can provide implications for the efficient allocation of the government's limited budget resources.

This paper is structured as follows. Section 2 presents data and research methodology, and section 3 shows the research results. Section 4 provides implications, discussions, and conclusions of the study.

2. Materials and Methods

Data from Korea National Science & Technology Information Service (NTIS) are used to analyze the performance of national R&D projects in the IT sector. NTIS is a national R&D knowledge information portal that provides information on national R&D projects such as projects, tasks, researchers, and achievements in one place. Its main purpose is to increase the efficiency of national R&D investment and to contribute to the improvement of research productivity by sharing and jointly utilizing information related to national R&D projects and science and technology, which are managed individually by department and institution [12].

NTIS's R&D projects are classified according to several criteria. Among them, the IT sector of the 6T classification is used as the subject of this study. The IT sector is classified by technology into core parts (T1), next-generation network infrastructure (T2), information processing systems and S/W (T3), and other information technologies (T4). The IT sector is classified into the basic research (BR), the applied research (AR), the development research (DR), and other research by R&D stage. The IT sector is divided into public research institutes (PRI), universities (Univ), private enterprises (PE), and other players. Among these, projects with other research stage and other players are excluded because there were no relevant projects in some case.

Therefore, the national R&D project corresponding to the IT sector is divided into 4 technologies, 3 R&D stages, and 3 research players, and 36 DMUs are created by adding up the input and performance of the projects corresponding to each group. Table 1 shows the number of projects per each category.

Table 1. The number of projects

Category	2010	2011	2012	2013	2014	2015	2016	2017	2018
By Technology									
T1	1,554	1,552	1,574	1,517	1,571	1,592	1,508	1,686	1,771
T2	631	652	693	661	637	619	652	808	798
T3	1,853	1,995	2,385	2,632	2,972	3,359	3,579	4,140	4,710
T4	1,027	1,100	1,312	1,501	1,759	1,705	1,824	1,998	2,265
By R&D Stage									
BR	1,648	1,767	1,943	2,021	2,304	2,407	2,673	3,358	3,291
AR	725	726	725	703	707	654	787	894	1,049
DR	2,692	2,806	3,296	3,587	3,928	4,214	4,103	4,380	5,204
By R&D Player									
PRI	579	545	601	649	681	690	799	814	819
Univ	2,534	2,656	2,885	2,933	3,220	3,211	3,235	3,632	3,625
PE	1,952	2,098	2,478	2,729	3,038	3,374	3,529	4,186	5,100

Efficiency is the ratio of inputs such as manpower, time, and equipment to outputs such as production and sales. DEA and SFA (Stochastic Frontier Analysis) are typically used to measure efficiency. The two methodologies differ in the probability error and whether or not a function is assumed when constructing the frontier line [13]. In the case of SFA, the production function is approached parametrically and probabilistically. Therefore, in order to calculate the efficiency, it is necessary to assume a specific function and an error term. Contrary to this, the DEA methodology does not need to assume a specific function, so it can be used even when the relationship between inputs and outputs is not clear. With this feature, DEA has the advantage of being able to consider multiple inputs and outputs related to the input-output relationship at the same time.

R&D projects involve various inputs such as research funds, equipment, and manpower, and the outputs of these projects, such as scientific paper, patent, and commercialization results, are also diverse. In addition, R&D inputs go through a complex process until they come out as outputs, and it is practically impossible to express them all in a direct relationship. Therefore, DEA, which can utilize multiple inputs and outputs without special assumptions, is suitable for measuring R&D efficiency. In this study, the DEA methodology is used to measure the R&D efficiency of national R&D projects in the IT sector.

However, DEA has a disadvantage in that it cannot observe dynamic changes over time [14]. This is because the efficiency can be calculated by calculating the frontier line based on a specific point in time, but the movement of the frontier line cannot be considered [15]. The Malmquist index (MI) introduced by Caves, et al. [16] can be utilized to measure the change in efficiency using DEA and panel data. The Malmquist index is an index that expresses the change between multiple views through a distance function, and it can be extended to the DEA-Malmquist index to measure the change in efficiency [17]. This is an equation of Malmquist Index:

$$\mathrm{M}(x^{t+1}, y^{t+1}, x^t, y^t)$$

$$= [\frac{D_0^t(x^t, y^t)}{D_0^t(x^{t+1}, y^{t+1})} * \frac{D_0^{t+1}(x^t, y^t)}{D_0^{t+1}(x^{t+1}, y^{t+1})}]^{\frac{1}{2}}$$

$$= [\frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^{t+1}, y^{t+1})}] \quad (1)$$

$$* [\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^{t+1}, y^{t+1})} * \frac{D_0^{t+1}(x^t, y^t)}{D_0^t(x^t, y^t)}]^{\frac{1}{2}} \quad (2)$$

