Environmental Performance and Industrialization : A Test of the Environmental Kuznets Curve for the Iridustrial Sector

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Masayuki Shimizu*

Abstract: This study aims to measure the environmental performance index (EPI) using a Data Envelopment Analysis (DEA) approach with time-series data for the industrial sector of high- and middle-income countries, and to investigate the existence of environmental Kuznets curve (EKC) for industrial EPI using panel data for 24 countries from 1993 to 2008. The main findings are summarized as follows. First, the middle-income countries are superior in terms of production efficiency to high-income countries. In particular, the performance of China has dramatically improved in terms of efficiency of producing desirable outputs. Second, high-income countries are superior in terms of emission efficiency than middle-income countries, and the perfomances of Chile and Indonesia have deteriorated in terms of efficiency of discharging undesirable outputs. Third, the time-series EPI has increased in both high- and middle-income countries since the late 1990s. Among all countries, China is the best performer, whereas Chile and Indonesia are the worst. Finally, the EKC for industrial EPI is followed a N-shaped relationship.

Key words: data envelopment analysis, environmental efficiency, environmental Kuznets curve, environmental performance index, panel data

JEL codes: C23, O14, O44

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1. Introduction

The purpose of this study is to measure the environmental performance index (EPI) using time-series data for the industrial sector of the developed and developing countries, which mainly belong to high- and middle-income countries, respectively. Further, through the use of a panel data set of EPI based on sulfur dioxide (SO_2) and nitrogen oxide (NO_X) emissions, this research examines whether the environmental Kuznets curve (EKC) hypothesis is applicable to the industrial sector from 1993 to 2008.

Industrialization is a major driver of economic growth in advanced industrial countries. However, it is also true that many of these countries have experienced severe health damage and environmental destruction due to industrial pollution. Even the newly industrializing countries in recent years have experienced serious environmental problems that threaten human health, as economic growth has been given priority and the production activity has rapidly expanded. Thus, it is an urgent task to improve the environmental performance, which represents the balance between the economy and the environment. Consequently, it is important to alleviate the burden on the environment caused by production activity in order to achieve sustainable development.

To deal with these challenges, it is necessary to grasp the environmental performance, and the objective of this work is to measure the EPI based on the industrial pollution, by applying a data envelopment analysis (DEA) approach. Further, in order to predict how the EPI changes with economic development, this study aims to investigate whether the EKC form exists. By finding the patterns of EPI with industrialization, this study provides policymakers with guidelines for harmonizing the relationship between economic development and environmental efficiency (EE).

The remainder of this paper is organized as follows. Section 2 presents a brief review of the literature. Section 3 derives the EPI and explains the data used, as well as specifies the EKC model in the panel data. Section 4 reports the results of the empirical analyses. Section 5 concludes the study and provides policy implications.

2. Literature Review

The DEA approach is a useful method to analyze the EE. Originally, the purpose of DEA was to identify a piecewise linear frontier that combines the most efficient decision making units (DMUs) using a nonparametric method, and it measures the efficiency based on the distance to inefficient DMUs and the frontier (Cook and Zhu, 2013). The primary characteristics of this approach are as follows. First, in the relationship between output and input, it is not necessary to determine a specific functional form. Second, multiple outputs and inputs can be considered simultaneously in the model. Third, it can simultaneously consider a reduction in outputs such as environmental pollutants.

In particular, the last characteristic is an important property connected with the assumption of joint production. Usually, if production activities are carried out, labor and physical capital are used as inputs to produce desirable outputs such as products and value added, while undesirable outputs such as air pollutants, water pollutants, and solid waste are also discharged as production byproducts. Färe et al. (1989) have considered undesirable outputs to match the theory of the production function, and have also introduced an assumption of the weak disposability of outputs, which implies not being able to reduce undesirable outputs without the burden of pollution reduction costs. In terms of practical applicability, many researchers have utilized the DEA model considering undesirable outputs.

Since Färe et al. (1989), many empirical studies have proposed various measures of EE by assuming the above two assumptions, i.e., the joint production of desirable and undesirable outputs and the weak disposability of outputs. Basically, the EE measured by the DEA approach can be divided into the following four types. First, the input-oriented model of EE showed by Färe et al. (1996), which is scaled at the maximum equi-proportionate rate of contraction in the inputs, while desirable and undesirable outputs are kept constant. Second, the input-undesirable output model of EE represented by Tyteca (1997), which is simultaneously scaled at the maximum equi-proportionate rate of contraction in the inputs and undesirable outputs, while desirable outputs are kept constant. Third, the desirable output-oriented model of EE applied by studies such as Färe et al. (2004), which is scaled at the maximum equi-proportionate rate of expansion in the desirable outputs, while inputs and undesirable outputs are kept constant. Fourth, the undesirable output-oriented model of EE used by studies such as Färe et al. (2014), which is scaled at the maximum equi-proportionate rate of contraction in the undesirable outputs, while inputs and desirable outputs are kept constant. Consequently, four types of EE obtained by the DEA approach can be measured only in one direction; namely, it is either the expansion direction or the contraction direction.

However, the directional distance function (DDF) approach proposed by Chung et al. (1997) is one of the methods to overcome the above weakness. The EE measured by the DDF approach can be divided into the following three types. First, the output-oriented model of EE developed by Chung et al. (1997), which is simultaneously scaled at the maximum equi-proportionate rate of expansion in the desirable outputs, and the maximum equi-proportionate rate of contraction in the undesirable outputs, while inputs are kept constant. Second, the input-desirable output model of EE introduced by Picazo-Tadeo et al. (2005), which is simultaneously scaled at the maximum equi-proportionate rate of contraction in the inputs, and the maximum equi-proportionate rate of expansion in the desirable outputs, while undesirable outputs are kept constant. Third, the input-output model of EE reflected by Picazo-Tadeo et al. (2005), which is simultaneously scaled at the maximum equi-proportionate rate of contraction in the inputs and undesirable outputs, and the maximum equi-proportionate rate of expansion in the desirable outputs.

