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Estimation of Productivity in the Korean Electricity Generation Sector: A Semi-Parametric Approach

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Abstract

This study estimated the level and growth of total factor productivity in the Korean electricity generation sector using plant-level panel data from over the period 2002-2019. In particular, we compared the productivity differences across different plant types. This study used a semiparametric estimation method that enables the control for the endogeneity of productivity shocks without using instrumental variables (IVs). It was found that steam power plants presented the highest total factor productivity, followed by internal combustion and combined cycle. The productivity growth fluctuated over time, ranging from -0.285% to 0.203%, and presented a declining trend during the sample period. The results also indicated that the load and plant factors significantly affected the total factor productivity of the plants. However, the age variable that may reflect the learning-by-doing effect did not affect plant productivity.

KRF Classification : B030902, B030904

Keywords : total factor productivity, Korean electricity generation sector, semiparametric method

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Ⅰ. Introduction

A range of indicators can be used to determine the productivity performance of a firm or industry. Utilities, such as electricity supply, often operate in markets that lack prices and costs determined under competitive conditions. In this case, the usual market indicators of performance, such as profitability and rate of return, cannot be used to accurately gauge a firm or industry's performance. It is possible that these financial indicators might reflect the distortions themselves rather than the performance of the firms or industry in question. In these circumstances, indicators of the level and change in productivity would be more appropriate performance indicators (Abbot, 2005).

One method of determining the level of productivity is to estimate the total factor productivity (TFP), which is the ratio of the total aggregate output quantity index to the aggregate input quantity index. TFP growth, therefore, is the difference between the growth of output and input quantity indices. There are two different ways to measure TFP: the frontier and non-frontier approaches. Under the non-frontier approach, it is assumed that firms are technically efficient, whereas in the frontier approach, the role of technical efficiency in overall firm performance is identified (Mahadevan, 2003). Within the frontier method, two main categories can be distinguished: stochastic frontier analysis (SFA) and data envelopment analysis (DEA). SFA relates to the average or central tendency behavior of firms, whereas DEA relates to the best performance and deviation of all performances from the frontier line (Cooper et al., 2007).

Growth accounting is a non-frontier approach that measures the growth of output, which is explained by the growth of different inputs such as labor, capital, and intermediate inputs, and by unaccounted or explained growth that represents productivity growth. Theories on growth accounting methods and applications have evolved over time, with key influential studies by Abramovitz (1956), Solow (1957), Kendrick (1961), Jorgenson and Griliches (1967), and Jorgenson et al. (1987).[1)]

This study estimated the productivity level and growth in the electricity generation sector in Korea. In the previous literature, to the best of our knowledge, there have been no studies that estimate TFP for the market. Hwang and Lee (2013) divided profit change into changes in facility growth, capital productivity, and input and output prices, and compared the sources of profit changes before and after the market reform in April 2001. Park and Lesourd (2000) estimated the efficiencies of 64 conventional fuel power plants in Korea using DEA. Heshmati (2013) estimated the productivity efficiency of the Korean electricity generation sector using a stochastic frontier model and Malmquist productivity index. The study indicates that productivity efficiency is affected by the facility type, maintenance costs, and real fuel costs. It also suggests that productivity efficiency was not affected by the restructuring of market reform in 2001.

This study adopted a different approach and used a semiparametric estimation method (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). An advantage of this approach is that we can control for the endogeneity of productivity shocks without using instrumental variables (IVs). This study used plant-level unbalanced panel data from 2002 to 2019 to estimate the level and growth of TFP. In particular, it compared productivity across different plant types—namely, steam power, combined cycle, and internal combustion—and analyzed the determinants of productivity. The remainder of this paper is organized as follows. Section II provides an overview of the Korean electricity generation sector. Section III