The Malmquist index indicates that the efficiency at time t+1 changed in proportion as much as the difference from 1 at time t. If the Malmquist index is higher than 1, it means that the efficiency at time t+1 has increased more than at time t, if it is less than 1, it means that the efficiency has decreased, and if it is 1, it means that there is no change in efficiency. The Malmquist index can be expressed as the multiplication of Equations (1) and (2). At this time, Equation (1) called the Catch-Up index or Efficiency Change (EC) indicates that the distance from the frontier line is reduced, which means the change in efficiency according to internal factors. Equation (2) called the Frontier-Shift index or Technical Change (TC) indicates that the frontier line is shifted, which means the change in efficiency due to external factors. Catch-Up index and Frontier-Shift index also indicate the rate of change based on 1 like the Malmquist index.

The Malmquist index can analyze the efficiency change at two time points, but it cannot measure the cumulative efficiency change over more time points. This is because the Malmquist index does not satisfy the circular test [17]. Therefore, in order to obtain the accumulated efficiency change over N years, the Cumulative Malmquist index, which uses the t, t+n time points as observation points, is used Hashimoto and Haneda [8]. In this study, the Cumulative Malmquist index was used to analyze changes in the efficiency of national R&D projects in the IT sector during the observation period.

As input variables for measuring R&D efficiency, government and private research funds in the meaning of economic inputs, and the number of researchers in the meaning of manpower input are set. As output variables, the contribution rate of papers and contribution rate of patents corresponding to the output of the research are used. Due to the characteristic of R&D, a time-lag may be required between the input variable and the output variable. However, in the case of national R&D projects, annual performance indicators are calculated and evaluated. Therefore, most of achievements is produced in the current year and the following year. Considering this, the output variable for the input variable t is set as the sum of t and t+1.

3. Results

3.1 Descripitive Statistics

First, public fund increased gradually, increasing by 75.89% from 54,641 in 2010 to 96,110 in 2018. In the case of private fund, it increased by 100.95% from 7,922 to 15,919 in 2010-2018, but the pattern of change is different from that of public fund. In particular, it increased more than threefold from 10,094 to 33,293 in 2011-2012. However, it decreased significantly by 40.96% in 2014-2015, and then gradually decreased to 15,919 in 2018. It seems that R&D projects in the IT sector have changed from government-oriented to internal R&D of enterprises since 2014. In the case of research manpower, unlike research expenses, it showed a decreasing trend in 2010-2012, but it continued to increase except in 2014 to record 2,679 people in 2018. R&D manpower also increased by 48.83% during 2010-2018.

Looking at the contribution rate of papers as an output variable, it showed an increasing trend in 2010-2012 and then decreased to 7,703 in 2013. After that, it increased by 61.74% in 2013-2014 to record 12,459. The contribution rate of papers at a similar level was calculated from 2014-2018, but recently decreased slightly in 2016-2018. The contribution rate of patents continued to increase until 2010-2014 to record 31,503, and after that, it showed a gradual decrease as in the contribution rate of papers. As a result, during 2010-2018, papers increased by 52.96% and patents by 38.55%. This is a small increase compared to the R&D inputs. This suggests that arithmetic efficiency is lowered. It needs to analyze this closely. Table 2 shows descriptive statistics for each year of input and output variables.