Other than these, there is pioneering research (Färe et al., 2003; 2004), which has considered the output-oriented model of EE in DEA without using the DDF approach. These studies propose the EPI, and the index is applied to the analysis of this research. The EPI can be basically derived by measuring two types of EE: one is the EE of the desirable output-oriented model and the other is that of the undesirable output-oriented model. Further, Färe et al. (2003; 2004) constructed the EPI corresponding to time-series data and cross-section data, respectively Thus, the index can be applied to this work based on time-series analysis.

There are some studies that have measured the EPI using time-series data or cross-section data. In the time-series analysis, Shimizu (2014) measured the time-series EPI, simultaneously accounting for carbon dioxide (CO_2) and sulfur emissions in Japan, the United States, and the United Kingdom for the long-run period of 1890–1992.[1] The study revealed that the environmental performance of these three countries had been the lowest before the Second World War. After the war, however, the performance has tended to recover sharply. In particular, Japan showed the highest performance among the three countries

Likewise, Shimizu (2016a) measured the time-series EPI, simultaneously accounting for SO_2, NO_X, and CO_2 emissions in South Korea, Taiwan, China, Malaysia, Thailand, and India for the period 1970–2008. The results showed that the environmental performance of these countries had remained almost unchanged during the period. Among the six countries, China was the best performer, while Thailand was the worst.

Meanwhile, Shimizu (2016b) analyzed the relationship between environmental performance and industrialization, similar to the current research. The study measured the time-series EPI in the industrial sector, simultaneously accounting for industrial SO_2 and NO_X emissions in Japan, South Korea, and China for the period 1970–2008. The study confirmed that the environmental performance of the industrial sector has improved basically in each country since the 2000s. However, it also found that the level of environmental performance differs for each country; Japan was the best performer, while China was the worst of the three countries.

Furthermore, Färe et al. (2003) estimated the factors of EPI in panel data at a country-level and examined the EKC hypothesis. The study measured the time-series EPI, simultaneously accounting for CO_2 emissions and solid particulate matter in 24 OECD countries for the period 1971–1990. The results indicated that Iceland, Sweden, and France showed high performance levels, while Mexico, Turkey, and Greece showed low performance levels. In addition, the study showed that the EKC hypothesis is supported; consequently, the EKC is followed by an inverted N-shape for EPI.

In the cross-section analysis, Färe et al. (2004) measured the cross-section EPI, simultaneously accounting for sulfur oxide (SO_X), NO_X, and CO_2 emissions for 17 OECD countries in 1990. The study found that France showed the best performance, while West Germany showed the worst performance, when considering all the three pollutants. However, when only SO_X and NO_X emissions are included, the result is different; consequently, Austria showed the best performance, while the United States showed the worst performance. In addition, the study clarified that the EKC hypothesis is not applicable when cross-section data are used.

Similarly, Yörük and Zaim (2006; 2008) measured the cross-section EPI, simultaneously accounting for the pairs of CO_2 and organic water pollutant (WP) emissions, CO_2 and NO_X emissions, and NO_X and WP emissions in 27 and 28

OECD countries for the period 1983–1998.[2] The results indicated that Poland was the best performer, while Switzerland was the worst in OECD countries. In addition, the study found that the EKC hypothesis is applicable when the pairs of CO_2 and WP emissions and CO_2 and NO_X emissions are considered, respectively.

As mentioned above, previous empirical studies have primarily focused on developed countries or high-income countries using macro data, except the study of Shimizu (2016a; 2016b). The current study contributes to the previous studies on the EPI in two aspects. First, this work measures the time-series EPI in the industrial sector, by including developing countries that belong to middle-income countries.[3] Second, this work examines the EKC hypothesis, which is relevant to industrialization, using a panel data set of industrial EPI, which simultaneously accounts for SO_2 and NO_X emissions in 24 developed and developing countries for the period 1993–2008. Based on the results obtained from the two aspects, this study proposes policy implications for policymakers to maintain a sustainable relationship between industrialization and the environment.

3. Models and Data

Measuring the environmental performance index

This section derives the EPI based on the DEA approach following Färe et al. (2003; 2004). First, this study uses the DEA framework applied as a pollution-generating technology in Färe et al. (2014), which is considered with the joint production of desirable and undesirable outputs. Let the vector of production factors (inputs) be represented by $x = (x_1, \ldots, x_N) \in R_+^N$, the vector of desirable outputs by $y = (y_1, \ldots, y_M) \in R_+^M$, and the vector of undesirable outputs by $b = (b_1, \ldots, b_J) \in R_+^J$. Then, the technology can be represented as follows:

$$P(x) = \{(x, y, b) : x \text{ can produce } (y, b)\}. \tag{1}$$

$P(x)$ is assumed to impose appropriate conditions; for example, $P(x)$ is bounded and a closed set, and inputs and desirable outputs are strongly disposable (Färe and Grosskopf, 2003). In terms of undesirable outputs, this study imposes two assumptions on $P(x)$: the null-joint outputs and weak disposability of outputs. The null-joint outputs assumption holds in the production process as follows:

$$(y, b) \in P(x), \text{ and } b = 0 \text{ then } y = 0. \tag{2}$$

This assumption implies that if desirable outputs are produced, undesirable outputs are also necessarily discharged. This means that the environment will be polluted as long as production activities are carried out. The weak disposability of outputs holds in the production process as follows:

$$(y, b) \in P(x) \text{ and } 0 \leq \theta \leq 1, \text{ then } (\theta y, \theta b) \in P(x). \tag{3}$$

This assumption shows that if the undesirable outputs are reduced, the desirable ones too must be reduced simultaneously at the same rate, when inputs are kept constant. This implies that it would be necessary to incur pollution reduction costs in order for the undesirable outputs to decrease; consequently, the opportunity cost due to emission control is measured as the decreased production of desirable outputs.

