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INTERNATIONAL COMPARISON OF ENVIRONMENTAL EFFICIENCY (1990–2008)

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ABSTRACT

In the 2000s, the deterioration of environmental conditions became an increasingly serious issue in developing countries, because this began to have a negative impact on their economic growth. According to the World Bank (2009), climate change arising from environmental deterioration could result in a permanent deceleration in economic growth in developing countries. To maintain sustainable development, these countries need to reduce environmental pollution without sacrificing economic growth. This appears to be a particularly challenging balancing task for developing countries, since they are confronted with serious environmental problems and low economic growth. In this study, we specifically focus on developing countries and the analysis of environmental efficiency, which simultaneously accounts for CO_2, SO_2, and NO_X. To accomplish this, we estimate the environmental efficiency of these three environmental pollutants using a Hicks–Moorsteen productivity index from 1990 to 2008 for both high income and low and medium income countries. Furthermore, using a cross-section data set and a panel data set of environmental efficiency, we examine whether the environmental Kuznets curve (EKC) hypothesis is applicable to all countries from the 1990s to 2000s. Several studies have estimated environmental efficiency and examined the EKC hypothesis in developed countries from the 1970s to 1990s; however, the developing countries were not addressed in this context until the 2000s. From our analysis, we obtain the following three results. First, we confirm that developed countries have low environmental efficiency. This means that developed countries have significant potential to reduce environmental pollutants but low potential for economic growth. Second, we recognize that environmental efficiency in developing countries differs by region and country. Some developing countries have significant potential to reduce environmental pollutants and high potential for economic growth. Third, we found that the EKC hypothesis examined for the three environmental pollutants is applicable from the 1990s to 2000s.

Key words: Hicks–Moorsteen productivity index, Environmental efficiency, Environmental Kuznets curve

JEL Classification: O13, Q53, Q56

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1. INTRODUCTION

This study's purpose is to estimate environmental efficiency using the Hicks–Moorsteen productivity index from 1990 to 2008. We estimate environmental efficiency using cross-section data of 88 countries in 2008, and time-series data of 66 countries from 1990 to 2008. In addition, through the use of a cross-section data set and a panel data set of environmental efficiency, we examine whether the environmental Kuznets curve (EKC) hypothesis is applicable from the 1990s to 2000s.

This study analyzes environmental efficiency and assumes that desirable outputs such as value-added Gross Domestic Product (GDP) and undesirable outputs such as environmental pollutants are jointly produced in production activities (Färe, Grosskopf, Lovell, and Pasurka, 1989). In other words, it is preferable to produce as many desirable outputs as possible, while producing as little undesirable outputs as possible. When we evaluate the performance of country, industry, and firm, we find that many studies in efficiency analysis have only estimated partial productivity or Total Factor Productivity (TFP). In production activities, however, firms produce not only value-added outputs but also environmental pollutants. Therefore, it is necessary to consider the assumption of joint production.

To estimate environmental efficiency, we employ the Hicks–Moorsteen productivity index used by Färe, Grosskopf, and Hernandez-Sancho (2004). This environmental efficiency measure can be separated into two quantity indices of desirable and undesirable outputs. In particular, we estimate the rate of expansion in desirable outputs and the rate of contraction in undesirable outputs compared to a hypothetical reference country or year, which represents the most inefficient country or year. This index has the advantage of being able to estimate joint production by using a Data Envelopment Analysis (DEA) framework. However, the DEA framework does not specify the functional forms in estimation techniques for two or more outputs. Therefore, the Hicks–Moorsteen productivity index is a useful model in this study.

In the relationship between economic development and the environment, a trade-off exists between GDP per capita and environmental pollution in the early phases of development. However, this trade-off is alleviated to some degree in the later phases of development. These relationships are the main bases of EKC, which particularly recognizes that environmental deterioration in the early phases of development is inevitable in many cases.[1] According to the World Bank (2009), however, climate change arising from environmental deterioration could result in a permanent deceleration of economic growth for developing countries. In other words, the trade-off may not in fact exist in the early phases of development. To maintain sustainable development, these countries need to focus on how to reduce environmental pollution without sacrificing economic growth. This is a particularly challenging balancing task in developing countries, since they are confronted with serious environmental problems and low economic growth. In this study, we specifically focus on estimating environmental efficiency in developing countries, and examine the applicability of the EKC hypothesis from the 1990s to 2000s.

Several studies estimated the Hicks–Moorsteen productivity index to examine the EKC hypothesis in developed countries. Färe, Grosskopf, and Hernandez-Sancho (2004) developed the Hicks–Moorsteen productivity index and estimated it for OECD countries in 1990 by using a cross-section data set. The results indicated that the EKC hypothesis was not applicable in 1990. They confirmed no significant relationship between GDP per capita and environmental efficiency, which simultaneously accounts for carbon dioxide (CO_2), sulfur oxide (SO_X), and nitrogen oxide (NO_X).

Similarly, Färe and Grosskopf (2003) estimated the Hicks–Moorsteen productivity index for OECD countries using a time-series data set covering the period 1971–1990. The main difference in the estimation between Färe, Grosskopf, and Hernandez-Sancho (2004) and Färe and Grosskopf (2003) lies in the target for comparison; the former uses cross-country comparisons based on a hypothetical reference country, whereas the latter considers intertemporal comparisons based on a hypothetical reference year. Through the use of a panel data set of environmental efficiency, the estimation results of Färe and Grosskopf (2003) suggest that the EKC hypothesis is applicable. The relationship between GDP per capita and environmental efficiency, which simultaneously accounts for CO_2 and solid particulate matter (SPM), takes the shape of an inverted N-curve during the studied period. The inverted N-curve shape in this context indicates that environmental efficiency deteriorates in the initial phase, improves in the second phase, and then deteriorates again in the third phase.