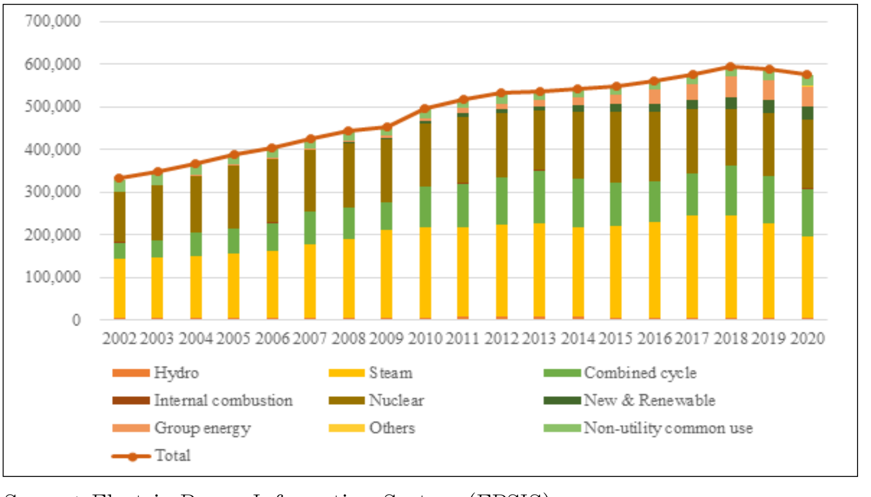
1) The first attempt to derive productivity change measurements for the electricity industry was undertaken by Kendrick (1961) as part of his work on productivity trends of the United States as a whole. He further refined it in subsequent work (1973, 1982; Kendrick and Grossman, 1980).

explains the model specifications and data. Section IV presents the empirical results, and Section V concludes the paper.

Ⅱ. An Overview of Korean Electricity Generation Sector

As of 2020, the total electricity generated was 575,269 gigawatt hours (GWh). Power generation peaked at 592,905 GWh in 2018 and declined thereafter. The major sources of power generation include steam, nuclear, combined cycle, and hydro, followed by group energy, new and renewable, hydro, and internal combustion.

〈Figure 1〉 Trends in electricity power generation (GWh)



Source: Electric Power Information System (EPSIS).
Note: Non-utility in common use is self-consumption. Others include by-product gas and waste heat.

In the Korean electricity market, the Korea Electric Power Company (KEPCO) and its subsidiaries represented 71.5% of power generation. Among the subsidiaries, Korea Hydro & Nuclear Power Co. (KHNP) had the largest share at 29.8%, followed by Korea South–East Power

(KOSEP), Korea Midland Power (KOMIPO), Korea East–West Power (KEWESPO), Korea Southern Power (KOSPO), and Korea Western Power (KOWEPO). The others were independent power producers (Table 1).

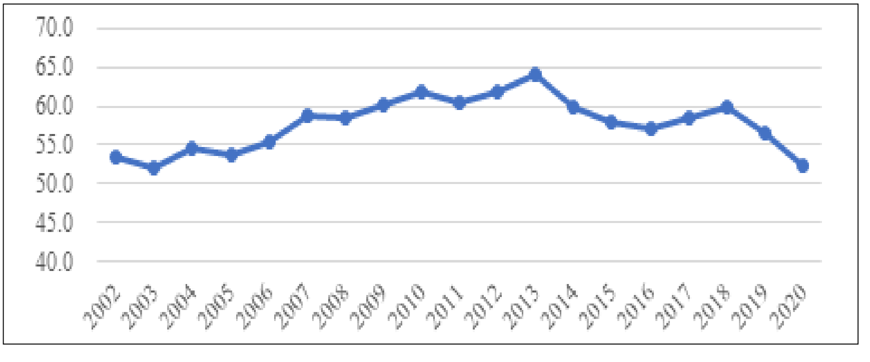
〈Table 1〉 Power generation by companies (MWh in 2020)

Company	Power Generated	Share (%)
KOSEP	51,775,424	9.4
KOMIPO	48,881,673	8.9
KOWEPO	39,974,937	7.2
KOSPO	43,429,459	7.9
KEWESPO	45,566,130	8.3
KHNP	164,610,133	29.8
KEPCO	284,490	0.1
KEPCO and subsidiaries	394,522,245	71.5
Others	157,639,915	28.5
Total generation	552,162,160	100

Source: Electric Power Information System (EPSIS).
Note: Non-utility self- consumption is not included in the total generation.

In total power generation, the share of thermal power plants, which include steam, combined cycle, and internal combustion, increased to 64% in 2013 and remained at more than 50% with a declining trend (Figure 2).