In this research, $P(x)$ is constructed by the DEA framework. Let the $k = (1, \ldots, K)$ index be represented by the observations of inputs and outputs, (x^k, y^k, b^k) for $k = 1, \ldots, K$. $P(x)$, based on the assumptions of null-joint outputs and weak disposability of outputs, can be shown as follows:

$$P(x) = \{(y, b): \tag{4}$$

$$\sum_{k=1}^{K} z_k y_{km} \geq y_m, \; m=1, \ldots, M,$$

$$\sum_{k=1}^{K} z_k b_{kj} = b_j, j=1, \ldots, J,$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n, \; n=1, \ldots, N,$$

$$\sum_{k=1}^{K} z_k = 1,$$

$$z_k \geq 0, k=1, \ldots, K\}.$$

The strict equality on undesirable output constraints is assumed to impose weak disposability in $P(x)$, and the null-jointness is assumed as follows:

$$\sum_{k=1}^{K} b_{kj}>0, j=1, \ldots, J, \tag{5}$$

$$\sum_{j=1}^{J} b_{kj}>0, k=1, \ldots, K. \tag{6}$$

z_k is an intensity variable, while the fourth constraint, which is $\sum_{k=1}^{K} z_k=1$, is assumed to impose variable returns to scale (VRS) technology in the production process.

Second, assuming that the production technology can be expressed as a pollution-generating technology and that the above assumptions are satisfied, this study defines two distance functions to construct the quantity indices of both desirable and undesirable outputs; one is the output distance function on the desirable outputs and the other is the input distance function on the undesirable outputs. The output distance function is defined as follows:

$$D_y(x, y, b) = \inf\{\theta: (x, y/\theta, b) \in P(x)\}. \tag{7}$$

This distance function means that the reciprocal of the $D_y(x, y, b) \leq 1$is technical inefficiency, which implies maximizing the desirable outputs as much as possible, when the inputs and undesirable outputs are kept constant; consequently, D_y measures the EE from the viewpoint of production efficiency in the desirable output-oriented model. In addition, D_y is homogeneous of degree +1 in the desirable outputs by definition.

Likewise, the input distance function is defined as follows:

$$D_b(x, y, b) = \sup\{\lambda: (x, y, b/\lambda) \in P(x)\}. \tag{8}$$

This distance function means that the reciprocal of the $D_b(x, y, b) \leq 1$is technical inefficiency, which implies minimizing the undesirable outputs as much as possible, when the inputs and desirable outputs are kept constant; consequently, D_b measures the EE from the viewpoint of emission efficiency in the undesirable output-oriented model.[4] In addition, D_b is homogeneous of degree +1 in the undesirable outputs by definition.

In the time-series analysis, Färe et al. (2003) shows the quantity indices of both desirable and undesirable outputs by using the output distance function D_y and the input distance function D_b, respectively. The quantity index of desirable outputs is expressed as a ratio of two output distance functions as follows:

$$Q_y\left(x^o,b^o,y^k,y^l\right) = \frac{D_y(x^o,y^k,b^o)}{D_y(x^o,y^l,b^o)}. \tag{9}$$

This means that when the same amount of undesirable outputs are discharged using the same amount of inputs as the reference year o, the EE measures the production efficiency of desirable outputs for year k and year l, respectively; consequently, $Q_y(x^o, b^o, y^k, y^l)$ is represented as a ratio of the EE in years k and l. Therefore, if the EE is higher in year k than in year l, year k is more efficient in terms of producing desirable outputs.

Likewise, the quantity index of undesirable outputs is expressed as a ratio of two input distance functions as follows:

$$Q_b\left(x^o,y^o,b^k,b^l\right) = \frac{D_b(x^o,y^o,b^k)}{D_b(x^o,y^o,b^l)}. \tag{10}$$

This means that when the same amount of desirable outputs are produced using the same amount of inputs as the reference year o, the EE measures the emission efficiency of undesirable outputs for year k and year l, respectively; consequently, $Q_b(x^o, y^o, b^k, b^l)$ is represented as a ratio of the EE in years k and l. Therefore, if the EE is higher in year k than in year l, year k is more efficient in terms of discharging undesirable outputs. Additionally, the above two quantity indices satisfy some properties, such as homogeneity, time reversal, transitivity, and dimensionality, according to Färe and Grosskopf (2003).

Finally, the time-series EPI is derived as a ratio of the two quantity indices as follows:

$$EPI^{k,l}\left(x^o,y^o,b^o,y^k,y^l,b^k,b^l\right) = \frac{Q_y(x^o,b^o,y^k,y^l)}{Q_b(x^o,y^o,b^k,b^l)}. \tag{11}$$

Therefore, if the production efficiency of desirable outputs and the emission efficiency of undesirable outputs are increased compared to the reference year, the EPI will improve; consequently, better environmental performance takes a higher score. Thus, the EPI is a model applying the Hicks–Moorsteen productivity index.

In order to seek the values of the output and input distance functions under VRS, this study uses the method of linear programming.[5] Following Färe et al. (2003), assume that the reference year o is the comparison year l. Let the $k = (1, \ldots, K)$ index be represented by the year in the sample. For each year $k' = 1, \ldots, K$ in each studied country, the study solves the output and input distance functions using two linear programming problems as follows:

$$\left(D_y\left(x^o,y^{k'},b^o\right)\right)^{-1} = \max\theta \tag{12}$$

$$\text{s.t.} \sum_{k=1}^{K} z_k y_m^k \geq \theta y_m^{k'},\ m=1,\ldots,M$$

$$\sum_{k=1}^{K} z_k b_j^k = b_j^o,\ j=1,\ldots,J$$

$$\sum_{k=1}^{K} z_k x_n^k \leq x_n^o,\ n=1,\ldots,N$$

$$\sum_{k=1}^{K} z_k = 1,$$

$$z_k \geq 0,\ k=1,\ \ldots,\ K,$$

and

$$\left(D_b\left(x^o, y^o, b^{k'}\right)\right)^{-1} = \min \lambda \tag{13}$$

$$\text{s.t.}\ \sum_{k=1}^{K} z_k y_m^k \geq y_m^o,\ m=1,\ \ldots,\ M$$

$$\sum_{k=1}^{K} z_k b_j^k = \lambda\ b_j^{k'},\ j=1,\ \ldots,\ J$$

$$\sum_{k=1}^{K} z_k x_n^k \leq x_n^o,\ n=1,\ \ldots,\ N$$

$$\sum_{k=1}^{K} z_k = 1,$$

$$z_k \geq 0,\ k=1,\ \ldots,\ K.$$

In order to solve the two linear programming problems, however, it is necessary to select the reference year. When the first year of the studied data is set as the reference year following Färe et al. (2003) and Zaim (2004), a part of linear programming problems is infeasible in this study.[6] To avoid infeasible solutions, this study decides to set a hypothetical year as reference to reflect the minimum desirable and undesirable outputs as well as maximum inputs, following Färe et al. (2004), since this approach has the advantage that there are no infeasible solutions in the above linear programming problems. Hence, this study assumes that the comparison year l is the reference year o which refers to the above hypothetical year, and obtains the EPI by comparing the selected year with the hypothetical reference year.

To measure the EPI, this study applied time-series data on the industrial sector for 24 high- and middle-income countries from 1993 to 2008. In this study, the industrial sector includes the mining, manufacturing, utilities (which includes electricity, gas, and water supply), and construction sectors. Desirable output refers to real value added at constant 2005 national prices (in millions), sourced from the Groningen Growth and Development Centre (GGDC) 10-Sector Database of Timmer et al. (2015).

Undesirable outputs refer to SO_2 and NO_X emissions (in thousand tonnes), which have caused significant industrial pollution depending on the progress of industrialization and have inflicted detrimental damage to human health. This study uses emissions resulting from fuel combustion activities and industrial processes, sourced from the Emission Database for Global Atmospheric Research (EDGAR) in version 4.2 of the European Commission, Joint Research Centre (EC-JRC)/ Netherlands Environmental Assessment Agency (PBL) (2011). As a source of industrial SO_2 and NO_X emissions, this study considers the emissions from the energy transformation sector (which includes electricity generation, petroleum refining, and other energy industries), which is the largest source of emissions in the modern society, as well as from the final consumption.

Inputs refer to the labor and capital stock. Labor is defined as the number of persons employed (in thousands), sourced from GGDC 10-Sector Database. Because it is difficult to estimate the capital stock of the industrial sector owing to data constraints, this study utilized the electricity consumption (in thousand tonnes of oil equivalent) sourced from the Energy Balances of OECD and non-OECD Countries of the International Energy Agency (IEA), which is a better proxy for capital stock adjusted for capital utilization rates (Burnside et al., 1995). As described above, this work employed one desirable output, two undesirable outputs, and two inputs in order to seek the EPI.[7]

Examination of the environmental Kuznets curve hypothesis

Through the application of the industrial EPI, which simultaneously accounts for industrial SO_2 and NO_X emissions from high- and middle-income countries for the period 1993–2008, this study investigates to verify whether the EKC hypothesis is supported. Typically, the standard EKC models in the panel data assume the following:

$$EPI_{it}=\beta_1 GDPPC_{it}+\beta_2(GDPPC_{it})^2+\mu_i+\lambda_t+\varepsilon_{it} \tag{14}$$

or

$$EPI_{it}=\beta_1 GDPPC_{it}+\beta_2(GDPPC_{it})^2+\beta_3(GDPPC_{it})^3+\mu_i+\lambda_t+\varepsilon_{it} \tag{15}$$

where the dependent variable represents the industrial EPI under VRS; *GDPPC* is GDP per capita and indicates the income level; i and t denote each country and year, respectively; μ_i and λ_t denote unobservable individual and time effects, respectively; and ε_{it} denotes an error term.

In equations (14) and (15), the parameters of *GDPPC* examine whether the EKC exists. Following the empirical result of Yörük and Zaim (2006), if the coefficients of β_1 and β_2 in equation (14) are shown to be negative and positive respectively, the EKC hypothesis is valid; thus, the EKC is described by a U-shape. Following the empirical result of Färe et al. (2003), if the coefficients of β_1, β_2, and β_3 in equation (15) are obtained as negative, positive, and negative, respectively, the EKC hypothesis is supported; thus, the EKC is described by an inverted N-shape. GDP per capita by country at constant 2010 US dollars are sourced from the World Development Indicators of the World Bank.

4. Empirical Results

Table 1 reports the results of the quantity index of desirable outputs in the industrial sector of the developed and developing countries, which is divided into high- and middle-income countries. The last column of the table shows the geometric mean of each country for the entire sample period. As a result, South Korea and Sweden are the highest performers among the high-income countries. However, among the middle-income countries, the index is the highest for China, India, and Malaysia, which surpasses South Korea and Sweden. In particular, China is overwhelmingly superior to these countries; this indicates that China has dramatically improved in terms of the efficiency of producing desirable outputs. Confirming the trend of the geometric mean for each year in both high- and middle-income countries, the index is gradually increasing in both groups. In terms of producing desirable outputs, however, the middle-income countries are more efficient than high-income countries in the overall trend.

Meanwhile, Table 2 reports the results of the quantity index of undesirable outputs in the industrial sector of the high- and middle-income countries. The last column of the table shows that South Korea and Spain had the highest quantity index among the high-income countries, while Chile and Indonesia had the highest among the middle-income countries. However, the index is higher for Chile and Indonesia than for South Korea and Spain. This suggests that Chile and Indonesia have deteriorated in terms of the efficiency of discharging undesirable outputs. For the overall trend of both groups, the results show that the index for high-income countries increased in the beginning of the 2000s and have subsequently had a decreasing trend, whereas that for middle-income countries has basically followed an increasing trend. Thus, in terms of discharging undesirable outputs, the high-income countries are more efficient than middle-income countries in the overall trend.

