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On the Decline of R&D Efficiency*

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Abstract

Following Bloom et al. (2019), we measure R&D efficiency at the industry level with a simple knowledge production function. We use not only the latest version of the Japan Industrial Productivity (JIP) database but also the EUKLEMS database. We find that R&D efficiency measured directly remains positive in the Japanese manufacturing sector, as would be expected under a simple endogenous growth theory. When we divide the period for estimation into two decades, we find that the direct measure of R&D efficiency declined in the second decade in many advanced countries. In particular, there is significant decline of R&D efficiency in the Japanese information service industry. However, we are not able to confirm the decline of R&D efficiency in the Japanese manufacturing sector in the econometric studies. From these results, there are two implications. First, the decline of R&D efficiency means decreasing returns with differences in scale in a knowledge production function. Second, the R&D policies that focus on the scale of R&D are insufficient. The government should implement R&D policies that address the decline and R&D efficiency differences between industries.

Keywords: R&D efficiency, Endogenous growth theory, Idea production function, JIP database, EUKLEMS database
JEL classification: O31, O33, O47

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1. Introduction

Most empirical studies in economics show that investment in Research and Development contributes positively to productivity improvement. Based on these studies, every country has tried to increase its R&D budget and made policies to provide incentives for R&D in the private sector. However, doubts are casted on the effects of R&D investment on productivity growth in the secular stagnation. For example, Japan has kept the R&D expenditures/GDP ratio at around 3%. Although this ratio is higher than that in the high growth era, productivity growth after the 1990s has been lower than then.

There are three approaches to understand the declining effects of R&D on productivity or economic growth. The first approach is based on studies developed by Griliches (1998). In his model, R&D stock (R_t) is related to the Solow residual (A_t) as follows:

$$A_t = R_t^{\mu}. \quad (1)$$

In this approach, the rate of return on R&D ($\pi_t^R = \frac{\Delta Y_t}{\Delta R_t}$) is measured by the regression of productivity growth ($\frac{\dot{A}_t}{A_t}$) on the R&D intensity ($\frac{\Delta R_t}{Y_t}$). Y_t is output. At the aggregate level, it seems that the rate of return on R&D becomes lower, because productivity growth has been lower, under the constant R&D intensity. As R&D efficiency (μ) is expressed as $\frac{\Delta Y_t}{\Delta R_t}\frac{R_t}{Y_t}$, the decline in the rate of return of R&D suggests a decline in the R&D efficiency. However, there are discussions challenging the above empirical studies. Using firm-level data, Motohashi (2008) showed the rate of return of R&D is constant at the firm-level, although it has decreased at the aggregate level. Using the firm-level data in the Census of Manufacturers, Ikeuchi et al. (2013) also pointed out that the overseas movement in R&D facilities causes the decline in R&D efficiency at the aggregate level, although the remaining R&D facilities keep the R&D efficiency constant.

In the second approach, the R&D efficiency is defined as the ratio of profits to R&D expenditures. From financial statements of Japanese companies, Sakakibara and Tsujimoto (2004) measured R&D efficiency as the ratio of the five-year sum of operational profits to the five-year sum of R&D expenditures, and showed its decline. Following their measure, Nihon Keizai Shimbun reported the recent decline in R&D efficiency.[1]

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[1] See the reports of Nihon Keizai Shimbun on February 26, 2018.

The last approach is based on a standard endogenous growth model. The key factor of the simple endogenous growth model is a knowledge production function (or an idea production function) which is expressed as follows:

$$\text{productivity growth } \left(\frac{\dot{A}_t}{A_t}\right) = \text{R\&D efficiency } (\gamma) * \text{number of researchers } (L_t^R) \quad (2)$$

As in Equation (1), R&D efficiency in the third approach has also declined at the aggregate level. However, a standard endogenous growth theory assumes constant R&D efficiency, that is, an increasing number of researchers (or increasing R&D expenditures) and stationary or decreasing productivity growth is not consistent with a standard endogenous growth theory.

Several studies have attempted to solve this puzzle.

At the theoretical level, Jones (1995) revised the standard endogenous growth model assuming a knowledge production function with decreasing return to knowledge. In his model, it was possible for productivity growth to be less than the growth in R&D expenditures. In the empirical studies, Ha and Howitt (2007) examined which endogenous model was consistent with the long-run trends of productivity growth and R&D expenditures. Using long-term data of productivity and R&D expenditures in the US, they concluded that the knowledge production function considering product proliferation was consistent with the data. Ngai and Samaniego (2011) focused on the industry differences in productivity growth and R&D intensity. They found that the relationship between productivity growth and R&D intensity depends on the parameters of the knowledge production function such as the capital intensity of R&D, knowledge spillovers, and diminishing returns to R&D.