〈Figure 2〉 Share of generation by thermal power plants (%)



Source: Electric Power Information System (EPSIS).

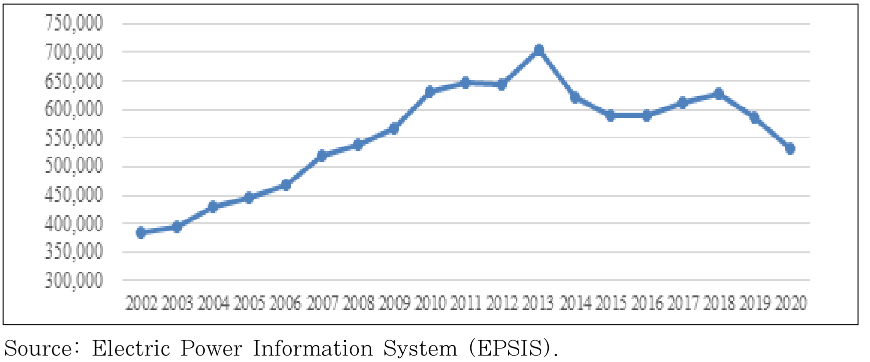
Steam power plants generate steam by burning anthracite coal, bituminous coal, heavy oil, and liquefied natural gas (LNG) and operate steam turbines to generate electricity. Combined-cycle plants produce electricity by using both gas and steam turbines. The heat waste from the gas turbine is routed to the steam turbine to produce extra electricity. They mostly use LNG as a fuel. Internal combustion plants use diesel as the primary fuel source. Table 2 shows the changes in the different types of fuel over time, and Figure 3 presents the trend in aggregated fuel consumption in billion kcal. The total fuel consumption peaked in 2013 and declined thereafter.

〈Table 2〉 Fuel consumption in thermal power plants

Year	Anthracite Coal		Bituminous Coal		Heavy Oil		Diesel Oil		Gas		Total
	1,000 ton	kcal/kg	1,000 ton	kcal/kg	1,000 kℓ	kcal/ℓ	1,000 kℓ	kcal/ℓ	1,000 ton	kcal/kg	Billion kcal
2002	2,751	4,583	40,311	6,127	4,528	9,940	277	9,029	5,983	13,023	385,027
2007	2,392	4,545	55,950	5,871	3,899	9,972	120	8,908	10,829	13,034	520,452
2012	1,797	4,750	78,805	5,057	3,272	9,766	141	8,903	15,321	13,273	643,652
2017	1,079	5,387	89,217	5,479	928	10,003	174	8,993	8,161	13,158	612,870
2018	992	5,265	89,549	5,373	1,013	10,069	215	8,932	9,890	13,096	628,043
2019	1,165	5,179	83,321	5,505	362	9,960	323	8,924	8,891	12,967	586,479
2020	971	5,090	69,094	5,597	283	9,872	169	8,929	10,144	13,335	531,237

Source: Electric Power Information System (EPSIS).
Note: Data from 2002 to 2017 were reported at five-year intervals, while more recent data after 2017 were reported annually. All annual data from 2002 to 2020 can be obtained by requesting it from the author.

〈Figure 3〉 Trends in total fuel consumption (billion kcal)



Source: Electric Power Information System (EPSIS).

Ⅲ. Model Specification and Data

This section explains the model for estimating productivity and the data used in the model estimation.

1. Model specification

Let us assume that a firm's production technology can be represented by the production function $F(\cdot)$, which relates to output (Y), inputs (X), and productivity shocks. In addition, let us assume that firms produce a homogeneous product using a Cobb-Douglas technology as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} . \quad (1)$$

where y_{it} is the log of output, k_{it} is the log of capital, l_{it} is the log of labor input, and m_{it} is the log of intermediate input. Parameters β_k, β_l, and β_m are the coefficients of the variables. The equation has two unobservables: the log of a firm's productivity ω_{it} and a residual ε_{it}, which has standard properties. If firms decide to maximize the present discounted value of current and future profits and optimally choose the level of inputs used in the production process as the solution to the dynamic profit maximization problem, then inputs are likely to be correlated with productivity shocks, ω_{it}. This is because profit-maximizing firms increase their output and use inputs in response to positive productivity shocks. This means that standard estimation methods such as ordinary least squares (OLS) yield inconsistent estimates. The correlation between labor and productivity shocks renders OLS estimates of the equation biased and inconsistent (Marshak and Andrews, 1944). Furthermore, standard approaches to endogeneity, such as the fixed-effects or within-group estimator and

IV method, do not necessarily work (Grilliches and Mairesse, 1995). The fixed-effects estimator may deal with the correlation at the cost of imposing productivity shocks with no time variation. IV methods are limited by the difficulty of finding appropriate instruments, that is, variables that are correlated with the endogenous variable but uncorrelated with the productivity term.

