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International Environmental Efficiency with CO_2 Using Meta Stochastic Frontier Analysis†

Ziyao Li* and Sangmok Kang**

ABSTRACT : We measure Environmental Efficiency (EE) based on CO_2 in four income groups from 1998 to 2018, using the Meta Stochastic Frontier Analysis method by Input Distance Function. Our results showed that economic growth and energy consumption would increase carbon dioxide emissions, and increasing labor and capital input will reduce it. Moreover, we compared Group Environmental Efficiency (GEE), Meta Environmental Efficiency (MEE), and Environmental Gap Ratio (EGR). The results showed that GEEs were be overestimated. Furthermore, the MEE showed a downward trend during this period. The lower-middle-income group had the highest EGR performance. High-income and upper-middle-income groups showed less efficiency in MEE and EGR. To improve environmental efficiency, we must reduce fossil fuels and find more scientific and technological ways to solve existing environmental problems as soon as possible.

Keywords : Environmental efficiency, Meta stochastic frontier analysis, Input distance function, CO_2 emissions

JEL Classifications : O4,Q1,C5

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* Ph.D Course, Economics, College of Economics and International Trade, Pusan National University, First author(e-mail: liziyao3721@hotmail.com)

** Professor, Economics, College of Economics and International Trade, Pusan National University, Corresponding author(e-mail: smkang@pusan.ac.kr)

메타확률 프런티어를 사용한 CO_2의 국제환경효율

리즈야오* · 강상목**

요 약 : 본 연구는 투입물 거리함수에 의한 메타확률 프런티어 방법을 사용하여 1998년부터 2018년까지 4개 소득그룹의 이산화탄소 기준의 환경효율성(EE)을 측정하였다. 에너지 소비가 이산화탄소 배출을 증가시키고, 노동과 자본투입을 증가하면 이산화탄소 배출을 감소시킬 것임을 보여주고 있다. 또한 그룹환경효율성(GEE: Group Environmental Efficiency), 메타환경효율성(MEE: Meta Environmental Efficiency) 및 환경격차(EGR: Environmental Gap Ratio)를 비교하였다. 결과는 GEE가 과대평가되고 MEE는 이 기간 동안 하향세를 보여주고 있다. 중하위 소득그룹의 EGR은 가장 높았다. 그리고 고소득 및 중상위 소득그룹의 MEE 및 EGR이 상대적으로 낮았다. 환경효율성을 높이려면 화석에너지를 저감하고 기준 환경 문제를 해결하는 방법이 보다 과학적이고 기술적인 방법을 찾아 필요가 있음을 시사한다.

주제어 : 환경효율, 메타확률 프런티어, 투입물 거리함수, 이산화탄소 배출

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* 부산대학교 경제학부, 박사과정, 제1저자(e-mail: liziyao3721@hotmail.com)

** 부산대학교 경제학부, 교수, 교신저자(e-mail: smkang@pusan.ac.kr)

Ⅰ. Introduction

Nowadays, many countries are pursuing economic growth while paying more attention to environmental protection. Economic activities produce desirable goods and services and bring undesirable output (Robaina-Alves et al., 2015). Human emissions of carbon dioxide and other greenhouse gases are the leading causes of global warming and present one of the world's most pressing challenges. When we think of global warming, we usually assume that a 1°C increase in temperature will not have a significant impact. But in fact, it will cause many major problems, such as extreme natural disasters, sea-level rise, etc., which will affect production and life, and even cause casualties. Recently, in the Leaders Summit on Climate, which convened the world's 17 largest economies and greenhouse gas emitters and included the leaders of other countries especially vulnerable to climate impacts or charting innovative pathways to a net-zero economy. Most of the participating countries have set a goal of achieving carbon neutrality by 2050. To achieve our goals, we did take some measures, such as reducing the use of fossil energy and closing high-polluting factories. However, due to the immaturity of technology or lack of supporting policies, environmental efficiency has declined. Improving environmental efficiency (EE) can reduce greenhouse gases (GHG) emissions, which is a force of job for sustainable growth and environmental protection. Some countries such as the USA, France, and many others have already entered a phase of increased gross domestic product (GDP) and reduced carbon emissions. However, the process is slow. Many developing and underdeveloped countries need new policies and technologies on environmental protection as well as economic growth.

So it is vital to estimate the EE to evaluate the existing environmental policies and make new decisions. In this article, we will measure the environmental efficiency of 164 countries and their distance from the environmental frontier. We usually think that high-income countries, or developed countries, have high levels of technology and do better at environmental protection, while countries with lower incomes have lower levels of technology and perform less well at solving environmental problems. We will test this idea and make recommendations for improving environmental efficiency in the context of sustainable development goals.

We compiled papers on EE in recent years. Several scholars evaluate EE by regional, area-level, or country-level data. Some analyses were focused on OECD countries (Zaim & Taskin, 2000a, 2000b; Färe et al., 2004; Arcelus & Arocena, 2005; Camarero et al., 2008; Halkos & Tzeremes, 2009). Li and Wang (2014) proposed that these studies did not evaluate technological heterogeneity. Koçak et al. (2021) indicated that only the USA ensures the EE in energy R & D expenditures among OECD countries. Furthermore, several studies for China estimated the regional or area-level environmental performances (Wang et al., 2013; Bi et al., 2014; Lin & Liu, 2015; Wu et al., 2020; Yue et al., 2021). Feng et al. (2017) used a Green Development Performance Index (GDPI) and the 165 countries database to evaluate the global patterns of green development performance and its influencing factors. Yang et al. (2020) find that the low economic development level is not necessarily associated with low EE and observed a greater EE improvement than production efficiency at the regional level.