Table 2. Descriptive statistics of input and output variables

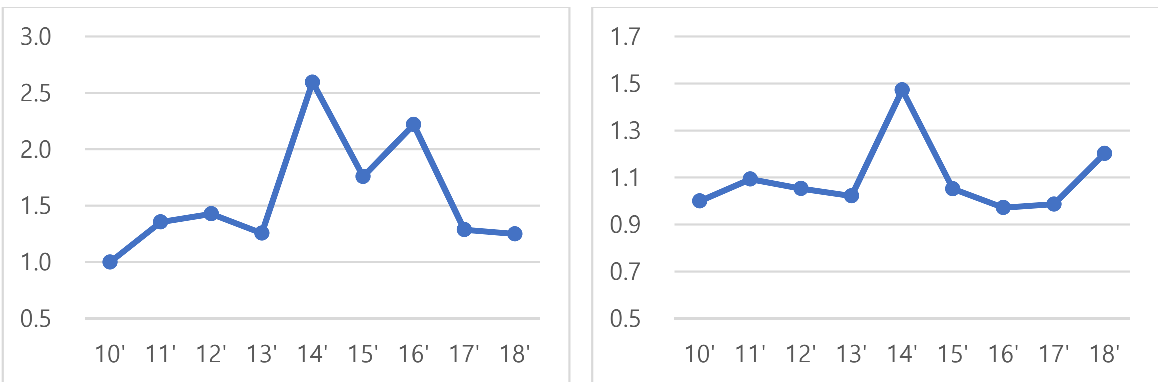
Variable	2010	2011	2012	2013	2014	2015	2016	2017	2018
Public Fund (million won)									
Mean	54,641	60,186	68,200	69,967	69,369	75,920	78,347	77,687	96,110
S.D.	59,193	70,960	87,128	89,201	86,358	99,317	99,899	99,796	102,039
Private Fund (million won)									
Mean	7,922	10,094	33,293	33,277	32,767	19,347	20,917	18,930	15,919
S.D.	11,326	17,800	62,861	61,404	60,263	36,780	39,787	38,942	33,765
R&D Manpower									
Mean	1,800	1,760	1,370	2,121	1,805	2,396	2,389	2,630	2,679
S.D.	1,655	1,800	1,405	2,542	2,302	3,216	3,375	4,091	4,589
Paper (%)									
Mean	7,289	8,370	8,806	7,703	12,459	12,219	12,533	11,574	11,149
S.D.	9,647	12,695	13,554	11,535	20,515	20,104	21,220	23,769	22,300
Patent (%)									
Mean	18,842	22,434	25,023	27,185	31,503	30,840	31,062	27,479	26,106
S.D.	14,203	17,308	19,146	21,170	27,294	26,224	29,801	30,822	29,197

3.2 Cumulative Malmquist Index

The DEA-Malmquist index was analyzed for all DMUs to find out changes in R&D efficiency in the IT sector. Table 3 and Figure 1 show the Cumulative Malmquist index in the IT sector. R&D efficiency in the IT sector peaked at 2.5953 in 2014. After that, it decreased again and became 1.2496 in 2018, increasing the efficiency by 24.96% compared to 2010. EC, which shows changes due to internal factors, also showed the highest value at 1.4729 in 2014. After that, it decreased until 2016 and then increased again, recording 1.2023 in 2018. TC, which means the change in efficiency due to external factors, showed an increasing trend until 2016 and was 2.1223. After that, it continued to decrease until 1.0107 in 2018. As a result, the change in R&D efficiency in the IT sector in 2018 seems to be due to internal factors.

Table 3. Cumulative Malmquist Index of IT sector

Index	2010	2011	2012	2013	2014	2015	2016	2017	2018
MI	1.0000	1.3555	1.4278	1.2564	2.5953	1.7583	2.2196	1.2873	1.2496
EC	1.0000	1.0933	1.0529	1.0219	1.4729	1.0521	0.9721	0.9865	1.2023
TC	1.0000	1.2449	1.3255	1.1794	1.6178	1.6442	2.1223	1.2667	1.0107



(a) (b)

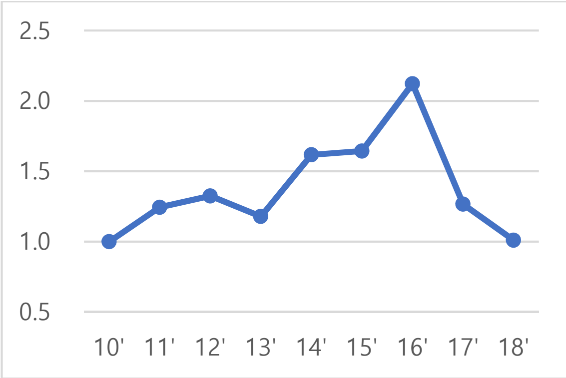


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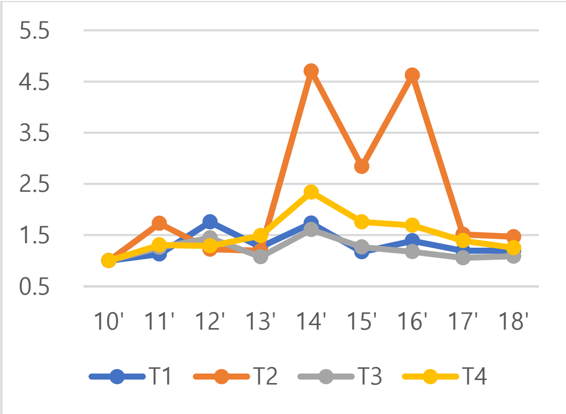
Figure 1. (**a**) Malmquist Index; (**b**) Efficiency Change; (**C**) Technical Change.