Rather than resorting to standard estimation methods, Olley and Pakes (1996) identified the equation from a dynamic model of firm behavior that allows for idiosyncratic uncertainty and specifies the information available when input decisions are made. This amounts to the assumption that firms decide to maximize the present discounted value of current and future profits in an environment in which productivity is the only unobserved source of firm-specific uncertainty. In particular, it was assumed that ωit follows an exogenous first-order Markov process. Additionally, the solution to the dynamic profit maximization problem generates a demand function if the proxy variable under certain assumptions can be inverted to define a firm's productivity as a function of observables, which is called the control function. To control for the correlation between unobservable productivity shocks and input levels, Olley and Pakes (1996) proposed using a firm's investment as a proxy variable for its productivity and a low-order polynomial to approximate the unknown control function:

$$i_{it} = g_t(k_{it}, \omega_{it}). \tag{2}$$

This equation indicates that investment is a function of the state variable k_{it}, and ω_{it}. Then, assuming that $g_t(k_{it}, \omega_{it})$ is strictly increasing in ω_{it}, we can invert the investment policy function:

$$\omega_{it} = g_t^{-1}(k_{it}, i_{it}). \tag{3}$$

However, when firms face substantial adjustment costs, the investment variable may not be appropriate because it may not fully respond to changes in productivity and may become severely truncated at zero. This led Levinsohn and Petrin (2003) to propose an alternative approach that uses intermediate inputs rather than investments in the control function:

$$m_{it} = \Phi_t(k_{it}, \omega_{it}). \tag{4}$$

Again, under the assumption that $\Phi_t(k_{it}, \omega_{it})$ is strictly increasing in ω_{it}, we get

$$\omega_{it} = \Phi_t^{-1}(k_{it}, m_{it}). \tag{5}$$

By plugging ω_{it} in the production function, we obtain

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \Phi_t^{-1}(k_{it}, m_{it}) + \varepsilon_{it}. \tag{6}$$

Thus, $\omega_{it} = \Phi_t^{-1}(k_{it}, \omega_{it})$ can be used to control for endogeneity. Equations (2) and (4) assume that labor and intermediate inputs are non-dynamic inputs selected simultaneously at t, after the firm has observed ω_{it}. Thus, Equation (6) can be written as follows:

$$y_{it} = \beta_l l_{it} + \Psi_t(k_{it}, m_{it}) + \varepsilon_{it}. \tag{7}$$

where $\Psi_t(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \Phi_t^{-1}(k_{it}, m_{it})$. Let us denote I_t as the firm's information set at t, and assume that the information set includes current and past productivity shocks but does not include future productivity shocks (Ackerberg et al., 2015). Under the assumption that the transitory shocks ε_{it} satisfy $E(\varepsilon_{it} \mid I_{it}) = 0$ and productivity shocks evolve according to the distribution, $p(\omega_{it+1} \mid I_{it}) = p(\omega_{it+1} \mid \omega_{it})$, ω_{it} can be decomposed into its conditional expectation at $t-1$ and an innovation term:

$$\omega_{it} = E[\omega_{it} \mid I_{t-1}] + \vartheta_{it} = E[\omega_{it} \mid \omega_{it-1}] + \vartheta_{it} = \Omega(\omega_{it-1}) + \vartheta_{it}. \quad (8)$$