In terms of measurement methods, we found that many studies used the DEA method. DEA is a nonparametric method for estimating production frontiers and efficiencies, accommodating multiple outputs and multiple inputs. Zhang et al. (2016) used a slack-based measure DEA (SBM-DEA) method to evaluate the environmental efficiency of China and investigated the affecting factors using the Tobit regression model. Ma et al. (2019) used the dynamic network DEA method to evaluate China's energy efficiency and environmental efficiency. Chen et al. (2020) show a new DEA cross-efficiency approach to assess environmental efficiency from self-evaluation and peer evaluation perspectives. Both of these papers considered the environmental variables as undesirable output. Moutinho & Madaleno (2021) used the SFA method to evaluate the economic and environmental efficiency of Asians and Africans. Although this study shows the heterogeneity of various regions through differences in energy consumption, it ignores the differences in the economic development of each country.

Another similar definition of EE is eco-efficiency, a popular crucial indicator consistent with sustainable development (Q.Liu, 2020). The eco-efficiency was first introduced by Schaltegger & Sturm (1990) and definite by The World Business Council for Sustainable Development (WBCSD) as a relationship between economic activities and the environmental cost.[1] Also, eco-efficiency was widely used at a regional and national level. Several studies for China focus on the difference between eastern, central, and western areas (Li et al., 2013; Chen, 2015; Dai et al., 2016; Yang & Zhang, 2018; Y. Liu, 2020). As for OECD countries' studies, Camarero et al. (2013) evaluated the eco-efficiency of 22 OECD countries from 1980 to 2008, find that Hungary, Turkey, Canada, and the United States had the worst performance, and the most eco-efficient country was Switzerland. Mavi et al. (2019) estimated both the eco-efficiency and eco-innovation of OECD countries using the two-stage network DEA method and also find that Switzerland is the highest in eco-efficiency.

We found that the previous studies have the following characteristics through these literatures, and we will also propose some different methods next. First, we mentioned above that reducing greenhouse gas emissions is as important as reducing air pollution. Most studies use CO_2 (representing greenhouse gases) and SO_2 (representing air pollution) as outputs, and some research added wastewater and dust pollution to study efficiency. Until now, there is no objective standard for measuring EE. CO_2 is the primary greenhouse gas emitted through human activities and is highly likely to have been the dominant cause of the observed warming since the mid-20th century (IPCC, 2014)[2]. CO_2 emissions are measured as an indicator of environmental degradation

1) Eco-efficiency is realized by the delivery of competitively priced goods and services that satisfy human needs and enhance quality of life, while ecological impacts and resource intensity are progressively reduced throughout the life-cycle to a level that is at least in line with the Earth's estimated carrying capacity (Schmidheiny & Stigson, 2000)

2) Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J. A., Clarke, L., Dahe, Q., & Dasgupta, P. (2014). Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. IPCC.

(Yang et al. 2015) and are a crucial factor in calculating the level of sustainable development (Chen et al. 2020). In this paper, we will also use CO_2 for measuring EE.

Second, most scholars adopted the DEA method in these studies and treated the environmental factors as undesirable outputs. Although the DEA method is a standard method of research efficiency, the function form is not specified and does not separates noise from the error term, and is easier to apply to situations with multiple inputs and output. We prefer the SFA method in this study, which uses a parametric approach to distinguish measurement errors from production inefficiency errors. Moreover, the distance function in the SFA method can solve the multiple inputs and outputs problem. Moreover, many scholars have proposed to treat pollution variables as bad output or an input. (Fare et al., 1989; Reinhard et al., 1999, 2000; Lansink et al., 2002; Zhou et al. 2006, 2007; Skevas et al., 2012; Chen et al., 2015; Coluccia, 2020). Reinhard et al. (2000), which provided a widely used method, treated the pollutant variables as an input to compare the differences in EE using SFA and DEA. Yang et al. (2015) chose domestic CO_2 emission and SO_2 emission as a substitute index for environmental impact. Inputs used in the production process can impact, either positive or negative, the environment, and EE aims to consider this impact in ranking economic units according to their level of efficiency (Graham, 2004). This paper will follow the Reinhard et al. (2000) method, treating pollution factors as an input variable.

Third, most studies are calculating China's environmental efficiency. This may be because China is facing severe environmental problems in the recent rapid economic development. The government also attaches great importance to this problem. Although some papers study OECD countries, we believe that environmental issues are a global issue, so we should choose a broader range of research objects, not confined to a particular region or country. To have a more comprehensive understanding of global environmental development trends, we selected data from 164 countries and regions.

Forth, it is generally recognized that countries differ in economic development, pollution policy. To consider the heterogeneity of nations, we divided 164 countries into four groups according to their income levels. We studied their environmental efficiency while considering each group's economic characteristics and technological level.

In short, It is difficult to find a previous study that measured environmental efficiency using a Meta Stochastic Frontier Analysis method that divides environmental efficiency into group efficiency and environmental efficiency gap targeting 164 countries around the world. In particular, this study is differentiated in that it measures MEE through a parametric method that considers probable errors rather than a nonparametric method that does not consider it used in previous studies. In particular, in most previous studies, SFA was used for group efficiency, and the DEA method was used for the second step. In contrast to this, in this study, an SFA approach is used for both steps 1 and 2 by supplementing the problem of not considering the probable error again in the second step. This study aims to estimate the Environmental Efficiency of 164 countries from 1998 to 2018 using the Meta Stochastic Frontier Analysis method by Input Distance Function. We classified 164 countries into four groups: high-income group, upper-middle-income group, lower-middle-income group, and low-income group. We will compare these four groups' Group Environmental Efficiency (GEE), Meta Environmental Efficiency (MEE), and Environmental Gap Ratio (EGR) and make corresponding recommendations based on these results.

In section 2, we introduce the Meta Stochastic Frontier Analysis method. In section 3, we present the empirical results based on the statistical data of 164 countries. In section 4, we offer our conclusions with relevant policy implications.