3.2.1 By Technology

Table 4 and Figure 2 show the change in efficiency by technology in the IT sector. In the case of T1, the highest record was 1.7552 in 2012. After that, in 2018, it was 1.1950, which increased the efficiency by 19.50% compared to 2010. Looking at the TC of T1, it showed a similar trend to the MI, and it was above 1.0000 in all years, indicating that the efficiency due to external factors increased. However, the EC showed the lowest level of 0.5387 in 2016 and 0.9812 in 2018, indicating that the efficiency due to internal factors decreased compared to 2010. In view of this, the change in MI of T1 is due to the external factor. T2 showed the most dramatic change. In particular, in the case of 2014, it was 4.7059, which showed an increase of 370.59% compared to 2010. In 2015-2016, the figures were also relatively high at 2.8394 and 4.6247, but after that it decreased significantly to 1.4673 in 2018. Both EC and TC showed a similar trend with a significant increase in 2014-2016, but the increase in EC was larger. Also, in 2017-2018, TC decreased significantly, unlike EC, and recorded 0.8795 in 2018, resulting in a decrease in efficiency due to external factors compared to 2010. In view of this, the MI of T2 is due to the internal factor. T3 showed the least change in efficiency. It recorded a high of 1.6062 in 2014, but returned to the same level of efficiency as in 2010 at 1.0854 in 2018. Unlike MI, EC and TC showed changes by year. However, as in 2016, the direction of change in the efficiency of EC and TC was reversed, indicating that the change in MI was small. In the case of T4, the efficiency gradually increased and recorded 2.3383 in 2014, and continued to decrease until 2018 to record 1.2507. From 2010 to 2017, efficiency was advocated by TC rather than by EC, but in 2018, it seems that the MI changed due to internal factors.

Table 4. Cumulative Malmquist Index by technology

Tech	2010	2011	2012	2013	2014	2015	2016	2017	2018
T1									
MI	1.0000	1.1280	1.7552	1.2691	1.7308	1.1713	1.3876	1.1913	1.1950
EC	1.0000	0.8801	1.0262	0.9410	0.9542	0.6134	0.5387	0.7918	0.9812
TC	1.0000	1.2952	1.6501	1.3069	1.7929	1.8737	2.4362	1.4552	1.1922
T2									
MI	1.0000	1.7282	1.2240	1.1926	4.7059	2.8394	4.6247	1.5129	1.4673
EC	1.0000	1.4730	1.0509	1.0446	2.5878	1.7469	2.0211	1.3004	1.5878
TC	1.0000	1.1857	1.1776	1.0946	1.5017	1.4579	1.8765	1.1092	0.8795
T3									
MI	1.0000	1.2595	1.4443	1.0746	1.6062	1.2653	1.1752	1.0541	1.0854
EC	1.0000	0.9904	1.1220	0.9690	1.0171	0.8316	0.5543	0.8282	1.0854
TC	1.0000	1.2690	1.2780	1.1713	1.6036	1.6221	2.1409	1.2698	0.9923
T4									
MI	1.0000	1.3062	1.2877	1.4894	2.3383	1.7572	1.6908	1.3908	1.2507
EC	1.0000	1.0296	1.0124	1.1329	1.3324	1.0166	0.7744	1.0255	1.1547
TC	1.0000	1.2297	1.1964	1.1450	1.5731	1.6233	2.0354	1.2327	0.9788



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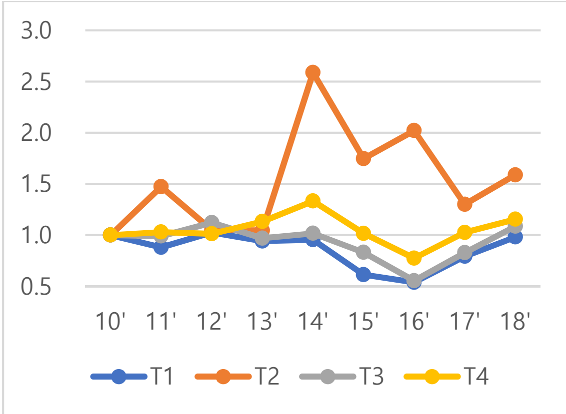