Given that $E[\vartheta_{it} \mid I_{t-1}] = 0$ and $E[\varepsilon_{it} \mid I_{it}] = 0$, implying that $E[\varepsilon_{it} \mid I_{it-1}] = 0$, the parameter estimates $\widehat{\beta_l}$ and $\widehat{\Psi_t}(k_{it}, m_{it})$ can be obtained from the following moment conditions:

$$E[\varepsilon_{it} \mid I_{it}] = E[y_{it} - \beta_l l_{it} - \Psi_t(k_{it}, m_{it}) \mid I_{it}] = 0. \quad (9)$$

The second moment condition can be used to estimate $\widehat{\beta_0}$, $\widehat{\beta_k}$, and $\widehat{\beta_m}$ from Equation (10):

$$\begin{aligned} E[\vartheta_{it} + \varepsilon_{it} \mid I_{it-1}] = E[&y_{it} - \beta_0 - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it} \\ &- \Omega(\Psi_{t-1}((k_{it-1}, m_{it-1})) - \beta_0 - \beta_k k_{it-1} \\ &- \beta_m m_{it-1} \mid I_{it-1}] = 0. \end{aligned} \quad (10)$$

However, Ackerberg et al. (2015) argued that these estimation strategies may suffer from identification issues. They showed that unless additional assumptions are made about the data-generating processes, the labor input may not vary independently of the nonparametric function estimated using the low-order polynomial; that is, if labor has no dynamic implications and is chosen with full knowledge of ω_{it}, labor demand can be written as $l_{it} = \mu(k_{it}, \omega_{it})$. With this data-generating process, substituting (5) into the equation yields

$$l_{it} = \mu(k_{it}, f_t^{-1}(k_{it}, m_{it})). \quad (11)$$

This implies that labor demand is functionally dependent on k_{it}, m_{it}, and t. If this is the case, the identification condition (9) fails. This suggests that the labor parameter cannot be separately identified from the nonparametric function of $\Psi_t(k_{it}, m_{it})$. To avoid this functional dependence problem, Ackerberg et al. (2015) assumed that firm-specific unobserved adjustment costs for labor input have dynamic effects. This assumption makes the input demand function conditional on the labor demand. Consequently, the labor input parameter cannot be identified in the first stage, and all coefficients are estimated in the second stage. Specifically, the firm's intermediate input is given by

$$m_{it} = \widetilde{\Phi}_t(k_{it}, l_{it}, \omega_{it}). \tag{12}$$

Again, under the assumption that $\widetilde{\Phi}_t(k_{it}, l_{it}, \omega_{it})$ is strictly increasing in ω_{it}, we obtain

$$\omega_{it} = \widetilde{\Phi}_t^{-1}(k_{it}, l_{it}, m_{it}). \tag{13}$$

Plugging Equation (13) into the production function will yield

$$\begin{aligned} y_{it} &= \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \widetilde{\Phi}_t^{-1}(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \\ &= \widetilde{\Psi}_t(k_{it}, l_{it}, m_{it}) + \epsilon_{it}. \end{aligned} \tag{14}$$

Then, the first stage moment condition is

$$E[\epsilon_{it} \mid I_{it}] = E[y_{it} - \widetilde{\Psi}_t(k_{it}, m_{it}) \mid I_{it}] = 0. \tag{15}$$

Note that the labor parameter and intermediate input are not identified in the first stage, unlike in Levinsohn and Petrin (2003). In

Ackerberg et al. (2015), the labor input parameter can be recovered together with other parameters from the second-stage conditional moment:

$$
\begin{aligned}
E[\vartheta_{it} + \epsilon \mid I_{it-1}] = E[&y_{it} - \beta_0 - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it} \\
&- \Omega(\widetilde{\Psi}_{t-1}(k_{it-1}, m_{it-1}) - \beta_0 - \beta_k k_{it-1} - \beta_m m_{it-1} \\
&- \beta_l l_{it-1} \mid I_{it-1}] = 0. \qquad (16)
\end{aligned}
$$

This study used the approach by Ackerberg et al. (2015) to estimate the coefficients of the productivity function (1). Using the estimated coefficient, we recovered individual plants' TFP, $\widehat{\omega_{it}}$, as follows:

$$
\exp(\widehat{\omega_{it}}) = \exp(y_{it} - \widehat{\beta_0} - \widehat{\beta_k} k_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_m} m_{it}). \qquad (17)
$$