II. Theoretic Model

This section introduces the theoretical models of EE using the Meta Stochastic Frontier Analysis method, which is estimated by a stochastic input distance function. The Meta Stochastic Frontier Analysis method can evaluate the group technical efficiency and the technology gap between the meta frontier and the group frontier. The stochastic distance function model uses a parametric approach to distinguish measurement errors from production inefficiency errors. This assumes a specific function on the frontier and introduces a distance function to solve multiple inputs and outputs.

The Meta Stochastic Frontier Analysis method was first introduced by Hayami (1969), Hayami and Ruttan (1970), who stated that "The meta production function can be regarded as the envelope of commonly conceived neoclassical production functions." Battese et al. (2001) applied a method to investigate the technology gap ratio (TGR). And then, Battese & Rao (2002) evaluated the technical efficiency using a stochastic meta frontier model. Battese et al. (2004), O' Donnell et al. (2008) provided a two-step mixed approach to estimate the group-specific frontiers and the meta frontier, solving the problem that the technical efficiency scores are relative to different production frontier, not the meta frontier. However, it has a problem that a linear programming problem estimated the TGR in the second step. Huang et al. (2014) proposed a new two-step approach to estimate the meta frontier by stochastic frontier method, which both used the SFA method in the two steps. Honma & Hu (2018) estimated the Total-factor Energy Efficiency (TFEE) and TGR of regions in Japan by using an input distance function. We will follow Huang et al. (2014) to make an input distance function to estimate the EE.

First, we are going to estimate the group efficiency. Follow the input distance function based on Färe & Primont (2012, pp.7), and the model which includes the technical inefficiency errors in the stochastic distance function found on Coelli et al. (2005, pp.264), we get the stochastic input distance function with environmental inefficiency error as:

$$-\ln x_n = \ln D_{input}\left(y,\ \frac{x}{x_n}\right) - u + v \tag{1}$$

Where $x$is the input, D_{input} is the input distance function, and y is the output. v is the random error latter, and is independent and identically distributed as $iid \sim (0, \sigma^2)$. u is the technical inefficiency error (TE), and we suppose this has truncated normal distribution with $iid \sim (\mu, \sigma^2)$. Then, the TE can be estimated as:

$$TE = E[\exp(-u) | (-u+v)] \tag{2}$$

The parametric approach to EE estimation should assume the type of production function. The Cobb-Douglas production function is not flexible because of its elasticity and scale characteristics. We follow the translog functional form for estimating. Eq.(3) is a stochastic input distance function composed of input and output, according to Coelli et al. (2005, pp 264).

$$\begin{aligned} \ln D_{kt} &= \alpha_0 + \sum_{r=1}^{s} \alpha_r \ln y_{rkt} + \frac{1}{2} \sum_{q=1}^{s} \sum_{r=1}^{s} \alpha_{qr} \ln y_{qrt} \ln y_{rkt} + \sum_{n=1}^{n} \beta_i \ln x_{ikt} \\ &\quad + \frac{1}{2} \sum_{h=1}^{n} \sum_{i=1}^{n} \beta_{hi} \ln x_{hkt} \ln x_{ikt} + \sum_{i=1}^{n} \sum_{r=1}^{s} \phi_{ir} \ln x_{hkt} y_{rkt} + v_{it} \\ &\quad k = 1, 2, \ldots, k; t = 1, 2, \ldots, T \end{aligned} \tag{3}$$

When production is executed on the frontier, the input distance function yields a value of 1. That is, the left side of Eq. (3) becomes $\ln D_{input} = \ln(1) = 0$ for all observations. To avoid the problem, according to Fare and Primot (1995), we have the following restriction:

$$\sum_{r=1}^{s} \alpha_r = 1, \sum_{r=1}^{s} \alpha_{qr} = \sum_{i=1}^{n} \beta_{hi} = \sum_{r=1}^{s} \phi_{ir} = 0 \tag{4}$$

Lovell et al. (1994) mentioned that a restriction of linear homogeneity in inputs is imposed on the function. We divide the input distance function and other inputs using the n^{th} input. Our model comes to the Eq. (5):

$$
\begin{aligned}
\ln(D_{kt}/x_{nkt}) = {} & \alpha_0 + \sum_{r=1}^{s}\alpha_r \ln y_{rkt} + \frac{1}{2}\sum_{q=1}^{s}\sum_{r=1}^{s}\alpha_{qr}\ln y_{qrt}\ln y_{rkt} \\
& + \sum_{n=1}^{n-1}\beta_i \ln(x_{ikt}/x_{nkt}) + \frac{1}{2}\sum_{h=1}^{n-1}\sum_{i=1}^{n-1}\beta_{hi}\ln(x_{hkt}/x_{nkt})\cdot \ln(x_{ikt}/x_{nkt}) \\
& + \sum_{i=1}^{n-1}\sum_{r=1}^{s}\phi_{ir}\ln(x_{hkt}/x_{nkt})\cdot y_{rkt} + v_{it} \\
& k = 1,\ 2,\ \ldots,\ k;\ t = 1,\ 2,\ \ldots,\ T
\end{aligned}
\tag{5}
$$