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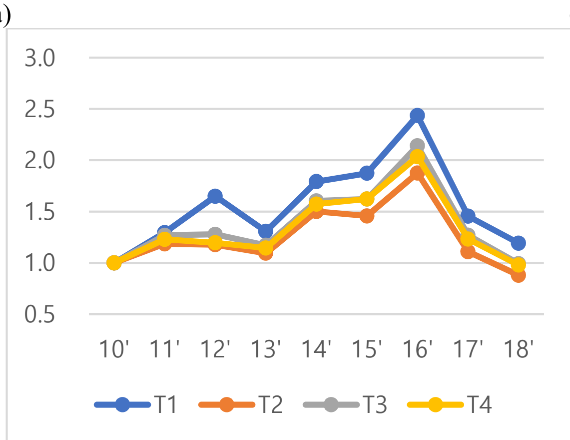

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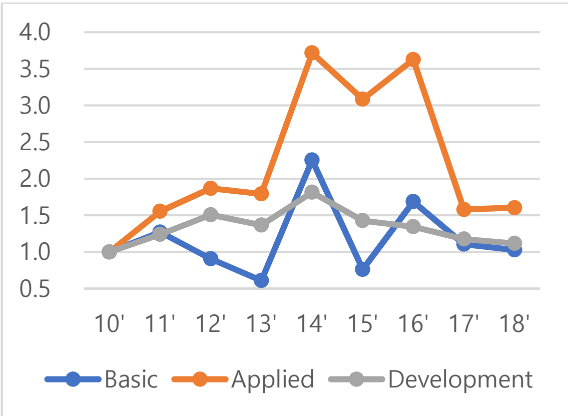
Figure 2. (**a**) Malmquist Index; (**b**) Efficiency Change; (**C**) Technical Change.

3.2.2 By R&D Stage

Table 5 and Figure 3 show the change in efficiency by R&D stage. The basic research showed the lowest figure among all at 0.6102 in 2013, and the efficiency increased again to 2.2539 in 2014. In 2013-2014, EC and TC increased and decreased in efficiency in the same direction, indicating a significant change in MI. As a result, in 2018, it was 1.0278, which did not change significantly compared to 2010. This is also the lowest number compared to other R&D stages as of 2018. In the applied research, all MI, EC, and TC values were over 1.0000 during the entire period. In particular, in 2014, it recorded 3.7176, the largest increase in efficiency. Since then, it has shown a decreasing trend, increasing the efficiency by 60.34% compared to 2010 in 2018. This is the largest increase in efficiency among the R&D stages as of 2018. EC and TC influenced the efficiency in a similar trend, and it seems that the effect of EC, an internal factor, is large in 2018. Development research showed little change compared to other R&D stages. Like other R&D stages, it peaked at 1.8144 in 2014, and has since decreased continuously. As a result, the efficiency changed to 1.1177 in 2018. In 2016, EC significantly decreased to 0.6630 and TC significantly increased to 2.0484, but in 2018, there was no significant change to 1.0818 and 1.0097.

Table 5. Cumulative Malmquist Index by R&D stage

Stage	2010	2011	2012	2013	2014	2015	2016	2017	2018
BR									
MI	1.0000	1.2719	0.9070	0.6102	2.2539	0.7617	1.6877	1.1061	1.0278
EC	1.0000	1.1267	0.7886	0.7519	1.3985	0.5841	0.7382	0.9254	1.0717
TC	1.0000	1.1507	1.1709	0.8905	1.3430	1.4222	2.0466	1.1901	0.9486
AR									
MI	1.0000	1.5550	1.8681	1.7927	3.7176	3.0848	3.6261	1.5796	1.6034
EC	1.0000	1.1840	1.2246	1.2906	1.9818	1.6938	1.5152	1.1184	1.4533
FTC	1.0000	1.2839	1.4419	1.2801	1.7291	1.8174	2.2719	1.3429	1.0737
DR									
MI	1.0000	1.2395	1.5083	1.3663	1.8144	1.4284	1.3449	1.1762	1.1177
EC	1.0000	0.9691	1.1454	1.0231	1.0383	0.8784	0.6630	0.9157	1.0818
TC	1.0000	1.3002	1.3637	1.3677	1.7813	1.6930	2.0484	1.2673	1.0097



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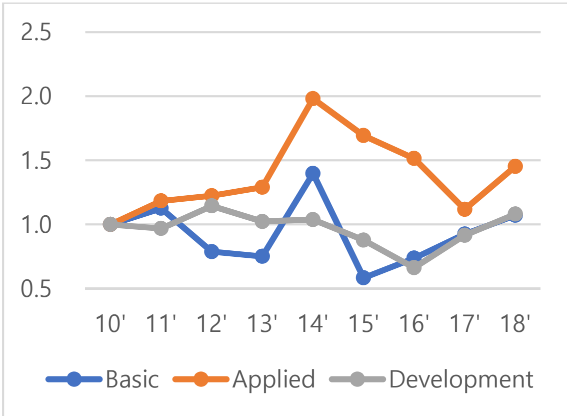