2. Data

The data used in this study were extracted from the Electric Power Statistics Information System (EPSIS). They include information on the volume of power generation, generation capacity, and fuel usage. Output was measured by the volume of power generation, capital was estimated by generation capacity, energy input was proxied by fuel usage, and labor was measured by the number of employees. The data were collected from 2002 to 2019. Our data cover thermal power plants that belong to five KEPCO subsidiaries: KOSEP, KOMIPO, KEWESPO, KOSPO and KOWEPO. The power plants of Korea Hydro and Nuclear Power (KHNP) were not included in the analysis, as they use different technology of production, and some variables such as fuel usage are not observed. The data are unbalanced panel data, as some power plants exited the market and stopped generating electricity during the sample period, and the others newly entered the market. There are two types of thermal power plants: steam power plants that use bituminous and anthracite coal and heavy oil as fuel, and combined power plants that use LNG or diesel. Table 3 shows the sample statistics of the variables used in the analysis. The variables are in logarithmic form. Labor represents the number of workers in each plant. The output, Q, is measured by the volume of power generation in megawatts hours (MWh), and capital, K, is measured by the generation capacity in 1000 kw. Fuel, F, is measured in millions of calories. The table indicates that the variable with the largest standard deviation is output, followed by fuel, labor, and capital. Table 4 displays the correlation coefficients among the variables, which reveal that the highest correlation coefficient is between output and fuel, at 0.9. The correlation coefficient remains at 0.64 between output and capital, and at 0.36 between output and labor.

〈Table 3〉 Sample statistics

Variable	Mean	Std. Dev.	Min	Max
ln(L)	5.03	1.15	2.35	8.32
ln(Q)	14.43	1.39	5.24	16.48
ln(K)	12.95	0.69	10.59	14.53
ln(F)	15.22	1.36	6.89	17.12

Note: The sample size is 1,447.

〈Table 4〉 Correlation coefficients

	ln(Q)	ln(L)	ln(K)	ln(F)
ln(Q)	1			
ln(L)	0.36	1		
ln(K)	0.64	0.54	1	
ln(F)	0.93	0.37	0.64	1

Note: The sample size is 1,447.

Ⅳ. Results

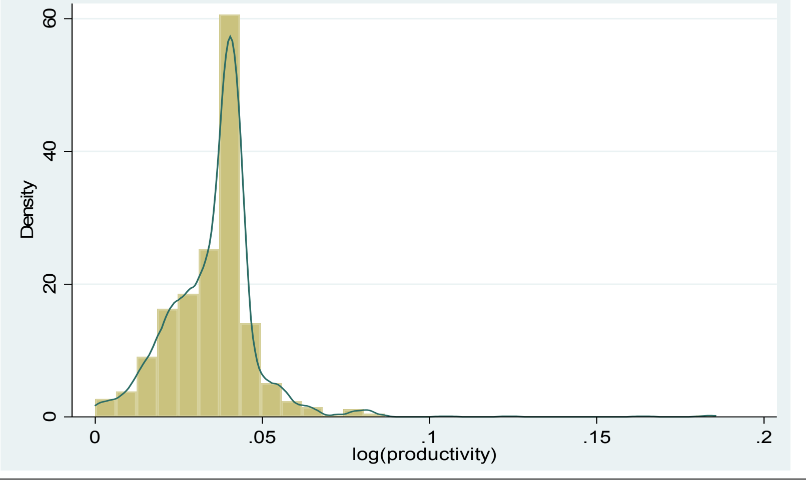
Table 5 presents the estimated coefficients of the production function. The coefficients of labor, capital, and fuel are significant at the 10%, 5%, and 1% levels, respectively. The results also show that the Wald test of constant returns to scale cannot be rejected at the 5% level, but it can be rejected at the 10% significance level.

〈Table 5〉 Estimated coefficient in the production function

Variable	Coefficients	Standard Error	T-value
ln(L)	0.017	0.009	1.889*
ln(K)	0.767	0.344	2.230**
ln(F)	0.513	0.206	2.490***

Note: 1. * significant at 10%; ** significant at 5%; *** significant at 1%.
2. Wald test of constant returns to scale: Chi2 = 3.04 (p = 0.0812).