Yörük and Zaim (2006, 2008) estimated the Hicks–Moorsteen productivity index for OECD countries using a cross-section data set covering the period 1983–1998. The results of both studies support the EKC hypothesis. These studies clarified a significant relationship

[1] See Grossman and Krueger (1993, 1995).

between GDP per capita and environmental efficiency, which simultaneously accounts for CO_2 and NO_X, CO_2 and water pollutants (WP), and NO_X and WP.

However, previous empirical studies focused solely on developed countries from the 1970s to 1990s, not considering developing countries. In view of previous empirical studies, this study focuses on developing countries from the 1990s to 2000s, and contributes to the previous empirical studies on environmental efficiency in three aspects. First, by estimating the capital stock of a larger sample of countries, it is possible to estimate environmental efficiency more accurately from the 1990s to 2000s. Second, applying EDGAR (2011), we conducted a detailed analysis and classified environmental pollutants as follows: CO_2, SO_2, and NO_X. These pollutants have a negative impact on the environment, in that they contribute to both global warming and air pollution. Third, we examine the relationship between GDP per capita and environmental efficiency with respect to these three environmental pollutants, instead of focusing on a single pollutant.

2. MODELS

In this study, we measure the Hicks–Moorsteen productivity index to estimate environmental efficiency. In the following discussion, we explain the Hicks–Moorsteen productivity index used in Färe, Grosskopf, and Hernandez-Sancho (2004).

Let the production factors be represented by x_n (n = 1, 2, 3,…), desirable outputs by y_m (m = 1, 2, 3,…), and undesirable outputs by b_j (j = 1, 2, 3,…). Then, technology T can be represented as follows:

$$T = \{(x_n, y_m, b_j): x_n \text{ can produce } (y_m, b_j)\} \tag{1}$$

Technology T shows that production factors produce desirable and undesirable outputs jointly. In this case, technology T assumes the characteristics of a weak disposability and null-joint production. Weak disposability is defined as follows:

$$\text{If } (x_n, y_m, b_j) \in T \text{ and } 0 \leq \theta \leq 1 \text{ then } (x_n, \theta y_m, \theta b_j) \in T$$

In this case, if undesirable outputs are reduced as much as possible, desirable outputs are also reduced simultaneously. Therefore, null-joint production is defined as follows:

$$\text{If } (x_n, y_m, b_j) \in T \text{ and } b = 0 \text{ then } y = 0$$

In this case, if as many desirable outputs are produced as possible, undesirable outputs are also necessarily produced. In addition to technology T, we impose a closed set and convexity. Then, the output distance function D_y is defined as follows:

$$D_y\ (x_n, y_m, b_j) = \inf \{\theta: (x_n, y_m / \theta, b_j) \in T \tag{2}$$

In equation (2), if undesirable outputs and factor inputs are kept constant, expansion in desirable outputs becomes possible, and thus the rate of expansion is defined as $1 / \theta \leq 1$.[2] Let us compare observation l to observation k on the basis of observation o. The quantity index of desirable outputs Q_y can be defined by using equation (2) as follows:

$$Q_y(\ x_n^o, b_j^o, y_m^k, y_m^l\ ) = \frac{\theta^k}{\theta^l} \tag{3}$$

which compares desirable outputs y^l and y^k, given inputs $x°$ and undesirable outputs $b°$. Therefore, this index indicates the rate of expansion in desirable outputs, i.e., if $Q_y > 1$, the rate of expansion in desirable outputs for observation k is greater than observation l, and consequently observation k is substantially more efficient than observation l.

On the other hand, the input distance function D_b in undesirable outputs is defined as follows:

$$D_b\ (x_n, y_m, b_j) = \sup \{\lambda: (x_n, y_m, b_j /\lambda)\ \in T \tag{4}$$

In equation (4), if desirable outputs and factor inputs are kept constant, the rate of contraction in undesirable outputs becomes possible $1 / \lambda \geq 1$.[3] Similar to the quantity index of desirable outputs Q_y, the quantity index of undesirable outputs Q_b can be defined by using equation (4) as follows:

$$Q_b(\ x_n^o, y_m^o, b_j^k, b_j^l\ ) = \frac{\lambda^k}{\lambda^l} \tag{5}$$

which compares undesirable outputs b^l and b^k, given inputs $x°$ and desirable outputs $y°$. Therefore, this index indicates the rate of contraction in undesirable outputs, i.e., if $Q_b < 1$, the rate of contraction in undesirable outputs for observation k is smaller than observation l, and consequently observation k is substantially more efficient than observation l.

In this study, environmental efficiency $EE^{k,l}$ derived from the Hicks–Moorsteen productivity index is as follows:

$$EE^{k,l} = \frac{Q_y}{Q_b} \tag{6}$$

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[2] In equation (2), constant returns to scale is assumed for desirable outputs.

[3] In technology T (x_n, y_m), usually the input distance function is $D_x\ (x_n, y_m) = \sup \{\lambda: (x_n/\lambda, y_m) \in T$, which holds desirable outputs fixed and contracts the inputs as much as possible. In equation (4), constant returns to scale is assumed for undesirable outputs.