According to Coelli et al. (1998), to obtain the function of EE, we replace $\ln D_{input}$, which cannot be observed, with u in Eq.(6), which is the EE error term. So, the first step of our estimation is:

$$
\begin{aligned}
-\ln(C_{it}) = {} & \beta_0 + \beta_y \ln Y_{it} + \beta_l \ln\left(\frac{L}{C}\right)_{it} + \beta_k \ln\left(\frac{K}{C}\right)_{it} + \beta_e \ln\left(\frac{E}{C}\right)_{it} \\
& + \frac{1}{2}\beta_{yy}\ln Y_{it}^2 + \frac{1}{2}\beta_{ll}\ln\left(\frac{L}{C}\right)_{it}^2 + \frac{1}{2}\beta_{kk}\ln\left(\frac{K}{C}\right)_{it}^2 + \frac{1}{2}\beta_{ee}\ln\left(\frac{E}{C}\right)_{it}^2 \\
& + \beta_{yl}\ln Y_{it}\ln\left(\frac{L}{C}\right)_{it} + \beta_{yk}\ln Y_{it}\ln\left(\frac{K}{C}\right)_{it} + \beta_{ye}\ln Y_{it}\ln\left(\frac{E}{C}\right)_{it} \\
& + \beta_{lk}\ln\left(\frac{L}{C}\right)_{it}\ln\left(\frac{K}{C}\right)_{it} + \beta_{le}\ln\left(\frac{L}{C}\right)_{it}\ln\left(\frac{E}{C}\right)_{it} + \beta_{ke}\ln\left(\frac{K}{C}\right)_{it}\ln\left(\frac{E}{C}\right)_{it} \\
& + v_{it} - u_{it}
\end{aligned}
\tag{6}
$$

Where D_{input} is the input distance function, L is labor employment, K is the capital stock amount, E is the energy consumption, C is the CO_2 emission amount, Y is for the gross domestic product (GDP). The subscript it means the i^{th} country in the t^{th} year. v is the random error and is independent and identically distribute as $iid \sim (0,\ \sigma_v^2)$. The distribution of u has been assumed by a non-negative one-side distribution in Aigner et al. (1977). Considering the EE changes systematically over time, we follow the Battese & Coelli (1992) method to estimate this error term. So the environmental inefficiency error term u is assumed to be as a truncated normal distribution $iid \sim (\mu, \sigma_u^2)$ and independently of v. The time-varying inefficiency error takes the form:

$$u_{it} = \exp\{-\eta(t-T)\} \cdot u_i \tag{7}$$

For the second stage, we estimate the meta frontier efficiency. Battese et al. (2004) and O'Donell (2008) proposed a two-stage mixed approach to estimate the meta frontier. In the first step, they used the stochastic output distance function to estimate the group efficiency. And in the second step, the meta frontier efficiency is calculated by the mathematical programming method. Then the relationship between the group efficiency and meta frontier efficiency is:

$$TE_{it}^{*} = TE_{it} \times TGR_{it} \tag{8}$$

TGR is the technology gap ratio, TE_{it}^{*} is the meta frontier efficiency of i^{th} countries at time t. TE_{it} is the group efficiency of i^{th} countries at time t. Nevertheless, this model would have unreasonable results that the $Y_{it}^{\max} = Y_{it}/TE_{it}$ because of the system error v_{it}. Huang et al. (2014) followed the first stage method and suggested using the SFA method in the second stage instead of the mathematical programming method. Both Battese et al. (2004) and Huang et al. (2014) used the output distance function, and the group maximum output level is $Y_{it}^{\max} = Y_{it}/TE_{it}$. In this paper, we maximize EE by considering CO_2 as an input variable and only if it is minimized. So, we follow Honma & Hu (2018) to estimate the optimal input by contracting the actual input should estimate by: $C_{it}^{\min} = C_{it} \times EE_{it}$. Our second-stage Meta SFA function becomes:

$$
\begin{aligned}
-\ln(C_{it}^{\min}) = {} & \beta_0 + \beta_y \ln Y_{it} + \beta_l \ln\left(\frac{L}{C}\right)_{it} + \beta_k \ln\left(\frac{K}{C}\right)_{it} + \beta_e \ln\left(\frac{E}{C}\right)_{it} \\
& + \frac{1}{2}\beta_{yy} \ln Y_{it}^2 + \frac{1}{2}\beta_{ll} \ln\left(\frac{L}{C}\right)_{it}^2 + \frac{1}{2}\beta_{kk} \ln\left(\frac{K}{C}\right)_{it}^2 + \frac{1}{2}\beta_{ee} \ln\left(\frac{E}{C}\right)_{it}^2 \\
& + \beta_{yl} \ln Y_{it} \ln\left(\frac{L}{C}\right)_{it} + \beta_{yk} \ln Y_{it} \ln\left(\frac{K}{C}\right)_{it} + \beta_{ye} \ln Y_{it} \ln\left(\frac{E}{C}\right)_{it} \\
& + \beta_{lk} \ln\left(\frac{L}{C}\right)_{it} \ln\left(\frac{K}{C}\right)_{it} + \beta_{le} \ln\left(\frac{L}{C}\right)_{it} \ln\left(\frac{E}{C}\right)_{it} + \beta_{ke} \ln\left(\frac{K}{C}\right)_{it} \ln\left(\frac{E}{C}\right)_{it} \\
& + v_{it}^* - u_{it}^* = \ln f^{Meta}(Y, X) + v_{it}^* - u_{it}^*
\end{aligned} \tag{9}
$$

And then, the TGR for country i at time t as:

$$TGR_{it} = \exp(-u_{it}^*) \tag{10}$$

Also, the time-varying inefficiency from Battese & Coelli (1992) defined by:

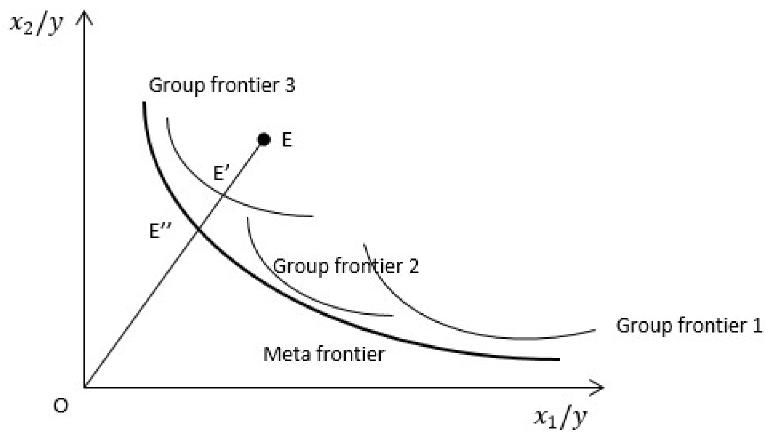
$$u_{it}^* = \exp\{-\eta(t-T)\} \cdot u_i^* \tag{11}$$