As in Motohashi (2008) and Ikeuchi et al. (2013), Bloom, Jones, Van Reenen, and Webb (2019) examined whether R&D efficiency is constant in the specific innovation cases such as semiconductors, agricultural innovation, and technological progress in new molecular entities. In all cases, they discovered there was a decline in research efficiency. Using firm-level data from Compustat and Census of Manufacturers, they also obtained similar results.

Our paper also focuses on the decline in R&D efficiency, following the last approach. Although we use industry-level data like Ngai and Samaniego (2011), we measure R&D efficiency following Bloom et al. (2019). Using the industry-level data has two advantages. One is that we are able to check the differences in R&D efficiency by industry as in Ngai and Samaniego (2011). The other is that we are able to compare R&D efficiency in Japan with those in other advanced countries using KLEMS type datasets such as the Japan Industrial Productivity database and the EUKLEMS database. Using both databases, we find that the rate of decline in R&D efficiency in the Japanese manufacturing sector is lower than those in other advanced countries. However, in the case of information services, the rate of decline in R&D efficiency in Japan is the highest among advanced countries.

In the next section, we show the theoretical background of R&D efficiency, following Bloom et al. (2019). We take two approaches to the measurement. The first approach shown in the third section is a direct measure of R&D efficiency based on Equation (2). In the fourth section, we measure R&D efficiency using an econometric approach. By taking this approach, we are able to find some features that affect R&D efficiency. As Bloom et al. (2019) expected, our estimation results show the possibility that intangibles affect R&D efficiency. Finally, we summarize our findings and state the policy implications.

2. Theoretical background

Bloom et al. (2019) tried to measure γ following Equation (2) in several fields of innovations. However, as Ngai and Samaniego (2011) indicates a knowledge production function includes not only researchers but also facilities used for R&D. Then, Bloom et al. (2019) estimated γ by replacing the number of researchers to R&D expenditures in terms of wages.

Bloom et al. (2019) justified this replacement using a simple endogenous growth model. They define a production function as follows:

$$Y_t = (A_t L_t)^{\theta} (K_t)^{1-\theta}. \quad (3)$$

Rearranging Equation (3), we obtain

$$Y_t = \left(\frac{K_t}{Y_t}\right)^{\frac{1-\theta}{\theta}} A_t L_t. \quad (4)$$

A simple knowledge production function is

$$\dot{A}_t = \gamma E_t. \quad (5)$$

From Equations (4), (5) and the definition of gross R&D expenditure ($E_t = s_t Y_t$) , we obtain

$$\frac{\dot{A}_t}{A_t} = \gamma \left(\frac{K_t}{Y_t}\right)^{\frac{1-\theta}{\theta}} s_t L_t. \quad (6)$$

From the condition of optimal labor input based on Equation (3),

$$\theta = w_t \frac{L_t}{Y_t}. \quad (7)$$

Equation (7) and the definition of R&D expenditure lead to

$$\frac{E_t}{w_t} = \frac{s_t L_t}{\theta}. \quad (8)$$

Substituting Equation (8) into Equation (6), we obtain

$$\frac{\dot{A}_t}{A_t} = \gamma \left(\frac{K_t}{Y_t}\right)^{\frac{1-\theta}{\theta}} \theta \frac{E_t}{w_t}. \quad (9)$$

When we define

$$\hat{\gamma} = \gamma \left(\frac{K_t}{Y_t}\right)^{\frac{1-\theta}{\theta}} \theta. \quad (10)$$

Equation (9) is expressed as follows:

$$\frac{\dot{A}_t}{A_t} = \hat{\gamma} \frac{E_t}{w_t}. \quad (11)$$

Bloom et al. (2019) argued that R&D expenditures deflated by wage (E/w) could be interpreted as "effective scientists" and proposed that they are able to use this term as a proxy for the number of scientists in Equation (2). Although $\hat{\gamma}$ depends on (K/Y), (K/Y) is constant along a balanced growth path. Then, the movement in $\hat{\gamma}$ is similar to that in γ.

3. The data and the overview of productivity growth and effective R&D

Bloom et al. (2019) examined whether R&D efficiency has declined, focusing on three specific innovation cases such as semiconductors, agricultural innovation, and technological progress in drags. As R&D efficiency is likely to be constant at the specific technology level or firm level, we would have been more successful focusing on specific technologies or use firm level data. However, the movement in productivity at the firm level is not stable. Although an endogenous growth theory assumes positive R&D efficiency in a knowledge production function, there are many firms that suffer from negative productivity growth in the long run. Even though we find negative productivity growth in a few industries, most industries show stable productivity growth. In addition, using industry level data, we examine the relationship between productivity difference and the difference in effective R&D expenditures as in Ngai and Samaniego (2011).