If Q_y is high and Q_b is low, then $EE^{k,l}$ is high; therefore, observation k is more efficient than observation l. Using a DEA, this study evaluates the output distance function D_y and the input distance function D_b. For each observation, the value of the output distance function D_y and the input distance function D_b computed by solving two linear programming problems is as follows:

$$\left(D_y\ \left(x_n^o, y_m^{k'}, b_j^o\right)\right)^{-1} = \max\theta \tag{7}$$

$$\begin{aligned}
& s.t. \\
& \sum_{k=1}^{K} z_k y_m^k \ \geq\ \theta y_m^{k'} \\
& \sum_{k=1}^{K} z_k b_j^k \ =\ b_j^o \\
& \sum_{k=1}^{K} z_k x_n^k \ \leq\ x_n^o \\
& z_k \geq 0
\end{aligned}$$

$$\left(D_b\ \left(x_n^o, y_m^o, b_j^{k'}\right)\right)^{-1} = \min\lambda \tag{8}$$

$$\begin{aligned}
& s.t. \\
& \sum_{k=1}^{K} z_k y_m^k \ \geq\ y_m^o \\
& \sum_{k=1}^{K} z_k b_j^k \ =\ \lambda b_j^{k'} \\
& \sum_{k=1}^{K} z_k x_n^k \ \leq\ x_n^o \\
& z_k \geq 0
\end{aligned}$$

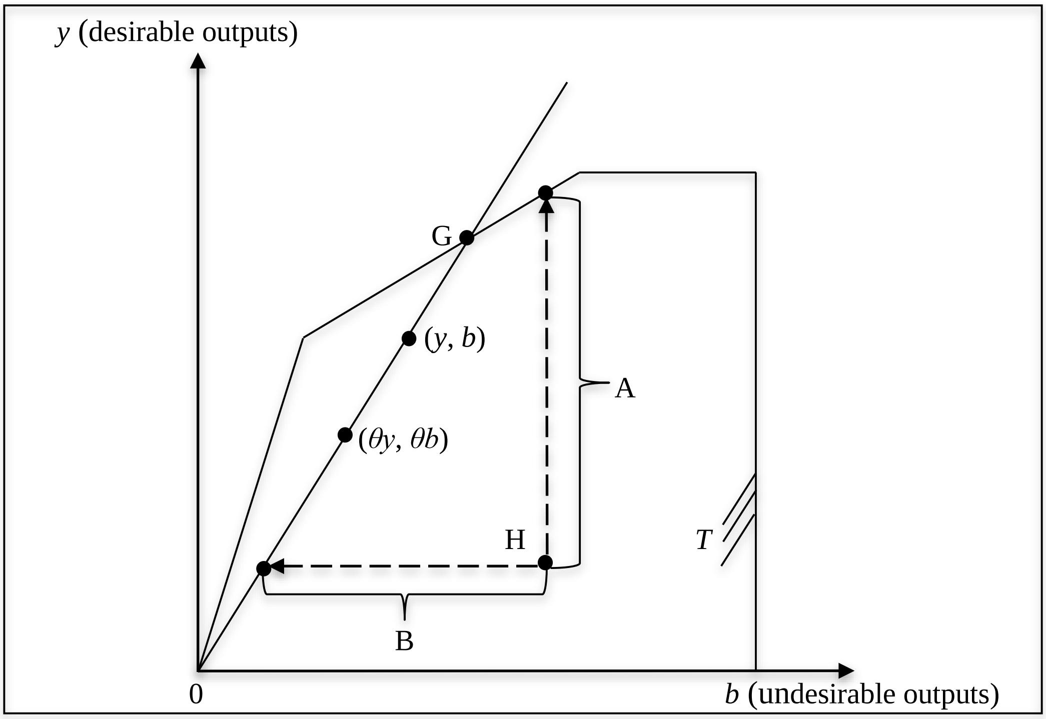
In this study, we estimate environmental efficiency by using cross-section and time-series data. There is a need for a feasible solution for the two linear programming problems. To address this, we must set the hypothetical reference country or year to reflect the minimum desirable outputs and the maximum undesirable outputs and inputs.[4] Thus, the hypothetical reference country or

[4] Other studies by using a cross-section data, such as Färe, Grosskopf, and Hernandez-Sancho (2004) chose the minimum desirable and undesirable outputs and the maximum inputs to represent the hypothetical reference country. Yörük and Zaim (2006, 2008) chose the average of each data set, and to avoid infeasible solutions, these studies used 3-year moving averages for each data set. Furthermore, other studies by using time-series data, such as Färe and Grosskopf (2003), chose the initial year in their data sets as the hypothetical reference year.

year is derived from a combination of the most inefficient value in our data sets. Environmental efficiency is obtained by comparing the selected country or year with the hypothetical reference country or year.

Figure 1 displays the interpretation of environmental efficiency based on the output distance function D_y and the input distance function D_b, respectively. Technology T illustrated in Figure 1 is represented by the production possibility frontier, i.e., it is the output possibilities set. Technology T meets both assumptions of weak disposability—its proportional reduction (θy, θb) in the straight-line segment between zero and G and null-joint production pass through the origin 0. In this study, the output distance function D_y and the input distance function D_b measure the distance of point H to the frontier. Point H is the hypothetical reference country or year, reflecting the minimum desirable outputs and the maximum undesirable outputs and inputs in our data sets.

Figure-1: The Interpretation of Environmental Efficiency



Note: Figure 1 refers to Färe, Grosskopf, and Pasurka (2007).

For environmental efficiency based on cross-section data (time-series data), the output distance function D_y measures the distance A in Figure 1. If the selected country (year) uses the maximum inputs and produces the maximum undesirable outputs, distance A represents how much potential exists to increase desirable outputs in the selected country (year). If distance A is long, the value of θ is large, and thereby, the quantity index of desirable outputs Q_y is high. This implies that there is a potential to increase GDP compared to the hypothetical reference country (year). In other words, it suggests that the selected country (year) has a high potential for economic growth.