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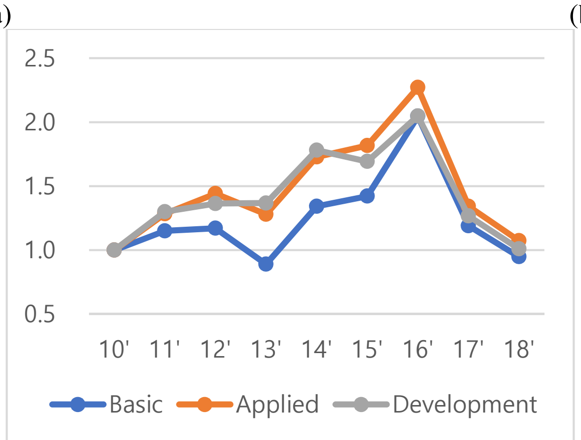

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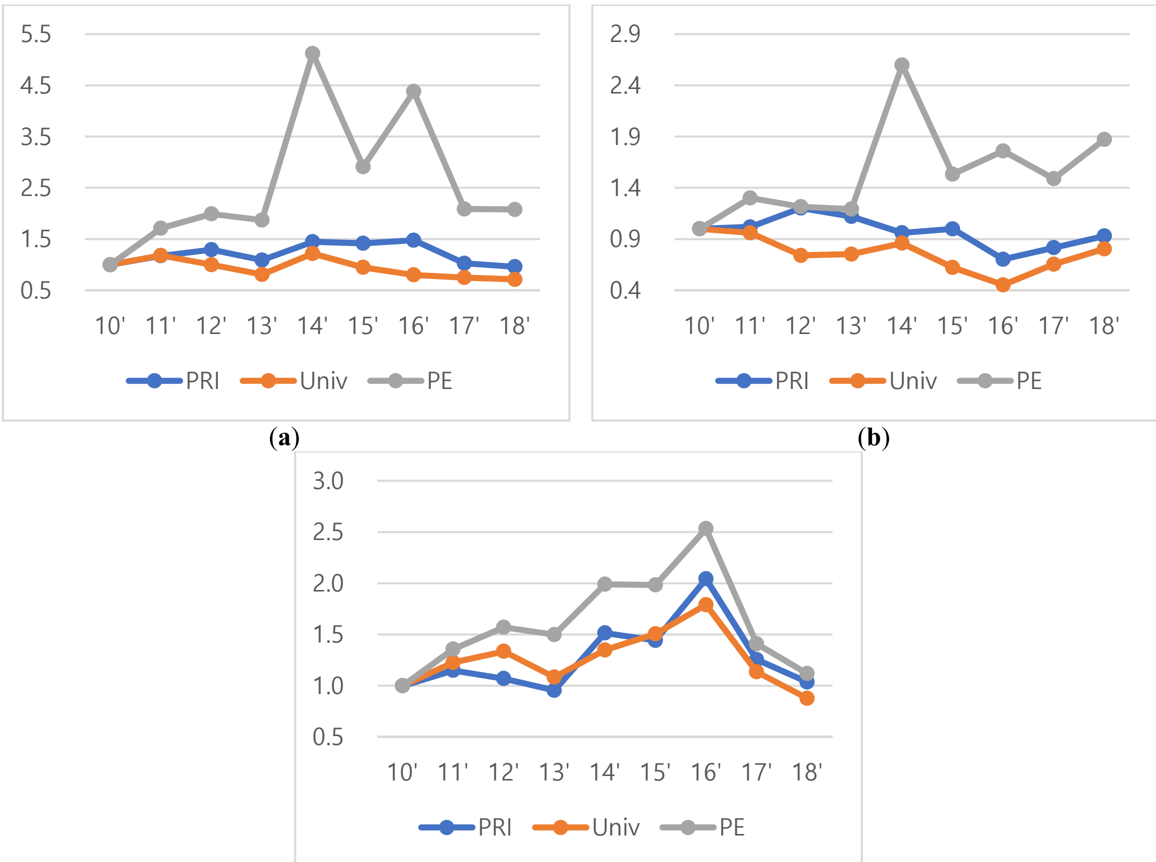
Figure 3. (**a**) Malmquist Index; (**b**) Efficiency Change; (**C**) Technical Change.