The meta environmental efficiency for i^{th} the country at the time $t(MEE_{it})$ can be obtained as:

$$MEE_{it} = GEE_{it} \times EGR_{it} \tag{12}$$

Figure 1 shows the relationship between meta frontier and group frontiers with an input distance function. The group technical efficiency is OE'/OE. And the technology gap ratio (TGR) is OE"/ OE'. The meta technical efficiency is OE''/OE. If TGR is more extensive, it indicates that the group frontier is closer to the meta frontier. This study called the distance from the group frontier to the meta frontier EGR (Environmental Gap Ratio). In the original model, the initial definition was TGR, and a larger value of this indicates that the group technical efficiency is close to the meta frontier. In this paper, we want to express how far the environmental group efficiency is from the environmental frontier, so it is defined as EGR.

〈Figure 1〉 Metafrontier and group frontiers



III. Empirical Analysis and Results

This study used 3,444 observations spanning 21 years, from 1998 to 2018, across 164 countries using the Meta Stochastic Frontier Method. The output variable used in the empirical analysis is the GDP (Y) of each country. The input variables are Labor (L), capital stock (K), energy consumption (E), and CO_2 emission(C).

The input distance function can include multiple inputs and outputs in the function to solve this problem. In our model, GDP is considered the desired output because this is a measure of economic development and considered the CO_2 emissions as environmental input variables.

To objectively compare EE by country, we use per capita variables that divide each variable by population. This is to prevent the problem that the size of the country may affect the size of the EE. Table 1 shows the definitions and units of variables to be used in empirical analysis.

〈Table 1〉 Variables' Unit and Definition in this study

Variable		Unit	Definition
Output	GDP: (GDP/P)	10 thousand 2017$ /per capita	Real GDP at constant 2017 national prices per person
	K: (K/P)	10 thousand 2017$ /per capita	Capital stock at constant 2017 national prices per person
Input	L: (L/P)	workers/per capita	The number of persons engaged divided by population
	E: (E/P)	TCE/ per capita	Tons of Coal Equivalent per person
	C: (CO_2/P)	kg/per capita	Annual production-based emissions of carbon dioxide per person

Note: The original energy consumption unit is "quad Btu" (quadrillion British thermal unit). We transfer it as Stander Coal using 1tce (a ton of coal equivalent) = 2.406×10^7 Btu.[3)]

The Penn World Table 10.0 provided labor, capital stock, and GDP data, while the Our Data in World Database provided the CO_2 emission amount (Feenstra et al., 2015; Ritchie & Roser, 2020). We got the energy consumption data from the U.S. Energy Information Administration (EIA). Also, to compare the group efficiency, we categorize 164 countries into four income groups using the World Bank's classification criteria by income level[4)].

3) National Institute of Standards and Technology of U.S., Special Publication 811(2019) 9th edition: https://www.nist.gov/pml/special-publication-811/

4) The World Data Bank's national classification by income using GDP is as follows: High income group, over 12,375$; Upper-middle income group, between 3,996$ and 12,375$; Lower-middle-income group, between 1,026$ and 3,995$; Low-income group, lower than 1,025$. For more information ,please visit: https://datahelpdesk.worldbank.org/knowledgebase/articles/378834-how-does-the-world-bank-classify-countries

〈Table 2〉 Summary of the data

Variables	Group	Obs.	Mean	Std.	Min.	Max.
GDP	High	1,071	4.056	2.098	0.935	16.652
	Upper-middle	987	1.216	0.552	0.038	4.124
	Lower-middle	840	0.461	0.249	0.046	1.225
	Low	546	0.163	0.090	0.051	0.622
L	High	1,071	0.506	0.066	0.297	0.761
	Upper-middle	987	0.426	0.076	0.240	0.597
	Lower-middle	840	0.390	0.080	0.175	0.600
	Low	546	0.391	0.071	0.217	0.573
K	High	1,071	20.860	10.146	2.507	72.304
	Upper-middle	987	5.101	2.609	0.713	13.280
	Lower-middle	840	2.255	2.605	0.070	17.343
	Low	546	0.707	1.137	0.112	8.123
E	High	1071	9.665	7.140	1.895	46.851
	Upper-middle	971	2.692	1.860	0.193	13.132
	Lower-middle	840	0.885	0.955	0.067	5.772
	Low	546	0.229	0.392	0.014	2.205
C	High	1,071	11.253	8.498	1.362	67.015
	Upper-middle	987	4.014	2.938	0.401	17.448
	Lower-middle	840	1.236	1.610	0.119	20.348
	Low	546	0.272	0.500	0.016	3.306

Note: No energy data for Montenegro and Serbia in 1998-2005.

Table 2 shows the summary of the data. We can see the significant differences exist among different groups. The high-income group has the highest average GDP, labor, and capital. The average GDP per capita for the high-income group is 0.041 million USD, and the average of the capital stock per capita is 0.209 million USD. Moreover, per capita energy consumption in high-income countries is more than 40 times that of low-income countries. Average CO_2 emissions per capita and average capital stock per capita show a positive relationship with average GDP. As we expected, high-income and Upper-middle income countries have high GDP while also having high energy consumption and CO_2 emissions. Therefore, for environmental management, especially in greenhouses gas emissions, we expect them to make more efforts.