On the other hand, the input distance function D_b measures distance B in Figure 1. If the selected country (year) uses the maximum inputs and produces the minimum desirable outputs, distance B represents how much potential exists to decrease undesirable outputs in the selected country (year). If distance B is long, the value of λ is small, and thereby, the quantity index of undesirable outputs Q_b is low. This implies that there is a potential to decrease environmental pollutants compared to the hypothetical reference country (year). In other words, it suggests that the selected country (year) has a high potential to prevent environmental pollution.

Therefore, if the quantity index of desirable outputs Q_y is high and the quantity index of undesirable outputs Q_b is low, then the environmental efficiency is high. This indicates that the selected country (year) has the potential to realize sustainable development. On the contrary, if the quantity index of desirable outputs Q_y is low and the quantity index of undesirable outputs Q_b is high, then the environmental efficiency is low. This indicates that the selected country (year) needs to confront serious environmental problems and low economic growth.

Next, we examine whether the EKC is applicable from the 1990s to 2000s. First, we analyze recent trends in 2008. This study estimates environmental efficiency using a cross-section data of 88 countries with our empirical cross-section data models as follows:

<u>*Cross-section Data Models*</u>

$$EE_i = \alpha_0 + \alpha_q q_i + \alpha_{qq} q_i^2 + \alpha_{D1} D_1 + \alpha_{D2} D_2 + \alpha_{D3} D_3 + \varepsilon_i \tag{9}$$

$$EE_i = \alpha_0 + \alpha_q q_{i,t-1} + \alpha_{qq} q_{i,t-1}^2 + \alpha_{D1} D_1 + \alpha_{D2} D_2 + \alpha_{D3} D_3 + \varepsilon_i \tag{10}$$

where, *EE* is environmental efficiency, which simultaneously accounts for CO_2, SO_2, and NO_X, in country *i*; *q* denotes the real GDP per capita of the country *i*; and *D* is a regional dummy variable, where D_1 is the Asia-Pacific regional dummy variable, D_2 is the African regional dummy variable, and D_3 is the Central and South American dummy variable.[5] We use dummy variables to capture region-specific factors such as climate, natural resources, population, and policy. Finally, ε_i denotes a disturbance term of the country *i*.

In equations (9), (10), and (11), the terms of *q* are variables representing the pattern of the EKC. If the EKC is applicable, the estimated parameter is expected to represent $a_q < 0$, $a_{qq} > 0$. In other words, the relationships between *EE* and *q* are described by a U-shape. In this regard,

[5] In this study, we estimated the dummy variables with reference to North America and Europe.

equation (10) is estimated by using the previous year's data because we consider reverse causality. In these cross-section data models, we use ordinary least squares (OLS) because it can increase the sample of countries.

Second, we review and analyze trends over the past 20 years. This study estimates environmental efficiency using time-series data for 66 countries from 1990 to 2008, and we use panel data. However, several empirical studies applying panel data analysis using environmental efficiency measured by DEA have addressed the potential for serial correlation (Managi and Jena, 2008; Managi and Kaneko, 2009). As a way to deal with the problem of serial correlation, these empirical studies use System Generalized Method of Moments (GMM) estimation using the dynamic panel data by Blundell and Bond (1998). According to Blundell and Bond (1998), the System GMM has two characteristics. First, the System GMM corrects for omitted variable bias by removing the fixed effects by taking first differences. Second, the System GMM corrects for endogeneity bias by adopting instrumental variables by taking lagged endogenous variables.[6] In this study, our empirical dynamic panel data model assumes the following:

Dynamic Panel Data Model

$$EE_{it} = \alpha_0 + \alpha_{EE}EE_{i,t-1} + \alpha_q q_{it} + \alpha_{qq} q_{it}^2 + \alpha_{D1}D_1 + \alpha_{D2}D_2 + \alpha_{D3}D_3 + \alpha_i + \alpha_t + \varepsilon_{it} \quad (11)$$

In equations (11), t denotes the year. We assume that the exogenous variables are regional dummies, and the endogenous variables are GDP per capita. The exogenous variables do not vary at different times. In addition, α_i and α_t denote an individual effect and a time effect in each country. Finally, we adopt the System GMM with one-step estimation using a heteroskedasticity-robust standard error.

3. DATA

In this study, we use country-level data. The data for our estimation of environmental efficiency comes from the World Development Indicators (WDI) and EDGAR version 4.2 databases.[7] The details are as follows.

- Desirable output: real GDP at 2000 prices by WDI.
- Labor force: total economically active population by WDI.

[6] See Roodman (2006) for the System GMM estimator.
[7] Since Taiwan is not included in the WDI, we obtain Taiwan's data from National Statistics.

- Capital stock: the level of capital stock in any given year is the sum of investment accumulated from the previous year. The estimates are obtained by the perpetual inventory method as follows:

$$K_t = \sum_{i=0}^{19} I_{t-i}(1-\alpha)^i$$

  where I is the real gross fixed capital formation at 2000 prices by WDI, α is the depreciation rate (0.05), and the lifetime of the capital stock is 20 years. The depreciation rate and lifetime are taken from the World Bank (2006).
- Undesirable output: CO_2, SO_2, and NO_X by EDGAR version 4.2 databases. We classify the environmental pollutants according to the type of data as prescribed by EDGAR (2011). CO_2 is a greenhouse gas, which primarily contributes to global warming. SO_2 is an acidifying gas, which primarily contributes to air pollution. NO_X is an ozone precursor gas and an acidifying gas, which contributes to both global warming and air pollution.