3.2.3 By R&D Player

Table 6 and Figure 4 show the change in efficiency by R&D players. Performance of public research institutes have the greatest decrease in efficiency. Excluding 2011 and 2014, the efficiency was below 1.0000 compared to 2010 for the entire period. In particular, in 2018, it was 0.7119, the largest decrease in efficiency during the period. TC had an effect on the efficiency increase, with the exception of 2018 being over 1.0000. However, EC was below 1.0000 for the entire period, which affected the decrease in efficiency. As a result, in 2018, both EC and TC were below 1.0000, indicating a significant decrease in efficiency. In the case of university-based research, it showed a value of 1.0000 or more in 2010-2017, but it was 0.9598 in 2018, indicating a 4.02% decrease in efficiency compared to 2010. In the case of EC, it was above 1.0000 from 2010 to 2013, but has been below 1.0000 since then. All TC values were above 1.000 except for 2013. In 2018, EC 0.9303 and TC 1.0366, the decrease in efficiency seems to be due to internal factors. The R&D efficiency of private enterprises showed the most change. In particular, it increased sharply to 5.1204 in 2014, and then showed a value of 2.0000 or more. In 2018, it was also high at 2.0771, increasing the efficiency by 107.71% compared to 2010. Both EC and TC showed values above 1.0000. In particular, in 2014, EC was 2.5977, which was higher than TC, which further contributed to the rapid increase in efficiency. In addition, EC recorded the second highest figure during period at 1.8718, while TC decreased to 1.1182 in 2018. This means that changes in the efficiency of private enterprises are caused by changes in internal factors.

Table 6. Cumulative Malmquist Index by R&D player

Player	2010	2011	2012	2013	2014	2015	2016	2017	2018
PRI									
MI	1.0000	1.1807	0.9994	0.8085	1.2184	0.9479	0.8010	0.7478	0.7119
EC	1.0000	0.9607	0.7407	0.7525	0.8597	0.6234	0.4532	0.6545	0.8047
TC	1.0000	1.2273	1.3358	1.0842	1.3486	1.5065	1.7906	1.1356	0.8772
Univ									
MI	1.0000	1.1735	1.2930	1.0898	1.4471	1.4168	1.4779	1.0272	0.9598
EC	1.0000	1.0183	1.2024	1.1209	0.9612	0.9996	0.7027	0.8161	0.9303
TC	1.0000	1.1499	1.0703	0.9552	1.5149	1.4425	2.0428	1.2550	1.0366
PE									
MI	1.0000	1.7124	1.9911	1.8710	5.1204	2.9102	4.3799	2.0868	2.0771
EC	1.0000	1.3008	1.2156	1.1922	2.5977	1.5333	1.7605	1.4888	1.8718
TC	1.0000	1.3575	1.5704	1.4989	1.9899	1.9837	2.5334	1.4095	1.1182



(c)

Figure 4. (**a**) Malmquist Index; (**b**) Efficiency Change; (**C**) Technical Change.

4. Discussion and Conclusion

This paper analyzed changes in the efficiency of R&D projects in the IT sector supported by the Korean government from 2010 to 2018 using DEA-Malmquist index. Hsu and Hsueh [18] analyzed the efficiency of 110 government-supported R&D projects in Taiwan to investigate the effect of government R&D subsidies on the technology efficiency of R&D projects. Park and Choi [19] analyzed the efficiency of biotechnology and nanotechnology projects supported by the Korean government and found that the average efficiency of nanotechnology was higher than that of biotechnology. However, there have been no studies analyzing changes in efficiency by sub-technology, R&D stage, and R&D player of IT sector.