For Japanese industry data, we use the latest version of Japan Industrial Productivity database (JIP2018). This database covers productivity, output, intermediate input, value added, labor input, and capital input in 100 industries. We obtain the data on productivity, R&D investment, and average wage (=labor compensation/labor hours) by industry from this database. We also use the EUKLEMS database released in 2017 to conduct an international comparison in R&D efficiency.[2] Like the JIP database, EUKLEMS provides data on productivity, value added, labor input, and capital input by industry in the US and the advanced countries in Europe. As the JIP2018 and EUKLEMS databases cover data from the late 1990s to 2015, we are able to compare the change in R&D efficiency among advanced countries. We summarize the variables used for the measurement of R&D efficiency in the Appendix.

Before going into the measurement of R&D efficiency, we provide an overview of the relationship between productivity growth and effective R&D (=R&D expenditures deflated by wage) using JIP2018. Although JIP2018 covers 54 manufacturing industries, we aggregate these industries into 11 sectors to follow the EUKLEMS industry classifications. As for TFP growth in each sector, we construct the value-added based TFP growth from output based TFP growth in the original industry in the JIP database using the Domar weight.

Figure 1-1 plots the TFP growth rate and the effective R&D. The straight line shows the fitted lines using all samples in the period from 1996 to 2015. We divide the data for two decades into two periods: from 1996 to 2005 and from 2006 to 2015. The dashed line shows the relationship in the first period and the dotted line shows the relationship in the second period. We find a positive relationship between productivity growth and the effective R&D, which partly supports a knowledge production function. The slope shows the degree of R&D efficiency. The slope in the second period seems to be little steeper than that in the first period. However, as shown in Figure 1-2 when we replace the gross effective R&D with the net effective R&D, the slope in the first period is steeper than that in the second period. In Figure 1-3, we replace TFP growth with labor productivity growth and use effective gross R&D. In this

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[2] For the latest version of EUKLEMS database, see Jäger (2017).

case, the result is similar to that in Figure 1-1. As the relationship between labor productivity growth and net effective R&D is similar to that in Figure 1-2, the additional R&D efficiency may decline.

(Place Figure 1 around here)

4. The measurement of R&D efficiency: The first approach

As for the decline in R&D efficiency, the results in the overview using JIP2018 are mixed. So, we take two approaches to measure R&D efficiency empirically. The first approach is a direct measurement of R&D efficiency. In this approach, using Equation (11), we measure $\hat{\gamma}$ directly from the data on productivity and R&D expenditures deflated by wage. In the first approach, we examine the change in R&D efficiency by industry. In addition, we compare R&D efficiency between Japan and other advanced countries by using the JIP2018 and EUKLEMS databases. In the second approach, we estimate $\hat{\gamma}$ based on Equation (11). The advantage of this approach is that we are able to check whether the change in R&D efficiency is significant or not.

4-1 The direct measurement of R&D efficiency in Japan

Using the data on productivity growth and effective R&D in JIP2018, we measure R&D efficiency in the manufacturing sector directly. We find that R&D efficiency is positive in the overall manufacturing sector. At the individual industry sectors, R&D efficiencies are generally positive. However, negative R&D efficiencies are found in a few industries such as textile and wood and paper products industries. The negative R&D efficiency is caused by negative TFP growth in the long run.

As in Figure 1, we divide the sample period into two periods: the first period is from 1996 to 2005 and the second period is from 2006 to 2015. However, in the second period, we find significant negative TFP growth in 2009 in many manufacturing industries, due to the global financial crisis. So, we treat the TFP growth rate in 2009 as an outlier and exclude it from the sample in the second period.

Table 1-1 shows the changes in R&D efficiency. As the measurement of R&D efficiency depends on types of productivity and effective R&D, we choose three types of combinations of productivity and effective R&D in the measurement of the R&D efficiency following Figure 1: TFP growth and effective gross R&D, TFP growth and net effective R&D,

and labor productivity growth and gross effective R&D.[34] The figures in the left side in each column express the ratios of the R&D efficiency in the second period to that in the first period. In the right side, we show the annual growth rate in the R&D efficiency.