4. ESTIMATION RESULTS

4.1. Environmental efficiency based on cross-section data

First, this study measures the Hicks–Moorsteen productivity index to estimate environmental efficiency using cross-section data of 88 countries in 2008. Estimation results of the Hicks–Moorsteen productivity index utilizing the quantity indices of both desirable and undesirable outputs are reported in Tables 1, 2, and 3. The geometric mean of these indices is calculated for each income level and region, and a comparison of cross-sectional environmental efficiency is developed.

Table 1: Cross-sectional Environmental Efficiency in High Income Countries

Country	Quantity index of desirable outputs	Quantity index of undesirable outputs	Hicks–Moorsteen productivity index
Canada	15	0.0002	67307
United States	1	0.0000	39312
Austria	58	0.0020	28862
Belgium	49	0.0020	24450
Switzerland	45	0.0030	14972
Germany	6	0.0004	15184
Denmark	74	0.0040	18558
Spain	18	0.0004	43796
Finland	85	0.0020	42642
France	9	0.0004	20348
United Kingdom	7	0.0003	21652
Greece	80	0.0010	79804
Ireland	97	0.0030	32343
Iceland	1090	0.0720	15142
Italy	11	0.0003	37475
Luxembourg	482	0.0320	15052
Netherlands	29	0.0020	14603
Norway	66	0.0030	22030
Portugal	104	0.0020	51917
Sweden	43	0.0030	14480

Table 1 (*continued*)

Cyprus	1060	0.0120	88360
Estonia	1395	0.0070	199273
Hungary	220	0.0030	73343
Australia	24	0.0003	96753
New Zealand	205	0.0050	40996
Japan	3	0.0001	19301
Korea, Republic of	17	0.0003	68054
Hong Kong	54	0.0020	27227
Macao	914	0.0600	15232
Taiwan	24	0.0004	54020
Brunei Darussalam	1927	0.0250	77066
Singapore	90	0.0030	30109
Geometric means	59	0.0017	34184

Table 2: Cross-sectional Environmental Efficiency in Low and Middle Income Countries

Country	Quantity index of desirable outputs	Quantity index of undesirable outputs	Hicks–Moorsteen productivity index
Bulgaria	648	0.0020	323763
Latvia	957	0.0310	30878
Turkey	35	0.0004	83906
Tajikistan	7660	0.0180	425582
China	5	0.0000	321425
Malaysia	94	0.0007	136092
Philippines	111	0.0010	110841
Thailand	74	0.0006	133471
Viet Nam	235	0.0010	235123
Indonesia	53	0.0003	187380
Bangladesh	178	0.0030	59182
India	16	0.0001	215549
Sri Lanka	543	0.0080	67936
Pakistan	122	0.0007	166238
Jordan	904	0.0060	150737
Syrian Arab Republic	461	0.0020	230294
Algeria	176	0.0020	87759
Egypt, Arab Rep.	90	0.0007	132303
Morocco	238	0.0020	119072
Tunisia	421	0.0050	84126
Cote d'Ivoire	1203	0.0190	63332
Cape Verde	15185	0.8230	18450
Gabon	2176	0.0220	98924
Guinea	3251	0.2140	15189
Senegal	2007	0.0180	111484
Ethiopia	859	0.0180	47721
Kenya	749	0.0100	74929
Madagascar	2532	0.0590	42924
Mauritius	2124	0.0390	54450
Sudan	625	0.0410	15246
Uganda	1175	0.0770	15255

Table 2 (*continued*)

Botswana	1592	0.0180	88469
Lesotho	13367	0.5880	22733
Mozambique	1644	0.0370	44437
Namibia	2245	0.1480	15168
Swaziland	7224	0.1390	51971
South Africa	71	0.0003	226476
Mexico	19	0.0003	64867
Costa Rica	559	0.0190	29421
Cuba	268	0.0030	89422
Dominican Republic	364	0.0050	72856
Guatemala	507	0.0090	56335
Honduras	1249	0.0130	96040
Nicaragua	2490	0.0230	108274
Panama	679	0.0100	67944
El Salvador	815	0.0160	50927
Brazil	15	0.0003	48375
Argentina	33	0.0009	36194
Bolivia	1155	0.0140	82495
Chile	125	0.0010	125332
Colombia	93	0.0020	46385
Ecuador	546	0.0040	136575
Peru	156	0.0060	25969
Paraguay	1389	0.0740	18767
Uruguay	469	0.0220	21318
Venezuela, RB	79	0.0008	93653
Geometric means	419	0.0058	71982

Tables 1 and 2 show the results of cross-sectional environmental efficiency, which simultaneously accounts for CO_2, SO_2, and NO_X in both high income and low and middle income countries.[8] In terms of environmental efficiency in global warming and air pollution, the geometric mean of environmental efficiency in low and middle income countries is higher than high income countries. The overall trend seen in low and middle income countries is that the quantity index of both desirable and undesirable outputs is high. With a progressive improvement in income levels, high income countries are low in environmental efficiency, which is reflected by a declining trend in the quantity index of both desirable and undesirable outputs.

Table 3 reports the results of regional environmental efficiency. Central Europe and Asia, South and Southeast Asia, and the Middle East and North Africa are high in environmental efficiency, i.e., the quantity index of desirable outputs is high and that of undesirable outputs is low. Compared to the most inefficient hypothetical reference country, this implies that there is a potential to increase GDP and decrease environmental pollutants.