According to the results of this study, the overall efficiency of IT sectors was the highest at 2.5953 in 2014 compared to 2010, and gradually decreased to 1.2496 in 2018, the lowest efficiency since 2010. As a result of dividing R&D efficiency into EC, which means a change in efficiency due to internal operating factors, and TC, which means a change in efficiency due to external innovation factors, EC was the highest at 1.4729 in 2014 and the second highest at 1.2023 in 2018. The EC for the rest of the year was very insignificant changes compared to 2010. Looking at this in connection with the analysis results of each sub-technology, it can be seen that the “next-generation network-based technology” field corresponding to T2 had a great influence. In particular, among the next-generation network-based technology fields, the EC of projects corresponding to the basic research and the applied research recorded 8.6360 and 8.6708, respectively, compared to 2010, overwhelming EC changes in other fields. This is seen as a result of the Giga Korea project, which the Korean government ambitiously started in 2013. The Giga Korea Project actively supported the development of 5G original technology with the aim of establishing a smart ICT environment where individuals can wirelessly enjoy giga bite-class services by 2020. In other words, the government's active support for the next-generation networks seems to have contributed to the increase in the efficiency of creating related patents and papers. In particular, next-generation network-based technologies require more R&D investment costs than other IT technologies, so they can be said to be areas that require active government support. Meanwhile, TC was the highest at 2.1223 in 2016, and the lowest at 1.0107 in 2018. This seems to be due to the fact that the TC in the “core parts” sector corresponding to T1 and the “information processing system and software” sector corresponding to T3 recorded the highest figures in 2016 of 2.4362 and 2.1409. In particular, in the T1 field, the TC of projects corresponding to the basic research and the applied research was 3.2006 and 2.9133, which was higher than that of other fields. This seems to reflect the results of the government and the private sector's partnership in policies to strengthen the competitiveness of system semiconductors, which are relatively inferior to memory semiconductors, and create an organic ecosystem. In addition, in light of the fact that T1's TC was always higher than other technology fields from 2011 to 2018, it seems that Korea has more competitiveness in hardware than in software fields.

Looking at the changes in efficiency by R&D stages, the basic research, the applied research, and the development research all showed the highest efficiency in 2014. In particular, the efficiency of projects in the applied research was higher than that of other stages over the entire period, and projects in the basic research recorded relatively lower efficiency than other stages. This is seen as a result of reflecting Korea's competitiveness in applied research rather than basic research in the IT R&D field. In addition, since the output is measured by papers and patents, it may be due to the relatively low performance of projects in the basic research and the high performance of projects in the applied research.

Finally, looking at the change in efficiency by R&D players, the efficiency of private enterprises was the highest over the entire period, and the efficiency of public research institutions was the lowest over the entire period. In particular, the efficiency of private enterprises recorded 5.1204 in 2014, overwhelmingly higher than that of public research institutes and universities. The efficiency of private enterprises was highest over the entire period because both EC and TC were measured higher than other players. In other words, private enterprises were operated more efficiently internally than other players, and it seems that they improved efficiency by acquiring external innovation well.

Unlike previous studies, this study is meaningful in that it analyzed the change in efficiency by sub-technology, R&D stage, and R&D player. Existing previous studies have shown only which projects or players had relatively high efficiency, while this study has been able to measure efficiency changes from various perspectives. As a result of analyzing Korea's IT sector R&D efficiency, the following characteristics were found. First, Korea's IT competitiveness has developed around hardware rather than software, and has developed around application and development research rather than basic research. In addition, it has developed around private enterprises rather than universities and public research institutes. Second, short-term efficiency improvement is possible in the case of projects in which large-scale investments are executed among the government's R&D projects. In particular, the role of the government is more important in the case of research fields related to infrastructure at the national level, or research fields in which large-scale research funds are required, such as in the next-generation network field. Third, Korea is more urgent to improve efficiency in the public sector than in the private sector. The R&D efficiencies of universities and public research institutes are relatively very low compared to private enterprises. Even in projects at the basic research stage, their R&D efficiencies were lower than that of private enterprises. This also causes problems in establishing the roles of universities and public research institutes in the national innovation system. According to previous studies on the national innovation system, one of the important roles of universities and public research institutes is to revitalize the local economy by spreading accumulated technology and knowledge to the industry [20]. Hatori [21] argued that universities and public research institutes contribute to innovation and inventions that are difficult for companies to create alone through research and development in various fields. In particular, according to the triple helix model proposed by Leydesdorff and Etzkowitz [22], various innovation achievements can be continuously created only when universities, public research institutes, and companies interact actively. Currently, two of the three pillars are very weak in Korea.

Although this study analyzed changes in the efficiency of R&D projects in the IT sector supported by the Korean government from 2010 to 2018, and drew policy implications to enhance national competitiveness in the era of the 4th industrial revolution and digital transformation, it has the following limitations. First, this study failed to consider the qualitative aspects of papers and patents by using only the quantitative values of papers and patents as outputs. Recently, the qualitative aspect is more important than simply quantitative outputs in R&D performance, but this has not been reflected. Second, since the analysis period was limited to 8 years, long-term efficiency changes could not be considered. Third, since only the Korean government's R&D projects were analyzed, this result cannot be generalized to other countries. In future studies, it is necessary to measure changes in R&D efficiency based on various qualitative indicators and long-term data.

Conflicts of Interest: The authors declare no conflict of interest.

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