Further, Table 3 reports the results of the time-series EPI based on both desirable and undesirable output quantity indices, which simultaneously accounts for SO_2 and NO_X emissions. The last column of the table shows that Sweden has the highest EPI among the high-income countries, and the result is consistent with the

Table 1. Quantity Index of Desirable Outputs in the Industrial Sector by Country, 1993–2008

Country	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	1993–2008
High-income countries																	
Denmark	1.000	1.069	1.126	1.138	1.199	1.215	1.273	1.323	1.304	1.284	1.275	1.296	1.313	1.349	1.345	1.334	1.236
France	1.000	1.010	1.045	1.036	1.049	1.085	1.117	1.166	1.195	1.196	1.208	1.227	1.247	1.255	1.289	1.274	1.146
Italy	1.000	1.039	1.078	1.081	1.085	1.094	1.098	1.139	1.149	1.153	1.134	1.146	1.149	1.182	1.200	1.162	1.117
Japan	1.117	1.091	1.098	1.124	1.135	1.079	1.068	1.098	1.032	1.000	1.021	1.066	1.091	1.107	1.144	1.086	1.084
South Korea	1.000	1.088	1.198	1.282	1.335	1.221	1.389	1.558	1.577	1.692	1.783	1.916	1.965	2.083	2.169	2.160	1.543
Netherlands	1.000	1.033	1.050	1.069	1.067	1.085	1.125	1.172	1.190	1.189	1.160	1.193	1.197	1.234	1.290	1.313	1.145
Spain	1.000	1.031	1.087	1.099	1.147	1.215	1.292	1.359	1.429	1.460	1.499	1.538	1.580	1.626	1.647	1.623	1.333
Sweden	1.000	1.067	1.155	1.171	1.224	1.294	1.389	1.473	1.460	1.570	1.653	1.927	2.041	2.174	2.299	2.232	1.516
United Kingdom	1.000	1.055	1.074	1.094	1.111	1.124	1.139	1.152	1.142	1.133	1.139	1.149	1.157	1.160	1.176	1.168	1.122
United States	1.000	1.067	1.092	1.113	1.148	1.179	1.220	1.234	1.183	1.203	1.217	1.280	1.285	1.312	1.316	1.257	1.191
Geometric mean	1.011	1.055	1.099	1.119	1.147	1.157	1.206	1.259	1.256	1.272	1.289	1.345	1.369	1.408	1.443	1.416	1.234
Middle-income countries																	
Argentina	1.094	1.161	1.119	1.189	1.289	1.316	1.227	1.198	1.134	1.000	1.144	1.271	1.368	1.490	1.587	1.650	1.253
Brazil	1.000	1.066	1.134	1.145	1.215	1.224	1.217	1.323	1.312	1.339	1.348	1.468	1.499	1.536	1.623	1.664	1.306
Chile	1.000	1.047	1.136	1.222	1.312	1.346	1.368	1.418	1.464	1.458	1.522	1.608	1.650	1.698	1.718	1.721	1.399
China	1.000	1.233	1.560	1.745	1.923	2.092	2.257	2.469	2.674	2.941	3.311	3.676	4.115	4.673	5.376	5.917	2.602
Colombia	1.000	1.095	1.159	1.139	1.156	1.178	1.117	1.131	1.135	1.164	1.220	1.290	1.351	1.441	1.524	1.585	1.221
India	1.000	1.099	1.222	1.311	1.361	1.403	1.484	1.558	1.590	1.695	1.815	1.988	2.169	2.433	2.653	2.740	1.646
Indonesia	1.000	1.106	1.218	1.325	1.346	1.127	1.136	1.214	1.261	1.304	1.332	1.357	1.355	1.379	1.466	1.522	1.271
Malaysia	1.000	1.100	1.280	1.439	1.536	1.393	1.506	1.669	1.613	1.681	1.795	1.923	1.984	2.070	2.137	2.146	1.604
Mexico	1.043	1.092	1.000	1.104	1.195	1.261	1.300	1.370	1.319	1.314	1.321	1.368	1.401	1.447	1.449	1.437	1.268
Morocco	1.000	1.033	1.070	1.116	1.174	1.202	1.225	1.279	1.340	1.377	1.439	1.495	1.567	1.642	1.751	1.818	1.324
Philippines	1.000	1.062	1.135	1.211	1.289	1.258	1.238	1.319	1.332	1.372	1.431	1.506	1.570	1.642	1.739	1.821	1.352
South Africa	1.000	1.022	1.053	1.068	1.095	1.083	1.081	1.135	1.157	1.186	1.196	1.250	1.316	1.379	1.445	1.460	1.175
Thailand	1.000	1.104	1.220	1.305	1.271	1.095	1.195	1.253	1.274	1.366	1.493	1.610	1.698	1.792	1.894	1.953	1.380
Venezuela	1.096	1.082	1.135	1.175	1.285	1.285	1.163	1.196	1.238	1.087	1.000	1.148	1.214	1.274	1.307	1.357	1.186
Geometric mean	1.016	1.092	1.168	1.240	1.305	1.287	1.298	1.365	1.381	1.398	1.460	1.564	1.641	1.735	1.831	1.888	1.396

Note: The country classification by income level is based on the World Bank database.