On the other hand, North America and Europe, East Asia and the Pacific, Sub-Saharan Africa, and Latin America and the Caribbean are low in environmental efficiency. There are two reasons for this. First, the quantity index of desirable outputs is low in North America and Europe, and East Asia and the Pacific. This implies that there is less potential to increase GDP in these countries. Second, the quantity index of undesirable outputs is high in Sub-Saharan Africa, Latin America, and the Caribbean, which indicates that there is less potential to decrease environmental pollutants.

Table 3: Geometric Means of Regional Environmental Efficiency

Region	Quantity index of desirable outputs	Quantity index of undesirable outputs	Hicks–Moorsteen productivity index
North America and Europe	38	0.0014	26726
Central Europe and Asia	659	0.0053	124399
East Asia and Pacific	33	0.0007	49748
South and Southeast Asia	137	0.0012	110386
Middle East and North Africa	295	0.0023	126187
Sub-Saharan Africa	1821	0.0423	43083
Latin America and Caribbean	278	0.0048	57607

[8] The basis for the classification between high income and low and middle income countries refers to the World Bank's income group standard.

Table 4: OLS Parameter Estimates in Eqs (9) and (10)

	All countries	
Dependent variable	Eq. (9)	Eq. (10)
GDP per capita	-8.22	-8.27
	[-4.18]***	[-4.21]***
(GDP per capita)^2	0.0001	0.0001
	[3.21]***	[3.24]***
Dummy1	15490	14767
	[0.76]	[0.72]
Dummy2	-95954	-96971
	[-2.97]***	[-3.00]***
Dummy3	-79408	-81154
	[-2.99]***	[-3.03]***
Constant	177648	178391
	[5.55]***	[5.57]***
R-squared	0.4579	0.4599
Adj-R-squared	0.4249	0.4270
N	88	88

Note: Values in parentheses are White's t-values. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Next, we examine whether the EKC hypothesis is applicable in 2008, by applying a cross-section data set of environmental efficiency. Estimation results of the OLS parameter are reported in Table 4. First, we investigate whether the model should include the dummy variable by F-test. In all countries, when we test H_0: $\alpha_{D1} = \alpha_{D2} = \alpha_{D3} = 0$, utilizing the F-test, we reject the H_0 at the 1% level. Thus, the dummy variables capture region-specific factors.

From Table 4, the estimated parameters of GDP per capita are all significantly negative and its quadratic terms are all significantly positive in all countries. This means that the EKC hypothesis is applicable in 2008. Therefore, the relationship between GDP per capita and environmental efficiency for the three environmental pollutants has the shape of a U-curve.

4.2. Environmental efficiency based on time-series data

Table 5: Time-series Environmental Efficiency in High Income Countries

	Geometric means of the 1990s			Geometric means of the 2000s		
Country	Quantity index of desirable outputs	Quantity index of undesirable outputs	Hicks–Moorsteen productivity index	Quantity index of desirable outputs	Quantity index of undesirable outputs	Hicks–Moorsteen productivity index
Canada	1.308	0.864	1.515	0.964	0.640	1.507
United States	0.882	0.834	1.058	0.652	0.630	1.036
Austria	0.904	0.885	1.021	0.717	0.703	1.020
Belgium	1.046	0.858	1.219	0.849	0.730	1.164
Switzerland	1.010	0.954	1.058	0.869	0.808	1.074
Germany	0.914	0.883	1.035	0.792	0.790	1.003
Denmark	0.903	0.807	1.119	0.737	0.694	1.062
Spain	0.919	0.905	1.015	0.667	0.614	1.088
Finland	0.903	0.808	1.117	0.658	0.610	1.078
France	0.941	0.916	1.028	0.772	0.734	1.052
United Kingdom	0.914	0.878	1.041	0.697	0.686	1.016
Greece	0.929	0.916	1.014	0.677	0.663	1.020
Ireland	0.793	0.772	1.027	0.409	0.399	1.024
Iceland	0.916	0.867	1.057	0.643	0.620	1.037
Italy	0.947	0.928	1.021	0.822	0.806	1.019
Luxembourg	0.826	0.822	1.005	0.531	0.505	1.051
Netherlands	0.891	0.791	1.127	0.688	0.652	1.055
Norway	0.846	0.770	1.098	0.640	0.619	1.033
Portugal	1.268	0.883	1.437	1.008	0.680	1.483
Sweden	1.014	0.847	1.197	0.771	0.685	1.126
Hungary	1.111	0.888	1.251	0.846	0.686	1.233
Australia	0.890	0.862	1.033	0.632	0.624	1.012
New Zealand	0.877	0.855	1.027	0.644	0.613	1.052
Japan	0.940	0.924	1.017	0.848	0.814	1.043
Korea, Republic of	0.743	0.737	1.009	0.463	0.451	1.026
Hong Kong	0.814	0.794	1.025	0.584	0.552	1.058
Taiwan	1.746	0.718	2.431	1.123	0.459	2.448