In the empirical analysis, we estimated the stochastic frontier translog input distance function. All of the models were conducted based on the assumption of time-varying technical efficiency, which was proposed by Battese & Coelli (1992). The sample data comprised strongly balanced panel data, and the estimates are calculated using the R program. Model (1)-Model (4) is the estimation of group efficiency, Model (5) was estimated using pooling data, and Model (6) and Model (7) represented the result of meta estimation.

As the theoretical model shows, the CO_2 estimation is a dependent variable, contains a negative (-) sign. So, the sign of the estimation result should be reversed in the estimate. In other words, if the sign of the estimation coefficient is negative (-), it has a positive (+) impact on CO_2 emission and vice versa.

〈Table 3〉 Estimation of Input Distance Function Using CO_2

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	High	Upper-Middle	Lower-Middle	Low	Pooling	Meta	C-D function
lnGDP	-0.114** (-1.97)	-0.207*** (-6.96)	-0.200*** (-6.43)	0.107** (2.37)	-0.141*** (-9.26)	-0.090*** (-7.84)	-0.077*** (-16.85)
$\ln(L/CO_2)$	1.102*** (10.02)	0.619*** (11.00)	0.822*** (34.61)	0.924*** (51.62)	0.923*** (62.34)	0.909*** (76.97)	0.901*** (197.16)
$\ln(K/CO_2)$	0.022 (0.29)	0.207*** (5.39)	0.098*** (5.07)	0.054** (2.54)	0.030** (2.56)	0.055*** (5.80)	0.090*** (17.85)
$\ln(E/CO_2)$	-0.037 (-0.47)	0.013 (0.26)	0.082*** (3.45)	0.083*** (3.12)	0.010 (0.78)	-0.008 (-0.80)	-0.011* (-1.94)
$\ln GDP^2$	0.106*** (5.28)	-0.017 (-1.41)	-0.105*** (-6.10)	0.034 (1.39)	-0.069*** (-10.46)	-0.054*** (-11.03)	
$\ln(L/CO_2)^2$	0.124*** (3.23)	-0.117*** (-4.31)	-0.049*** (-3.72)	0.058*** (6.95)	-0.014** (-2.11)	-0.004 (-0.71)	
$\ln(K/CO_2)^2$	0.038* (1.68)	-0.097*** (-5.37)	0.002 (0.17)	0.001 (0.12)	0.013* (1.92)	0.004 (0.84)	
$\ln(E/CO_2)^2$	-0.183*** (-8.21)	0.069*** (3.52)	-0.025* (-1.94)	-0.021** (-1.98)	0.006 (0.66)	0.003 (0.40)	

〈Table 3〉 Estimation of Input Distance Function Using CO_2 (Continued)

VARIABLES	(1) High	(2) Upper-Middle	(3) Lower-Middle	(4) Low	(5) Pooling	(6) Meta	(7) C-D function
lnGDPln(L/CO_2)	0.050** (2.27)	-0.070*** (-5.13)	-0.076*** (-6.72)	0.012 (1.51)	-0.024*** (-3.96)	-0.019*** (-4.10)	
lnGDPln(K/CO_2)	0.012 (0.68)	-0.026*** (-2.89)	0.041*** (4.65)	-0.021** (-2.10)	0.005 (1.01)	0.013 (3.50)	
lnGDPln(E/CO_2)	-0.039** (-2.02)	0.077*** (4.02)	0.034*** (2.70)	0.054*** (4.44)	0.014** (2.27)	0.003*** (0.55)	
ln(L/CO_2)ln(K/CO_2)	-0.020 (-0.72)	0.084*** (4.69)	0.021*** (2.71)	-0.048*** (-8.32)	-0.008 (-1.50)	0.001 (0.14)	
ln(L/CO_2)ln(E/CO_2)	-0.045 (-1.61)	-0.029 (-1.39)	0.053*** (4.38)	0.011 (1.49)	0.003 (0.57)	-0.004 (-0.84)	
ln(K/CO_2)ln(E/CO_2)	0.040 (1.32)	-0.023 (-0.97)	-0.048*** (-5.62)	0.007 (0.85)	-0.015** (-2.40)	-0.009* (-1.90)	
Constant	0.964*** (6.01)	0.871*** (13.62)	1.270*** (29.85)	1.323*** (29.87)	1.275*** (61.30)	1.389*** (87.25)	1.144*** (98.65)
σ^2	0.016*** (12.79)	0.022*** (7.68)	0.041*** (19.21)	0.034** (2.23)	0.042*** (12.48)	0.120*** (4.04)	0.025*** (21.12)
γ	0.926*** (142.24)	0.950*** (304.54)	0.961** (442.10)	0.980*** (108.70)	0.964*** (467.43)	0.988*** (319.76)	0.949*** (570.87)
μ	0.244*** (7.70)	0.292*** (5.71)	0.397*** (8.63)	0.207*** (3.50)	0.404*** (12.67)	0.051 (0.48)	0.305*** (9.74)
η	-0.007*** (-7.78)	-0.009*** (-8.43)	-0.008*** (-9.35)	-0.015*** (-10.29)	-0.004*** (-8.18)	-0.001*** (-3.18)	-0.007*** (-17.48)
Log-likelihood	1926.667	1550.183	1370.581	1140.093	5637.619	5848.071	5058.262
Obs.	1071	971	840	546	3428	3428	3428
Number of countries	51	47	40	26	164	164	164

Note: **P*-value ≤ 0.1, ***P*-value ≤ 0.05, ****P*-value ≤ 0.01.

Table 3 shows the estimates of EE based on CO_2 emission. We can find that increases in emissions tend to be proportional to increases in economic growth. Moreover, labor, capital stock in all models have a significantly negative (-) impact on CO_2 emission. That is, each country tries to reduce CO_2 emissions by increasing labor and capital. So, we can improve our investment in these inputs and achieve the goal of increasing EE while as economic growth.