We find that the R&D efficiency measured from TFP growth and the effective gross R&D in the second period is greater that in the first period in all industries except basic metals and fabricated metal products, except machinery and equipment industry. In the case of the second combination of TFP growth and net effective R&D, the variance of change in the R&D efficiency is larger than that in the first column. In basic metals and fabricated metal products, except machinery and equipment industry, we do not show the ratio of R&D efficiency because they become negative due to the decline in the R&D stock. In the case of the third combination, the R&D efficiency in the second period has declined compared to the first period in the overall manufacturing sector, although we obtain opposite results in the specific industries of chemical, electric machinery and general machinery industries. The difference in TFP growth and labor productivity growth is the movement in the capital labor ratio. The lower capital accumulation in the second period compared to the first period leads to low R&D efficiency in the second period in the third case.

In Table 1-1, we measure $\hat{\gamma}$ in Equation (11). However, from Equation (10), $\hat{\gamma}$ depends on (K/Y). Although we assume (K/Y) is constant, it is likely to change in the long run. So, we show γ taking account of change in (K/Y) in Table 1-2. The results of γ are similar to those in $\hat{\gamma}$.

(Place Table 1 around here)

4.2 International comparison

The Japan Industrial Productivity database is a KLEMS type database like the EUKLEMS database. Thus, we compare the movements in R&D efficiency among advanced countries. As in shown in Table 1, we divide the sample period (from 1996 to 2015) into two periods (from 1996 to 2005 and from 2006 to 2015). However, the starting years for Germany, the UK, and the US differ from Japan and France. The starting years of Germany, the UK and the US are 1997, 1999, 2000. As we focus on the overall manufacturing sector and information service, we do not recognize the data on 2009 as an outlier.

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[3] When we examine the relationship between TFP growth and net R&D expenditures, we replace gross R&D expenditures to net R&D expenditures in a knowledge production function. In this case, we assume the past R&D stock does not depreciate,

[4] When we examine the effects of R&D expenditures on productivity growth, we usually assume that the past R&D expenditures affect the current TFP growth. However, as we examine the long-run relationship between productivity growth and R&D expenditures along the balanced growth path, we do not use lagged R&D expenditures in our analysis.

Table 2 shows that the R&D efficiency has declined from the first period to the second period in the manufacturing sector in all advanced countries, when we measure it using the data on TFP growth rate and effective gross R&D expenditures. Among advanced countries, the rate of decline in R&D efficiency of Japan is the lowest. On the other hand, the rate of decline in the R&D efficiency in the US manufacturing sector is the highest. However, when we measure the R&D efficiency using the data on TFP growth data and net effective R&D expenditures, we find the R&D efficiency in Japan and the US has increased. The results imply that the accumulation in R&D assets has slowed much in the second period. When we measure the R&D efficiency adjusting the movement in the capital output ratio, the rate of decline in the R&D efficiency becomes higher. From Equation (10), when the capital output ratio increases, $\hat{\gamma}$ is larger than γ. The fast rate of decline is due to the increase in the capital output ratio in the second period for the manufacturing sector in the advanced countries except the UK.

In the case of information service, we are not able to find the change in R&D efficiency measured by TFP growth rate and effective gross R&D expenditures, because the TFP growth rate in this industry in the second period is negative. In the other advanced countries except Germany, the R&D efficiency has declined in the second period. However, we are able to estimate the change in R&D efficiency measured by TFP growth and effective net R&D expenditures, because both factors in the R&D efficiency are negative. We find that the rate of decline in the R&D efficiency in Japan has slowed much in the second period. When we measure the R&D efficiency adjusting the movement in capital output ratio, it has increased in Germany, the UK, and the US. These results imply that the R&D efficiency in the Japanese information service industry has declined quickly in the recent decade compared to other advanced countries.

(Place Table 2 around here)

4-3 **R&D efficiency using patent data**

As seen in Sections 4-1 and 4-2, the TFP growth rate in some industries is negative, even if we take the long-term data. So, as an alternative approach, we measure the R&D efficiency replacing TFP growth to patent growth rate (= patent applications divided by the stock of patents). These patent data are from the Institute of Intellectual Property Patent Database and aggregated by SNA-based industry classification.

Table 3 shows the ratios of R&D efficiency in the second period to those in the first period by industry. As the patent data includes the data in 2009, the ratio in the R&D efficiency in the manufacturing sector as a whole is negative. The rate of decline using patent data is faster than using TFP growth data. The R&D efficiencies in all manufacturing industries except the textile industry have declined in the second period. Particularly, rates of decline in the R&D

efficiency are higher than those in other industries.

(Place Table 3 around here)

5. The measurement of R&D efficiency: The second approach

In section 4, we examine whether the R&D efficiency has declined in the second period compared to the R&D efficiency in the first period. Although we do not find the decline in R&D efficiency when we exclude the data in 2009, most of the measurements in R&D efficiency show its decline. However, we do not find significant differences in the R&D efficiency between the first and second periods.