Table 2. Quantity Index of Undesirable Outputs in the Industrial Sector by Country, 1993–2008

Country	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	1993–2008
High-income countries																	
Denmark	1.000	1.000	1.070	1.531	1.235	1.248	1.267	1.000	1.179	1.185	1.269	1.170	1.059	1.205	1.046	1.000	1.146
France	1.000	1.000	1.074	1.126	1.074	1.200	1.130	1.143	1.138	1.131	1.112	1.053	1.185	1.105	1.058	1.000	1.094
Italy	1.000	1.073	1.178	1.038	1.046	1.002	1.000	1.066	1.000	1.046	1.092	1.119	1.100	1.096	1.000	1.000	1.052
Japan	1.000	1.057	1.057	1.068	1.050	1.005	1.026	1.035	1.000	1.031	1.034	1.029	1.045	1.000	1.070	1.000	1.031
South Korea	1.000	1.116	1.261	1.379	1.517	1.225	1.326	1.490	1.541	1.536	1.085	1.101	1.028	1.027	1.017	1.000	1.212
Netherlands	1.000	1.000	1.000	1.035	1.066	1.058	1.006	1.024	1.054	1.064	1.080	1.095	1.122	1.000	1.013	1.000	1.038
Spain	1.000	1.074	1.242	1.062	1.214	1.242	1.520	1.477	1.493	1.637	1.490	1.522	1.553	1.229	1.209	1.000	1.293
Sweden	1.000	1.000	1.081	1.233	1.135	1.153	1.085	1.042	1.002	1.014	1.025	1.010	1.000	1.052	1.034	1.000	1.052
United Kingdom	1.000	1.045	1.170	1.236	1.000	1.022	1.029	1.104	1.183	1.148	1.178	1.104	1.109	1.124	1.062	1.000	1.092
United States	1.000	1.033	1.029	1.048	1.111	1.190	1.225	1.250	1.190	1.142	1.116	1.122	1.110	1.091	1.109	1.000	1.108
Geometric mean	1.000	1.039	1.113	1.166	1.137	1.131	1.151	1.151	1.165	1.178	1.141	1.125	1.123	1.090	1.060	1.000	1.109
Middle-income countries																	
Argentina	1.000	1.040	1.000	1.112	1.131	1.346	1.381	1.339	1.211	1.000	1.000	1.309	1.292	1.445	1.626	1.639	1.225
Brazil	1.000	1.052	1.104	1.163	1.181	1.124	1.208	1.294	1.222	1.096	1.010	1.027	1.000	1.021	1.030	1.000	1.092
Chile	1.000	1.112	1.230	1.502	1.828	1.953	2.179	1.866	1.567	1.280	1.000	1.447	1.923	2.000	2.114	2.004	1.573
China	1.000	1.000	1.112	1.167	1.115	1.153	1.053	1.000	1.000	1.040	1.206	1.445	1.587	1.733	1.855	2.174	1.250
Colombia	1.019	1.000	1.029	1.012	1.000	1.106	1.054	1.105	1.112	1.083	1.079	1.000	1.054	1.000	1.046	1.000	1.043
India	1.000	1.000	1.038	1.115	1.071	1.103	1.215	1.000	1.081	1.221	1.269	1.253	1.504	1.869	1.996	2.119	1.262
Indonesia	1.003	1.000	1.000	1.000	1.290	1.000	1.333	1.058	1.000	1.100	1.681	1.890	1.961	2.188	2.315	2.427	1.370
Malaysia	1.000	1.000	1.119	1.277	1.255	1.361	1.034	1.000	1.013	1.244	1.000	1.212	1.337	1.316	1.560	1.471	1.187
Mexico	1.000	1.000	1.042	1.096	1.182	1.300	1.252	1.244	1.209	1.161	1.115	1.094	1.147	1.096	1.000	1.000	1.117
Morocco	1.000	1.063	1.046	1.000	1.027	1.012	1.092	1.049	1.067	1.170	1.140	1.000	1.125	1.110	1.134	1.000	1.063
Philippines	1.000	1.379	1.626	1.675	1.838	1.890	1.412	1.164	1.225	1.049	1.130	1.215	1.131	1.000	1.056	1.095	1.276
South Africa	1.000	1.026	1.052	1.139	1.203	1.238	1.139	1.116	1.005	1.000	1.040	1.070	1.013	1.000	1.046	1.000	1.065
Thailand	1.000	1.131	1.351	1.466	1.451	1.309	1.385	1.179	1.005	1.000	1.000	1.282	1.319	1.263	1.000	1.000	1.184
Venezuela	1.000	1.000	1.028	1.000	1.292	1.326	1.144	1.244	1.473	1.637	1.567	1.031	1.082	1.045	1.157	1.000	1.173
Geometric mean	1.002	1.053	1.116	1.179	1.254	1.276	1.253	1.174	1.145	1.139	1.144	1.214	1.288	1.311	1.357	1.338	1.199

Table 3. Environmental Performance Index in the Industrial Sector by Country, 1993–2008