We confirm that the gamma (γ), mu (μ), eta (η), Log-likelihood values reveal the suitability of the meta stochastic distance model (model6). The gamma[5] is 0.988—that is, the environmental inefficiency error accounts for 98.8% of the total variance, which comprises the environmental inefficiency error and random error. That is, most of the errors comprise environmental inefficiency errors. Since the distribution of environmental inefficiency error terms is $iid \sim (\mu, \sigma_u^2)$ as the truncated normal distribution, the distribution u is symmetric at about $\mu = 0.051$ at the interval of zero (0) or more. The eta (η) shows the form of time variation of the environmental gap inefficiency. The efficiency gap of the environment decreased slightly with time. If there is no inefficiency of the environment, we require the ordinary least square (OLS) estimation without maximum likelihood estimation (MLE). We will explain why there is a downward trend in EE in the following efficiency analysis.

To demonstrate the appropriateness of the stochastic frontier translog input distance function, we do the hypothesis test following Battese et al. (2004). The test statistic of the LR test is calculated as $L = -2[L(H_0) - L(H_1)]$. The threshold value is a value of 1% significance level. Table 4 shows the result of the text. For the first test, $L(H_0)$ =5637.619 is the Log-likelihood value from the pooled regression, which ignores the group technological heterogeneity. $L(H_1)$=5848.071 is the sum of all income groups' estimation Log-likelihood. Therefore, L=72.028 can reject the H0 hypothesis at the 1% level.[6] Therefore, technical heterogeneity among the different groups' exits. For the second text, the H0: Meta frontier is a Cobb-Douglas function rejected by L=1579.618 at a 1% level. It means that the meta frontier function is a translog form function.

5) $\gamma = \dfrac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$

6) By following Battese et al. (2004) and Zhang & Wang (2015), the difference between the number of pooled regression coefficients and the sum of the four groups' coefficients is the degree of freedom.

〈Table 4〉 Hypothesis test

Null hypothesis	$L(H_0)$	$L(H_1)$	Chi-square value	Critical value	Decision
(1) There is no technical heterogeneity in group efficiency	5637.619	5848.071	420.904***	66.206	Rejected
(2) Meta frontier is a Cobb-Douglas function	5058.262	5848.071	1579.618**	23.209	Rejected

Note: *P-value ≤ 0.1, **P-value ≤ 0.05, ***P-value ≤ 0.01.

Above, we regressed the model by two steps; since each group has different characteristics, we will compare their specific EE values next. [7]Table 5 reports the EE of each group relative to group frontier (model1-4), pooled frontier (model 5), and meta frontier (model 6). For the case of group frontier, the average GEE of 4 groups is 0.723, 0.627, 0.594, and 0.811. Comparatively, the average Pooled EE was decreased to 0.530, 0.598, 0.636, and 0.650. In particular, the EE relative to the meta frontier was 0.407, 0.503, 0.578, and 0.621. As we mentioned in section 2, the EE estimated by pooled frontier is biased. Based on these results, EE estimation among different income groups without considering the environmental gap would lead to biased estimates, and EE tends to be overestimated. This also proves that it is the right choice for us to use the meta frontier to measure EE.

〈Table 5〉 Summary of the Group Estimation

Group	GEE	Pooled	MEE	EGR
High income group	0.723	0.530	0.407	0.567
Upper-middle-income group	0.627	0.598	0.503	0.803
Lower-middle income group	0.594	0.636	0.578	0.973
Low-income group	0.811	0.650	0.621	0.765
Average	0.678	0.594	0.510	0.764

7) Due to space limitations, the efficiency of each country is not presented here. For the details of the GEE, EGR, MEE, please connect the author.

According to Eq. (12) and Figure 1, MEE is calculated based on GEE and EGR. Like previously mentioned, EGR shows the distance from the group efficiency to the environmental frontier. Therefore, a larger value indicates that the actual EE is closer to the potential level of environmental technology. As Table 5 shows, the lower-middle-income group has the highest mean value of the efficiency gaps as 0.973, which means that this group is very close to the environmental frontier. We think that this does not indicate that this group has an advantage in environmental technology. This is because they have just started their economic development, and the emission of CO_2 is relatively balanced with economic growth. If the economy continues to develop, or if the industry is transferred from the developed countries, the current balance will may be broken.

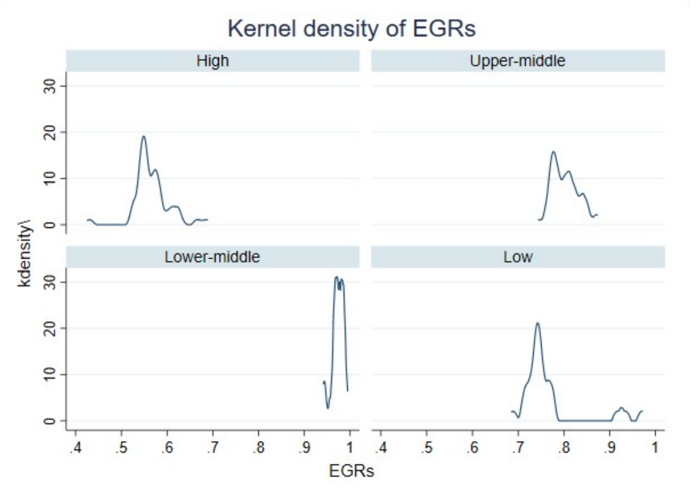
We expect that the high-income group has better technology to deal with environmental problems, EGR will show an increasing trend. However, it is still declining from our results and the EGR is the lowest in the four groups. As Table 3 shows, there is a positive relationship between GDP and CO_2 emissions. This means that high CO_2 emissions is accompanied by economic growth. We think this may also be due to the excessive use of fossil energy in production and consumption in these countries. High-income countries should formulate stricter policies to control carbon emissions and narrow the gap with the environmental frontier. This also indicated that high-income countries had made efforts to reduce carbon dioxide emissions during this period but have not sufficiently reduced carbon dioxide emissions caused by high economic growth. In other words, the environmental technology we have now cannot effectively solve environmental problems.