Therefore, we examine the change in the R&D efficiency econometrically. Based on Equation (11), we estimate the following equations.

$$\frac{\dot{A_{it}}}{A_{it}} = \text{const.} + \gamma_1 \left(\frac{E_{it}}{w_{it}}\right) + \gamma_2 D_2 \left(\frac{E_{it}}{w_{it}}\right) + year + D_i + \varepsilon_{it}, \qquad (12\text{-}1)$$

$$\frac{\dot{A_{it}}}{A_{it}} = \text{const.} + \gamma_1 \left(\frac{E_{it}}{w_{it}}\right) + \gamma_2 D_2 \left(\frac{E_{it}}{w_{it}}\right) + \gamma_3 \left(\frac{E_{it}}{w_{it}}\right)(ICT_{it}) + year + D_i + \varepsilon_{it}. \qquad (12\text{-}2)$$

In Equations (12-1), (12-2), γ_1 shows the R&D efficiency and γ_2 is the change in the R&D efficiency in the second period. D_2 is a dummy for the second period and ICT_{it} is ICT investment. We make two types of ICT investment. One is the real ICT investment deflated by ICT investment price, and the other is ICT investment deflated by wage like effective R&D expenditures. The data source is the JIP2018 database. In our estimation, we use the industry level data at the original classifications. Estimation methods are OLS with industry and year dummies and fixed effects estimations with year dummy.

Table 4-1 show the estimation results when we use the data on the TFP growth rate and effective gross R&D. All R&D efficiencies are positive and significant. The dummies in the second period are negative. We find that the sum of $\gamma_1 + \gamma_2$ is always positive and significant. γ_3 is negative and significant in all estimations, which means that ICT investment does not contribute to the improvement in R&D efficiency.

In Table 4-2, we show the estimation results of when we replace TFP growth to labor productivity growth. As labor productivity depends on the capital labor ratio, we include it in the estimation. As in Table 4-1, we find that the R&D efficiency is positive and significant in all columns. We also find that γ_2 is negative and $\gamma_1 + \gamma_2$ is significant, excluding column (3).

From these estimations, we do not find significant evidences of the decline of R&D efficiency in the second period, although we confirm the positive R&D efficiency in the manufacturing sector.

(Place Table 4 around here)

6. Concluding remarks and discussions for future research

Based on a simple knowledge function introduced in Bloom et al. (2019), we measure the industry-level R&D efficiency using KLEMS type databases such as JIP database and EUKLEMS database. We take two types of approaches to the measurement in the R&D efficiency. In the first approach where we measure the R&D efficiency directly, we find that the R&D efficiency is positive in the manufacturing sector. This finding supports the theory that a simple knowledge function holds in the long run. Although R&D efficiency has declined in many advanced countries, it does not decline when we exclude 2009 data . In particular, the decline in R&D efficiency in the Japanese information service industry is significant. In the second approach using econometric methods, the results also support the notion that R&D efficiency is positive but we find a significant evidence on its decline..

These results have two implications; one is a theoretical implication and the other is a policy implication. The first implication is that the decline in R&D efficiency is consistent with a knowledge production function with decreasing returns to scale rather than a simple knowledge production function as Ha and Howitt (2007) and Ngai and Samaniego (2011) had pointed out. Ngai and Samaniego (2011) emphasized that a parameter indicating decreasing return to scale affects the industry differences in R&D efficiency.

The second implication is related to R&D policies. Traditional R&D policies implemented by the government focus on the scale of R&D expenditures, assuming R&D efficiency is constant. However, our results imply that the government should account for movements and industry differences in R&D efficiency to improve productivity.

We also measure R&D efficiency at the firm level for future research. As there are many data pointing to negative productivity growth, Bloom et al. (2019) use sales revenue, market capitalization, employment, revenue labor productivity data instead of TFP data measuring the R&D efficiency at the firm level. Ha and Howitt (2007) argued that a knowledge production function with product variety explains the long run trends of R&D and productivity. If we obtain product level data used in Kawakami and Miyagawa (2013) and Miyagawa, Edamura, and Kawakami (2017), we should be able to understand R&D efficiency using a more sophisticated knowledge production model.