〈Figure 4〉 Distribution of productivity level



The estimated TFP levels of power plants are presented in Figure 4, with the productivity level estimated in logarithmic form. The average level of productivity is 0.043, with 95% confidence intervals of [0.037, 0.048]. The density distribution in the figure shows that the majority of power plants exhibit the average productivity level, while a relatively small proportion of plants display low or high levels of productivity. However, the figure does not provide information about the source of productivity differences, which could be related to the types of power plants or individual plants' efficiency. Therefore, we group the power plants according to their plant and fuel types to investigate any differences in productivity.

Productivity differences across various plant types are presented in Table 6, where steam power exhibits the highest level of productivity, followed by internal combustion and combined cycle. Table 7 displays the productivity levels across plants that use different fuel types. Power plants that use oil as fuel demonstrate higher productivity levels than coal power plants or those that use gas. Notably, the productivity differences within the same fuel type plants are greater for oil-powered plants.

〈Table 6〉 Productivity across different plant types

Plant Type	Mean	Standard Error	95% Confidence Interval
Steam power	0.046	0.003	(0.040, 0.052)
Combined cycle	0.027	0.003	(0.022, 0.032)
Internal combustion	0.029	0.006	(0.017, 0.041)

Note: Productivity was estimated in logarithmic form.

〈Table 7〉 Productivity across different fuel types

Fuel Type	Mean	Standard Error	95% Confidence Interval
Coal	0.042	0.001	(0.040, 0.045)
Oil	0.057	0.011	(0.035, 0.079)
Gas	0.025	0.001	(0.020, 0.029)

Note: Productivity was estimated in logarithmic form.

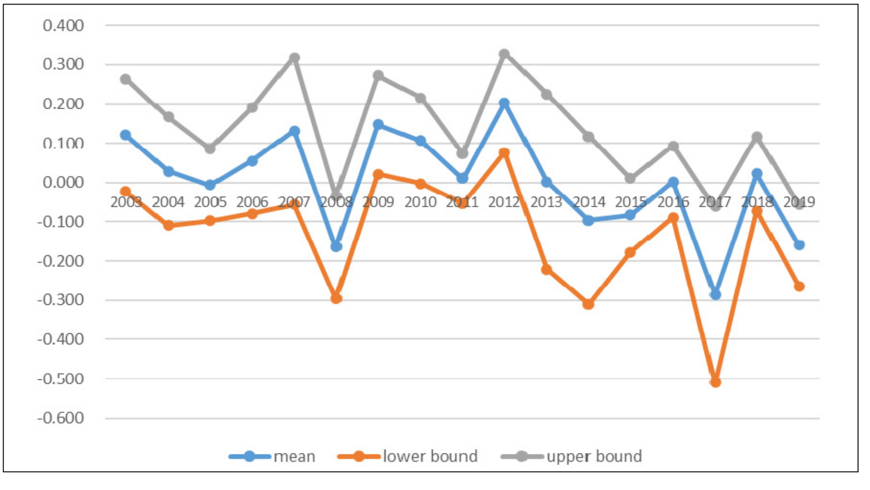
Table 8 shows annual growth in productivity during the sample period. The mean is the average annual growth of individual plants. The mean productivity growth ranges from -0.285% to 0.203%. Figure

5 shows the trends of the mean and 95% confidence interval and indicates that productivity growth fluctuated over time and presented a declining trend during the sample period.

〈Table 8〉 Productivity growth (%)

Year	Mean	Standard Error	95% Confidence Interval
2003	0.121	0.073	(-0.023, 0.265)
2004	0.029	0.070	(-0.109, 0.167)
2005	-0.005	0.047	(-0.098, 0.087)
2006	0.056	0.069	(-0.079, 0.190)
2007	0.132	0.096	(-0.056, 0.320)
2008	-0.164	0.067	(-0.295, -0.033)
2009	0.147	0.064	(0.022, 0.272)
2010	0.107	0.055	(-0.002, 0.216)
2011	0.011	0.032	(-0.053, 0.074)
2012	0.203	0.064	(0.077, 0.329)
2013	0.003	0.114	(-0.220, 0.225)
2014	-0.096	0.109	(-0.309, 0.118)
2015	-0.083	0.048	(-0.177, 0.011)
2016	0.002	0.046	(-0.088, 0.093)
2017	-0.285	0.114	(-0.510, -0.061)
2018	0.023	0.048	(-0.072, 0.118)
2019	-0.159	0.053	(-0.263, -0.056)