Table 6: Time-series Environmental Efficiency in Low and Middle Income Countries

Country	Geometric means of the 1990s: Quantity index of desirable outputs	Geometric means of the 1990s: Quantity index of undesirable outputs	Geometric means of the 1990s: Hicks–Moorsteen productivity index	Geometric means of the 2000s: Quantity index of desirable outputs	Geometric means of the 2000s: Quantity index of undesirable outputs	Geometric means of the 2000s: Hicks–Moorsteen productivity index
China	3.710	0.589	6.295	1.532	0.245	6.242
Malaysia	0.694	0.687	1.009	0.420	0.413	1.018
Philippines	1.476	0.857	1.722	1.030	0.604	1.705
Thailand	0.749	0.728	1.029	0.535	0.498	1.074
Indonesia	0.755	0.747	1.011	0.549	0.509	1.078
Bangladesh	2.060	0.791	2.605	1.266	0.492	2.574
India	2.407	0.767	3.139	1.350	0.440	3.069
Sri Lanka	1.608	0.732	2.197	1.038	0.479	2.168
Pakistan	1.766	0.815	2.167	1.215	0.542	2.242
Algeria	0.943	0.841	1.121	0.697	0.695	1.003
Egypt, Arab Rep.	1.816	0.842	2.156	1.196	0.537	2.226
Morocco	1.628	0.864	1.885	1.158	0.622	1.861
Tunisia	0.819	0.788	1.040	0.529	0.515	1.026
Cote d'Ivoire	1.337	0.865	1.545	1.167	0.702	1.662
Gabon	0.878	0.846	1.038	0.789	0.702	1.124
Senegal	1.706	0.841	2.029	1.181	0.577	2.047
Kenya	1.526	0.899	1.698	1.177	0.693	1.697
Madagascar	0.932	0.900	1.036	0.718	0.625	1.148
Sudan	0.781	0.694	1.125	0.449	0.445	1.008
Lesotho	0.834	0.810	1.029	0.596	0.580	1.027
South Africa	0.927	0.909	1.020	0.694	0.669	1.038
Mexico	1.484	0.831	1.786	1.110	0.656	1.693
Costa Rica	1.828	0.754	2.423	1.170	0.488	2.400
Cuba	0.865	0.814	1.062	0.635	0.607	1.047
Dominican Republic	1.781	0.747	2.383	1.077	0.449	2.396
Guatemala	0.833	0.792	1.052	0.585	0.545	1.074
Honduras	0.853	0.819	1.040	0.604	0.528	1.144
Nicaragua	0.905	0.862	1.051	0.629	0.588	1.069
El Salvador	1.502	0.742	2.024	1.100	0.563	1.955
Brazil	0.893	0.845	1.057	0.693	0.662	1.047
Argentina	0.736	0.700	1.051	0.600	0.572	1.049
Bolivia	0.835	0.703	1.187	0.609	0.604	1.009
Chile	0.707	0.696	1.016	0.460	0.452	1.017
Colombia	1.367	0.815	1.678	1.053	0.640	1.644
Ecuador	1.554	0.856	1.815	1.187	0.637	1.862
Peru	1.698	0.769	2.207	1.167	0.544	2.143
Paraguay	1.143	0.778	1.469	0.979	0.706	1.387
Uruguay	1.236	0.735	1.681	1.073	0.698	1.536
Venezuela, RB	1.508	0.844	1.788	1.294	0.705	1.835

In this section, we measure the Hicks–Moorsteen productivity index to estimate environmental efficiency using time-series data of 66 countries from 1990 to 2008. Tables 5 and

6 reported the estimation results of the Hicks–Moorsteen productivity index utilizing the quantity indices of both desirable and undesirable outputs. We observe how the environmental efficiency of each country changes over time, and a comparison of time-series environmental efficiency is obtained.

Tables 5 and 6 report the results of time-series environmental efficiency in both high income and low and middle income countries. With respect to the environmental efficiency in global warming and air pollution in each country, this study makes a comparison between the 1990s (1990–1999) and 2000s (2000–2008). In the 1990s and 2000s, the high income countries with the exception of Taiwan are low in environmental efficiency. From the 1990s to 2000s, environmental efficiency in high income countries varies only slightly, because the quantity indices of both desirable and undesirable outputs in the 2000s tend to be lower than the 1990s. This implies that there is less potential to increase GDP compared to the most inefficient hypothetical reference year, but the potential to decrease environmental pollutants in the 2000s.

Meanwhile, environmental efficiency in low and middle income countries differs from country to country. In the 1990s and 2000s, environmental efficiency in China is the highest among the countries studied, while the values of Bangladesh, India, Sri Lanka, Pakistan, Egypt, Senegal, Costa Rica, the Dominican Republic, and Peru are relatively high—above 2.0. Observing the common trend of these countries during the period studied, from the 1990s to 2000s, the quantity indices of both desirable and undesirable outputs have sharply declined in many countries. Similar to the results for high income countries, this implies that there is less potential to increase GDP but the potential to decrease environmental pollutants in the 2000s.

Table 7: Panel Unit-root Test in First Differences Data

Variable	Unit-root test	Statistic	*p* -value
Environmental efficiency	Levin-Lin-Chu unit-root test	-21.925	0.000
	Im-Pesaran-Shin unit-root test	-19.452	0.000
GDP per capita	Levin-Lin-Chu unit-root test	-6.795	0.000
	Im-Pesaran-Shin unit-root test	-9.501	0.000
(GDP per capita)^2	Levin-Lin-Chu unit-root test	-4.453	0.000
	Im-Pesaran-Shin unit-root test	-7.702	0.000

Note: The null hypothesis indicates that panels contain unit root.

Next, we examine whether the EKC hypothesis is applicable from the 1990s to 2000s, by using a panel data set of environmental efficiency. To adopt System GMM estimation, we investigate the stationarity of each variable by the panel unit-root test of Levin, Lin, and Chu

(2002) and Im, Pesaran, and Shin (2003). In Table 7, we report the estimation results of both the Levin-Lin-Chu and Im-Pesaran-Shin unit-root tests using first differences data, and we reject the null hypothesis of the unit root in each variable.