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Table 1-1 R&D Efficiency in the Japanese manufacturing sector

	TFP growth and effective gross R&D		TFP growth and effective net R&D		Labor productivity growth and effective net R&D	
	Change in R&D efficiency	Annual change in R&D efficiency	Change in R&D efficiency	Annual change in R&D efficiency	Change in R&D efficiency	Annual change in R&D efficiency
TOTAL MANUFACTURING	**1.41**	**3.53%**	**2.30**	**8.68%**	**1.21**	**1.91%**
Chemicals and chemical products	**2.97**	**11.50%**	**0.60**	**-4.92%**	**0.42**	**-8.27%**
Rubber and plastics products, and other non-metallic mineral products	**1.37**	**3.21%**	**0.15**	**-17.41%**	**0.08**	**-22.77%**
Basic metals and fabricated metal products, except machinery and equipment	**0.61**	**-4.86%**	**NA**	**NA**	**NA**	**NA**
Electrical and optical equipment	**1.57**	**4.61%**	**314.95**	**77.76%**	**273.91**	**75.29%**
Machinery and equipment n.e.c.	**2.71**	**10.47%**	**3.95**	**14.72%**	**1.63**	**5.01%**
Transportation equipment	**0.88**	**-1.28%**	**0.82**	**-1.93%**	**0.45**	**-7.58%**

*** In the second period, we exclude the values in 2009 due to the large negative productivity growth caused by the global financial crisis.**

Table 1-2 R&D Efficiency adjusted by capital output ratio in the Japanese manufacturing sector

	TFP growth and effective gross R&D		TFP growth and effective net R&D		Labor productivity growth and effective net R&D	
	R&D efficiency	Annual change in R&D efficiency	R&D efficiency	Annual change in R&D efficiency	R&D efficiency	Annual change in R&D efficiency
TOTAL MANUFACTURING	**1.48**	**4.01%**	**2.41**	**9.18%**	**1.27**	**2.38%**
Chemicals and chemical products	**3.29**	**12.65%**	**0.67**	**-3.94%**	**0.47**	**-7.32%**
Rubber and plastics products, and other non-metallic mineral products	**1.47**	**3.93%**	**0.16**	**-16.84%**	**0.08**	**-22.23%**
Basic metals and fabricated metal products, except machinery and equipment	**0.49**	**-6.94%**	**NA**	**NA**	**NA**	**NA**
Electrical and optical equipment	**1.39**	**3.37%**	**279.31**	**75.63%**	**242.91**	**73.20%**
Machinery and equipment n.e.c.	**3.03**	**11.73%**	**4.43**	**16.04%**	**1.83**	**6.21%**
Transport equipment	**0.73**	**-3.07%**	**0.69**	**-3.71%**	**0.38**	**-9.26%**

*** In the second period, we exclude the values in 2009 due to the large negative productivity growth caused by the global financial crisis.**

Table 2 International comparison in R&D Efficiency

Manufacturing	TFP growth and effective gross R&D		TFP growth and effective net R&D		Adjusted R&D efficiency using Equation (10)	
	R&D efficiency	Annual change in R&D efficiency	R&D efficiency	Annual change in R&D efficiency	R&D efficiency	Annual change in R&D efficiency
Japan	0.65	-4.20%	1.01	0.86%	0.54	-5.17%
France	0.23	-13.66%	0.16	-16.81%	0.21	-14.43%
Germany	0.50	-6.67%	0.77	-2.52%	0.36	-9.69%
UK	0.44	-7.81%	NA	NA	0.49	-6.81%
US	0.06	-24.96%	1.23	2.13%	0.06	-25.17%

Information service	TFP growth and effective gross R&D		TFP growth and effective net R&D		Adjusted R&D efficiency using Equation (10)	
	R&D efficiency	Annual change in R&D efficiency	R&D efficiency	Annual change in R&D efficiency	R&D efficiency	Annual change in R&D efficiency
Japan	NA	NA	0.53	-6.22%	NA	NA
France	0.31	-10.91%	0.14	-18.08%	0.43	-8.06%
Germany	3.80	14.29%	4.82	17.04%	3.12	12.04%
UK	0.25	-12.85%	0.74	-2.97%	1.01	0.08%
US	0.22	-13.88%	13.82	30.03%	1.30	2.68%

Table 3 R&D Efficiency using patent data

	Change in R&D efficiency	Annual change in R&D efficiency
TOTAL MANUFACTURING	**0.56**	**-5.64%**
Food products, beverages and tobacco	**0.74**	**-2.98%**
Textile	**1.03**	**0.33%**
Paper and Pulp	**0.49**	**-6.85%**
Chemicals and chemical products	**0.58**	**-5.32%**
Coke and refined petroleum products	**1.44**	**3.73%**
Ceramic, stone and clay products	**0.76**	**-2.75%**
Primary metal	**0.72**	**-3.20%**
Fabricated metal products	**0.57**	**-5.48%**
General purpose, production and business-oriented machinery	**0.40**	**-8.70%**
Electronic parts, devices and electronic circuits	**0.55**	**-5.87%**
Electrical machinery, equipment and supplies	**0.81**	**-2.05%**
Information and communication electronics equipment	**0.63**	**-4.46%**
Transportation equipment	**0.47**	**-7.25%**
Other manufacturing	**0.40**	**-8.79%**