〈Figure 5〉 Trend of productivity growth



To identify the sources of productivity differences, we regressed the estimated productivity on plant characteristics. These characteristics include the load factor, plant factor, auxiliary use factor, and age of the power plants. The load factor is the average load divided by the peak load, and the plant load is the average load divided by the generating capacity. The auxiliary use factor is the auxiliary use divided by the gross generation. Table 9 shows the regression results. Three models were used to estimate the effects of the plant characteristics on productivity. All three indicated that plant productivity is affected by load and plant factors, but not by the auxiliary use factor and age. The age variable can capture the learning effects of plant production. However, this effect may not perform well in the Korean electricity generation sector.

〈Table 9〉 Effects of plants' characteristics on productivity

Variable	OLS	Fixed Effect	Random Effect
Load factor	0.018 (0.006)***	0.043 (0.025)*	0.033 (0.017)*
Plant factor	0.015 (0.005)***	0.014 (0.005)***	0.016 (0.005)***
Auxiliary use factor	0.042 (0.024)*	0.017 (0.001)	0.019 (0.015)
Age	-0.0002 (0.0001)	0.001 (0.001)	0.0003 (0.0003)
Constant	0.023 (0.004)***	-0.014 (0.038)	0.008 (0.012)
R-squared	0.211	-	-
N	1,447	1,447	1,447

Note: The numbers in parentheses represent the standard errors. Significance levels are indicated by ***, which denotes significance at 1%; **, which denotes significance at 5%; and *, which denotes significance at 10%. The reported results are based on robust standard errors.

Ⅴ. Conclusion

This study estimated the level and growth of total productivity in the Korean electricity generation sector using plant-level panel data. We compared the productivity differences across different plant types. It was found that TFP was the highest, followed by internal combustion and combined cycle. The productivity growth fluctuated over time, ranging from -0.285% to 0.203%, and presented a declining trend during the sample period. The results also indicated that the load and plant factors significantly affected the TFP of the plants. However, the age variable that may reflect the learning-by-doing effect did not affect plant productivity. This suggests that the output increase mainly depended on the increase in inputs such as capital, fuel, and labor rather than on technological progress and management skills.

This study makes several novel contributions to the existing literature. Firstly, it represents the first attempt to estimate TFP for the Korean power generation sector. Additionally, the semi-parametric method employed in this paper has not been previously applied to the electricity generation sector, to the best of our knowledge. Moreover, this paper uses panel data of power plants to not only identify productivity differences across various plant types and fuel types but also investigate the sources of productivity differences attributable to plant characteristics. These issues have received limited attention in the literature and require further research.

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한국 전력 생산 부문의 생산성 추정: 준비모수방법론 접근 방식

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논문초록

본 논문은 2002년부터 2019년까지의 발전소 개별 데이터를 이용하여 한국 전력 생산 부문의 생산성을 추정하였다. 특히, 발전소의 종류에 따른 생산성의 차이를 검증하였다. 생산성은 총요소생산성을 이용하여 생산성 수준과 증가율을 추정하였다. 생산함수 추정에 있어서 중요한 이슈는 생산성 충격과 노동과 자본 등의 변수들과 상관관계를 가지는 내생성의 문제이다. 본 연구에서는 내생성 문제를 해결하기 위해서 준비모수방법론을 이용하였으며 이 방법론은 도구변수를 사용하지 않고도 내생성 문제를 해결하게 하여 준다. 추정결과 기력발전이 가장 높은 생산성을 나타내었고 내연발전, 복합화력 순으로 생산성이 추정되었다. 생산성 증가율은 연도별로 -0.285%에서 0.203% 정도로 변동성을 나타내었으며 분석기간에 걸쳐 감소하는 추세를 보였다. 또한 발전소 부하율과 이용율은 총요소생산성에 유의한 결과를 미치고 있으나 발전소 설립 이후 발전 기간은 생산성에 영향을 미치지 못하고 있어 발전 경험에 따른 비용 감소 효과는 나타나고 있지 않을 것으로 추정되었다.

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