Country	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	1993–2008
High-income countries																	
Denmark	1.000	1.069	1.053	0.743	0.971	0.973	1.004	1.323	1.106	1.084	1.005	1.108	1.239	1.120	1.286	1.334	1.078
France	1.000	1.010	0.973	0.920	0.977	0.903	0.989	1.020	1.050	1.057	1.086	1.166	1.052	1.136	1.218	1.274	1.047
Italy	1.000	0.969	0.915	1.041	1.037	1.092	1.098	1.069	1.149	1.102	1.038	1.024	1.045	1.078	1.200	1.162	1.061
Japan	1.117	1.032	1.038	1.052	1.081	1.073	1.042	1.060	1.032	0.970	0.988	1.036	1.044	1.107	1.070	1.086	1.051
South Korea	1.000	0.975	0.950	0.929	0.880	0.996	1.047	1.045	1.024	1.102	1.643	1.739	1.912	2.029	2.132	2.160	1.273
Netherlands	1.000	1.033	1.050	1.033	1.000	1.025	1.118	1.145	1.130	1.118	1.074	1.089	1.066	1.234	1.273	1.313	1.103
Spain	1.000	0.960	0.875	1.035	0.945	0.978	0.850	0.920	0.957	0.892	1.006	1.011	1.017	1.324	1.362	1.623	1.031
Sweden	1.000	1.067	1.068	0.950	1.078	1.122	1.281	1.414	1.457	1.548	1.613	1.908	2.041	2.067	2.223	2.232	1.441
United Kingdom	1.000	1.009	0.918	0.885	1.111	1.099	1.107	1.044	0.965	0.986	0.967	1.041	1.044	1.032	1.108	1.168	1.028
United States	1.000	1.033	1.062	1.062	1.033	0.991	0.996	0.987	0.993	1.054	1.090	1.141	1.158	1.203	1.187	1.257	1.075
Geometric mean	1.011	1.015	0.988	0.960	1.009	1.023	1.048	1.094	1.078	1.080	1.130	1.195	1.220	1.292	1.361	1.416	1.112
Middle-income countries																	
Argentina	1.094	1.117	1.119	1.069	1.139	0.978	0.888	0.895	0.937	1.000	1.144	0.971	1.059	1.031	0.976	1.007	1.023
Brazil	1.000	1.014	1.027	0.985	1.029	1.089	1.007	1.022	1.073	1.221	1.334	1.430	1.499	1.504	1.576	1.664	1.196
Chile	1.000	0.941	0.924	0.814	0.718	0.689	0.628	0.760	0.934	1.138	1.522	1.111	0.858	0.849	0.813	0.859	0.889
China	1.000	1.233	1.402	1.496	1.725	1.814	2.144	2.469	2.674	2.829	2.745	2.544	2.593	2.696	2.898	2.722	2.082
Colombia	0.981	1.095	1.126	1.125	1.156	1.065	1.060	1.024	1.020	1.075	1.130	1.290	1.282	1.441	1.457	1.585	1.171
India	1.000	1.099	1.177	1.176	1.271	1.272	1.221	1.558	1.471	1.388	1.430	1.586	1.443	1.302	1.329	1.293	1.304
Indonesia	0.997	1.106	1.218	1.325	1.043	1.127	0.852	1.147	1.261	1.185	0.792	0.718	0.691	0.630	0.633	0.627	0.928
Malaysia	1.000	1.100	1.145	1.127	1.224	1.024	1.456	1.669	1.592	1.351	1.795	1.587	1.484	1.573	1.370	1.459	1.351
Mexico	1.043	1.092	0.960	1.007	1.011	0.970	1.039	1.101	1.091	1.131	1.185	1.250	1.221	1.320	1.449	1.437	1.135
Morocco	1.000	0.972	1.022	1.116	1.143	1.188	1.123	1.219	1.256	1.178	1.262	1.495	1.393	1.479	1.545	1.818	1.245
Philippines	1.000	0.770	0.698	0.723	0.701	0.665	0.876	1.133	1.087	1.307	1.266	1.239	1.388	1.642	1.647	1.663	1.059
South Africa	1.000	0.997	1.001	0.938	0.910	0.875	0.949	1.017	1.152	1.186	1.151	1.169	1.299	1.379	1.382	1.460	1.103
Thailand	1.000	0.976	0.902	0.890	0.875	0.837	0.863	1.063	1.268	1.366	1.493	1.256	1.287	1.419	1.894	1.953	1.165
Venezuela	1.096	1.082	1.104	1.175	0.995	0.969	1.016	0.962	0.840	0.664	0.638	1.114	1.121	1.219	1.129	1.357	1.012
Geometric mean	1.015	1.037	1.046	1.051	1.041	1.009	1.036	1.163	1.206	1.227	1.276	1.288	1.274	1.323	1.349	1.411	1.165

findings of Färe et al. (2003). Furthermore, South Korea is the second highest after Sweden. In contrast, Spain and the United Kingdom are the lowest performers. However, China is overwhelmingly the highest in terms of EPI among the middle-income countries, and the finding is consistent with the outcomes of Shimizu (2016a). India and Malaysia are the second and third highest, respectively, after China. In contrast, Chile and Indonesia are the worst performers. Among all countries, China is the best performer, whereas Chile and Indonesia are the worst. Regarding the overall trend of both groups, the EPI in high- and middle-income countries has improved since the late 1990s. However, the improvement factors of EPI are basically different between both groups. Consequently, the EPI in the high-income countries have tended to increase due to improved emission efficiency of undesirable outputs, compared to middle-income countries. In contrast, the EPI in the middle-income countries have tended to increase due to improved production efficiency of desirable outputs, compared to high-income countries.

Finally, this study investigates the existence of EKC for industrial EPI using panel data for 24 countries from 1993 to 2008. Since the panel data is included in time-series data, which covers 16 years, however, it is necessary to confirm the stationarity of the panel data. Table 4 reports the results of the panel unit root test, using the LLC test of Levin et al. (2002), the IPS test of Im et al. (2003), and the Fisher-ADF (Augmented Dickey-Fuller) and Fisher-PP (Phillips-Perron) tests, in accordance with Maddala and Wu (1999). In the level data, the results do not reject the null hypothesis, that is, the panels contain unit roots, excluding EPI of LLC test. However, the results of the first-difference data reject the null hypothesis. Thus, it is subsequently assumed that each variable is integrated with order one (i.e., I (1)).

Table 4. Panel Unit Root Tests

	Levels		First Difference	
Tests	EPI	GDPPC	EPI	GDPPC
LLC	−2.271**	3.405	−12.533***	−10.570***
IPS	0.327	5.031	−8.930***	−5.304***
ADF	45.857	25.943	158.347***	89.954***
PP	49.617	10.607	209.528***	84.541***

Notes: The exogenous variables are the individual effects and time trend.
** Significant at the 5% level. *** Significant at the 1% level.

If it is revealed that the unit roots are included in the panel data, there is potential for the problem of spurious regression. Hence, it is also necessary to investigate whether a long-run cointegrating relationship exists among variables, using the panel cointegration tests of Pedroni (2000). Table 5 reports the results of the panel cointegration test, and shows that the null hypothesis, that is, there is no cointegration, is conclusively rejected in four of the seven statistics. Thus, it is subsequently assumed that the variables have a long-run relationship.