Businessoriented → business-oriented

machinary → machinery

Informantion → Information

Table 4-1 Estimated R&D Efficiency (Dependent variable: TFP growth)

	[1]	[2]	[3]	[4]	[5]	[6]
[A] RD/W	**0.0201** ***	**0.0201** ***	**0.0660** **	**0.0660** ***	**0.0592** *	**0.0592** **
	(0.0056)	(0.0047)	(0.0286)	(0.0233)	(0.0309)	(0.0258)
[A.1] 2006-2015	**-0.0074**	**-0.0074**	**-0.0014**	**-0.0014**	**-0.0041**	**-0.0041**
	(0.0087)	(0.0055)	(0.0084)	(0.0084)	(0.0087)	(0.0076)
[C] RD/W × ICT			**-0.0514** *	**-0.0514** **		
			(0.0289)	(0.0256)		
[C'] RD/W × ICT/W					**-0.0406**	**-0.0406**
					(0.0300)	(0.0279)
Constant	**-0.0031**	**0.0004**	**-0.0327**	**-0.0216**	**-0.0267**	**-0.0167**
	(0.0264)	(0.0140)	(0.0321)	(0.0190)	(0.0320)	(0.0196)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	No	Yes	No	Yes	No
Fixed Effect	No	Yes	No	Yes	No	Yes
R^2	0.1584		0.1614		0.1606	
R^2 (within)		0.1120		0.1151		0.1143
R^2 (between)		0.0900		0.1999		0.2393
R^2 (overall)		0.0908		0.0836		0.0836
Obs.	1,080	1,080	1,080	1,080	1,080	1,080
t test p-value						
[A] + [A1] = 0	0.0700	0.0053	0.0314	0.0403	0.0885	0.0958
[A] + [C] = 0			0.0036	0.0026	0.0004	0.0003

(Note) (a) Robust standard errors in parentheses.

Table 4-1 Estimated R&D Efficiency (Dependent variable: labor productivity growth)

	[1]	[2]	[3]	[4]	[5]	[6]
[A] RD/W	**0.0232** ***	**0.0232** ***	**0.0499** *	**0.0499** ***	**0.0539** *	**0.0539** ***
	(0.0055)	(0.0040)	(0.0296)	(0.0177)	(0.0286)	(0.0181)
[A.1] 2006-2015	**-0.0047**	**-0.0047**	**-0.0013**	**-0.0013**	**-0.0022**	**-0.0022**
	(0.0086)	(0.0059)	(0.0081)	(0.0075)	(0.0084)	(0.0072)
[C] RD/W × ICT			**-0.0299**	**-0.0299**		
			(0.0297)	(0.0199)		
[C'] RD/W × ICT/W					**-0.0318**	**-0.0318**
					(0.0269)	(0.0199)
K/L	**-0.0093**	**-0.0093**	**-0.0128**	**-0.0128**	**-0.0136**	**-0.0136**
	(0.0516)	(0.0808)	(0.0512)	(0.0786)	(0.0512)	(0.0780)
Constant	**0.0083**	**0.0160**	**-0.0064**	**0.0059**	**-0.0072**	**-0.0047**
	(0.0444)	(0.0597)	(0.0480)	(0.0597)	(0.0476)	(0.0615)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	No	Yes	No	Yes	No
Fixed Effect	No	Yes	No	Yes	No	Yes
R^2	0.1539		0.1549		0.1553	
R^2 (within)		0.0903		0.0915		0.0919
R^2 (between)		0.0907		0.1303		0.1568
R^2 (overall)		0.0621		0.0582		0.0576
Obs.	1,078	1,078	1,078	1,078	1,078	1,078
t test p-value						
[A] + [A1] = 0	0.0126	0.0000	0.1112	0.0355	0.0752	0.0320
[A] + [C] = 0			0.0000	0.0000	0.0000	0.0000

(Note) (a) Robust standard errors in parentheses.