Table 8 reports the estimation results of the one-step System GMM parameter. Using the AR2 test, we cannot reject the null hypothesis that the disturbance term in the first differences has no order-2 serial correlation. This means that the disturbance term has no serial correlation. Also, we can reject the null hypothesis applying the Sargan test of over-identifying restrictions. Thus, the instrumental variables used in the System GMM estimation are valid.

Table 8: System GMM Parameter Estimates in Eq. (11)

Dependent variable	All countries
(Environmental efficiency) $_{-1}$	0.973
	[72.58]***
GDP per capita	-1.83E-06
	[-2.48]**
(GDP per capita)^2	2.52E-11
	[1.95]*
Dummy1	0.007
	[1.08]
Dummy2	-0.016
	[-1.71]*
Dummy3	-0.010
	[-1.17]
Constant	0.056
	[2.69]***
AR2 test (*p* -value)	0.250
Sargan test (*p* -value)	0.484
N	1188

Note: Values in parentheses are *t*-values. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Similar to the results of the cross-section analysis, the estimated parameters of GDP per capita are significantly negative, and its quadratic terms are significantly positive in all countries. Therefore, we can conclude that the EKC hypothesis is applicable in all countries from the 1990s to 2000s. This means that the relationship between GDP per capita and environmental efficiency for the three environmental pollutants has the shape of a U-curve. In other words, environmental efficiency is generally associated with the level of GDP per capita.

5. CONCLUSION

In this study, we estimated environmental efficiency in developed and developing countries, which simultaneously accounts for CO_2, SO_2, and NO_X, and examined the applicability of the EKC hypothesis from the 1990s to 2000s. From the results of this study, we obtained the following three implications. First, we can confirm that the high income countries, many of which belong to North America and Europe, East Asia and the Pacific, have low environmental efficiency. Moreover, environmental efficiency in high income countries is relatively constant or changes only slightly from the 1990s to 2000s. This result suggests that developed countries have a significant potential to reduce environmental pollutants but a low potential for economic growth.

Second, it is evident that environmental efficiency in low and middle income countries differs by region and country from the 1990s to 2000s. Central Europe and Asia, South and Southeast Asia, and the Middle East and North Africa have high environmental efficiency, while environmental efficiency remains low in Sub-Saharan Africa, Latin America and the Caribbean. This result suggests that some developing countries have significant potential to reduce environmental pollutants and high potential for economic growth. In this regard, developing countries as a whole displayed a diminished potential for economic growth from the 1990s to 2000s, while exhibiting enhanced potential to reduce environmental pollutants.

Finally, we found that the EKC hypothesis as applied to the three environmental pollutants is applicable from the 1990s to 2000s. From the estimation of dynamic panel data, we can confirm that the relationship between GDP per capita and environmental efficiency forms a U-curve. Therefore, a trade-off exists between GDP per capita and environmental pollution, such as global warming and air pollution. In the future, environmental efficiency concomitant with economic development is expected to rapidly worsen in some developing countries.

REFERENCES

Färe, R. and S. Grosskopf. 2003. New Directions: Efficiency and Productivity. Kluwer Academic Publishers, Boston.

World Bank. 2006. Where is the Wealth of Nations?: Measuring Capital for the 21st Century. Washington, D.C.

World Bank. 2009. World Development Report 2010: Development and Climate Change. Washington, D.C.

Blundell, R. and S. Bond. 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometric*s 87 (1): 115–143.

Im, K.S., M.H. Pesaran, Y. Shin. 2003. Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics* 115(1): 53–74.

Färe, R., S. Grosskopf, C.A.K. Lovell, C. Pasurka. 1989. Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach. *Review Economics and Statistics* 71 (1): 90–98.

Färe, R., S. Grosskopf, C. Pasurka. 2007. Pollution Abatement Activities and Traditional Productivity. *Ecological Economics* 62 (3-4): 673–682.

Färe, R., S. Grosskopf, F. Hernandez-Sancho. 2004. Environmental Performance: An Index Number Approach. *Resource and Energy Economic*s 26 (4): 343–352.

Grossman, G.M. and A.B. Krueger. 1995. Economic Growth and the Environment. *Quarterly Journal of Economics* 110 (2): 353–377.

Levin, A., C.-F. Lin, C.-S.J. Chu. 2002. Unit Root Tests in Panel Data: Asymptotic and Finite-sample Properties. *Journal of Econometrics* 108(1): 1–24.

Managi, S. and P.R. Jena. 2008. Environmental Productivity and Kuznets Curve in India. *Ecological Economics* 65 (2): 432–440.

Managi, S. and S. Kaneko. 2009. Environmental Performance and Returns to Pollution Abatement in China. *Ecological Economics* 68 (6): 1643–1651.

Yörük, B.K. and O. Zaim. 2006. The Kuznets Curve and the Effect of International Regulations on Environmental Efficiency. *Economics Bulletin* 17 (1): 1–7.

Yörük, B.K. and O. Zaim. 2008. International Regulations and Environmental Performance. *Applied Economics* 40 (7): 807–822.

Grossman, G.M. and A.B. Krueger. 1993. Environmental Impacts of a North American Free Trade Agreement. (in: P, Garber-ed., *The US Mexico Free Trade Agreement*), MIT Press, Cambridge, MA, pp. 165–177.

Roodman, D. 2006. How to Do xtabond2: An Introduction to “Difference” and “System” GMM in Stata. Working Paper Number 103, Center for Global Development.

European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL). 2011. *Emission Database for Global Atmospheric Research (EDGAR), release version 4.2*, http://edgar.jrc.ec.europa.eu, [Accessed 3.2.2012]