Table 5. Panel Cointegration Tests

	Panel statistics			
	v-Statistic	rho-Statistic	PP-Statistic	ADF-Statistic
Eq. (14)	−0.781	2.326	−2.385***	−4.373***
Eq. (15)	−2.326	3.816	−2.297**	−5.170***
	Group statistics			
	rho-Statistic	PP-Statistic	ADF-Statistic	
Eq. (14)	3.683	−6.113***	−5.292***	
Eq. (15)	5.136	−8.830***	−6.163***	

Notes: The exogenous variables are the individual effects and time trend.
** Significant at the 5% level. *** Significant at the 1% level.

Next, this study tests the model specification to verify the EKC hypothesis. From Table 6, the results of the F-test show that equation (14) includes only the unobservable time effects and equation (15) includes both the unobservable individual and time effects. In equation (14), the result of the Breusch–Pagan test shows that the random effects (RE) model is selected, and the result of the test of over-identifying restrictions, rather than the Hausman test proposed by Arellano (1993) and Wooldridge (2002), shows conclusively that the fixed effects (FE) model is selected. In equation (15), the result of the test of over-identifying restrictions indicates that the fixed effects (FE) model is selected.

Table 6 also reports the results of testing the EKC for EPI in the industrial sector. As the results of the standard EKC models, which are shown in equations (14) and (15), the coefficients of GDP per capita in equation (15) are significantly positive, the quadratic terms are significantly negative, and the cubic terms are again significantly positive. Consequently, the EKC depicts an N-shape. This means that industrial EPI improves in the initial phase, deteriorates in the second phase, and then improves again in the third phase as income level grows. However, this is not in accordance with the EKC form showed by Färe et al. (2003). This implies that the industrial EPI of the middle-income countries is expected to decline with economic development, and thus environmental performance in developing countries will deteriorate in the future.

5. Conclusion

This study attempted to measure the industrial EPI, which simultaneously accounts for SO_2 and NO_X emissions arising from industrial pollution, and to examine whether the EKC for industrial EPI is applicable, using panel data analysis. The main findings are summarized as follows.

1. From the results of the quantity index of desirable outputs, the performance of middle-income countries is higher in terms of production efficiency than high-income countries in the overall trend. Especially, the performance of China has dramatically improved in terms of efficiency of producing desirable outputs.

Table 6. Test of the Environmental Kuznets Curve for the Environmental Performance Index in the Industrial Sector

	Eq. (14)		Eq. (15)	
	FE	RE	FE	RE
GDPPC	8.33e-05*	1.61e-06	2.21e-04***	3.15e-05
	(4.72e-05)	(1.45e-05)	(8.15e-05)	(2.81e-05)
$(GDPPC)^2$	−8.14e-10	−3.75e-11	−5.24e-09**	−1.22e-09
	(5.07e-10)	(3.15e-10)	(2.36e-09)	(1.08e-09)
$(GDPPC)^3$			4.33e-14*	1.26e-14
			(2.23e-14)	(1.10e-14)
Constant	−0.7921	1.4764***	−2.0577*	1.3364***
	(1.3270)	(0.1477)	(1.2253)	(0.1515)
R^2	0.6897	0.1773	0.7118	0.1094
F-test: individual effects	1.99		3.08**	
F-test: time effects	3.55***		3.50***	
Breusch–Pagan test		828.18***		791.11***
Test of overidentifying restrictions	36.34**		49.71***	
Observations	384	384	384	384

Notes: Values in parentheses of FE and RE are robust standard errors, which are clustered on provinces.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

2. From the results of the quantity index of undesirable outputs, the performance of high-income countries is higher in terms of the emission efficiency than middle-countries in the overall trend. However, the performance of Chile and Indonesia have deteriorated in terms of efficiency of discharging undesirable outputs.
3. From the results of the time-series EPI, EPI has increased in both high- and middle-income countries since the late 1990s. Among all countries, China is the best performer, whereas Chile and Indonesia are the worst.
4. From the estimation results of the EKC models, the EKC hypothesis is followed a N-shaped relationship.

The four findings have the following implications. From to the first and third findings, the improvement factor of EPI tends to be different between high- and middle-income countries; consequently, the former is the enhancement of emission efficiency of undesirable outputs, and the latter is the enhancement of production efficiency of desirable outputs. In middle-income countries, however, it is expected that improving production efficiency will slow down as in high-income countries. According to the four findings, the EPI is expected to decline with economic development in many middle-income countries, and it will be necessary to prevent the deterioration of environmental performance in the future. Thus, the government will require further efforts to promote improvement of emission efficiency, and the policymakers should focus more on diffusing environmental technology such as improving energy efficiency and generating clean energy. As future research tasks, if the study can clarify detailed determinants of environmental performance, it will be able to derive more concrete policy proposals.

Notes

1 Shimizu (2014; 2016a) examined long-run changes in environmental

performance using the time-series emission intensity index (EII) based on Zaim (2004), which is derived through the same process as EPI. Zaim (2004) measured the EII of the U.S. manufacturing sectors by state using both the time-series and cross-section analyses for the period 1972–1986.

2 In this regard, Yörük and Zaim (2008) measured the cross-section EII similar to Zaim (2004).

3 The country classification is based on the World Bank's categorization.

4 In general, the input distance function is expressed by Dx(x, y) = sup{β: (x/β, y)∈P(x), which holds desirable outputs as fixed and decreases the inputs as much as possible.

5 Although constant returns to scale (CRS) is basically assumed in many previous studies such as Färe and Grosskopf (2003) and Färe et al. (2004), this study uses VRS technology because not only technologically developed countries but also technologically developing countries are included in the analysis.

6 In the cross-section analysis, such infeasible solutions have also appeared in previous resarches of Yörük and Zaim (2006; 2008), which takes a hypothetical reference country as the mean of the data.

7 However, this study has the limitation of datasets. Regarding the industrial classification, although the EDGAR and IEA' s data basically follow the same industrial classification, it differs from GGDC 10-Sector Database. For example, EDGAR and IEA' s data do not include part of the water supply industry, but this study uses the data as it is, since it is difficult to consistently adjust the data.

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