Figure 1-1 TFP growth and Effective Gross R&D

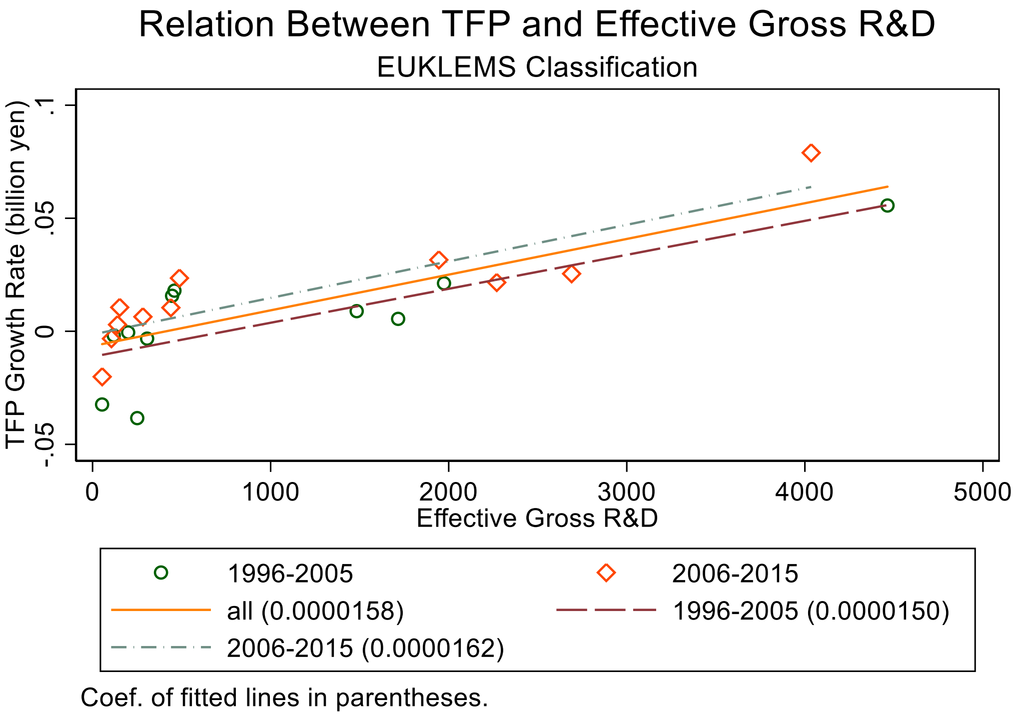

Figure 1-2 TFP Growth and Effective Net R&D

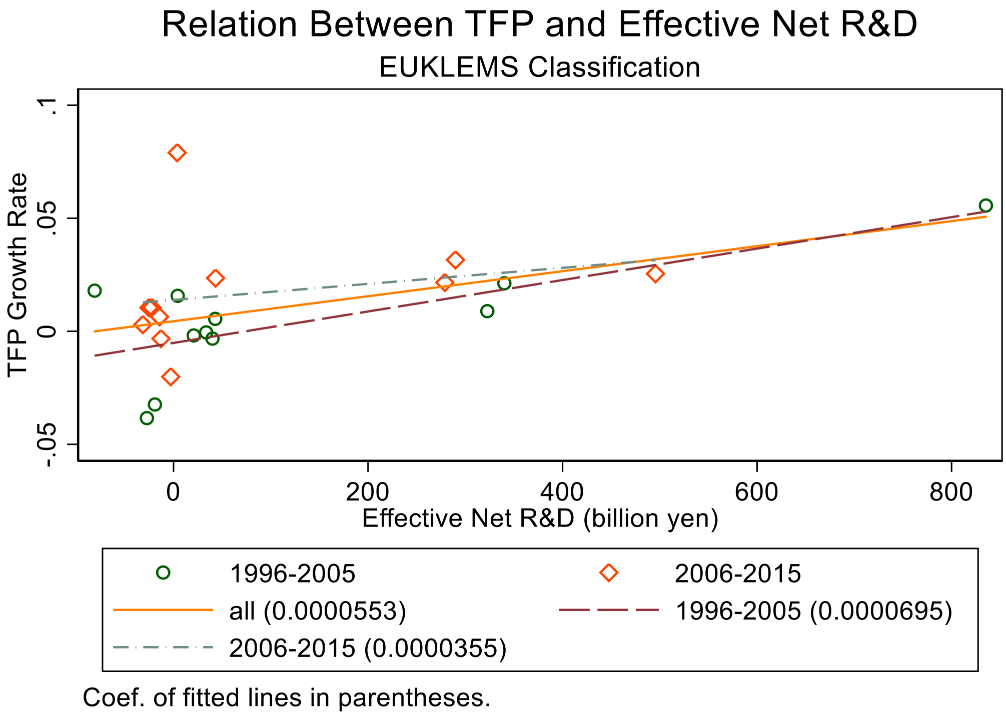

Figure 1-3 Labor Productivity Growth and Effective Gross R&D