The Kernel density of EGRs in different groups is shown in Figure 2. The EGRs in the lower-middle-income group have the highest value among the four groups, of which the values are mainly concentrated in the range of 0.9-1.0. The high-income group's EGRs are primarily concentrated in the range of 0.5-0.6. Since the hypothesis that no technological heterogeneity in group efficiency is rejected[8], results indicate a big environmental gap among different income groups.

8) The hypothesis test from Table 4.

Based on the above description of EGR, let us compare GEE and MEE again. The Kernel density of GEE and MEE in different groups is illustrated in Figure 3. We see that, except for the lower-middle-income group, all other group's MEE is distributed to the left of GEE, which means these GEEs tend to be overestimated.

〈Figure 2〉 Kernel density of EGRs in different income groups



〈Figure 3〉 Kernel density of GEE and MEE in different income groups

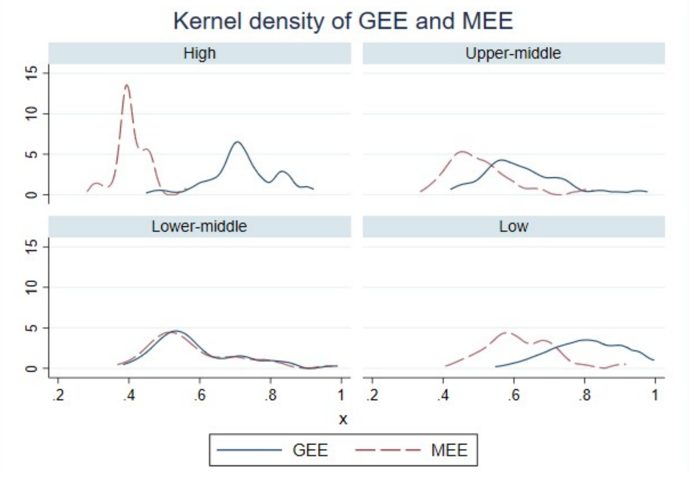


Figure 4 shows that all groups' and average MEE has decreased over time. For the reasons that contributed to the continued decline in EE, first, as Jevons' paradox proposed[9], the improvement of technical efficiency increased the overall consumption of coal, iron, and other resources rather than saving them. Increasing the consumption of fossil energy will lead to a continuous increase in CO_2 emissions. Although the use of renewable energy will reduce carbon emissions, power generation increased from 19.12% to 26.26% between 1998 and 2018, but the global per capita carbon emissions still increased from 4.03 tonnes per capita to 4.77 tonnes.[10] Second, the carbon dioxide damage increased from 178 million USD to 383 million USDs during 1998 and 2018 (as 2017 constant). Furthermore, from 2009 to 2018, the proportion of carbon dioxide damage cost in GNI increased from 1.5% to 2.1%.[11] That means carbon dioxide's damage to the environment and economic development is gradually expanding. Our results show that capital and CO_2 emissions are inversely proportional; that is to say, increased investment can reduce CO_2 emissions, but it has not reached the level of simultaneously increasing economic growth and reducing carbon dioxide. Third, we must control the global average temperature rise within 1.5 degrees in terms of climate policy. According to the IPCC 2019 special report[12], the current climate policy will reduce emissions, but the speed is not fast enough to reach international targets. We expect that in recent years, through effective environmental policies, environmental

9) Alcott, B. (2005). Jevons' paradox. *Ecological economics*, *54*(1), 9-21.

10) Data from BP Statistical Review of World Energy.

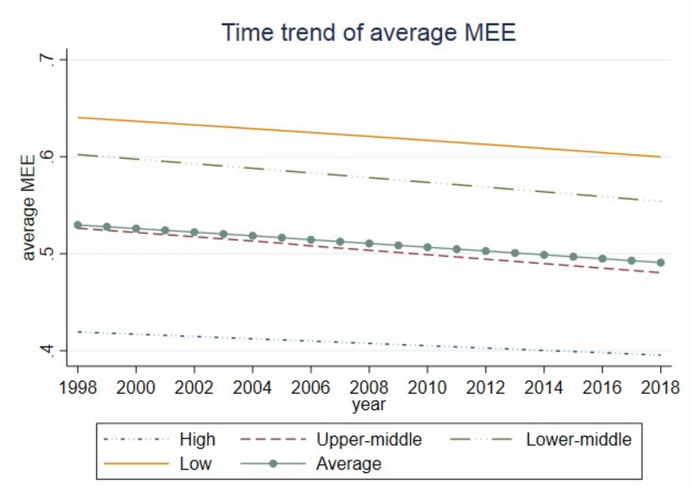
11) Data from World Bank Databank. Topic: Adjusted savings: carbon dioxide damage (% of GNI) and (current US$). Cost of damage due to carbon dioxide emissions from fossil fuel use and the manufacture of cement, estimated to be US$40 per ton of CO_2 (the unit damage in 2017 US dollars for CO_2 emitted in 2020) times the number of tons of CO_2 emitted. Pollution damage from emissions of carbon dioxide is calculated as the marginal social cost per unit multiplied by the increase in the stock of carbon dioxide. The unit damage figure represents the present value of global damage to economic assets and to human welfare over the time the unit of pollution remains in the atmosphere.

12) Shukla, P. R., Skea, J., Calvo Buendia, E., Masson-Delmotte, V., Pörtner, H. O., Roberts, D. C., ... & Malley, J. (2019). IPCC, 2019: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

efficiency will be improved. In particular, it is expected that high-income countries can make more efforts to improve the environment and achieve better results. Although we have many efforts to make a better environment, we have not reached the standard to change the status quo truly.

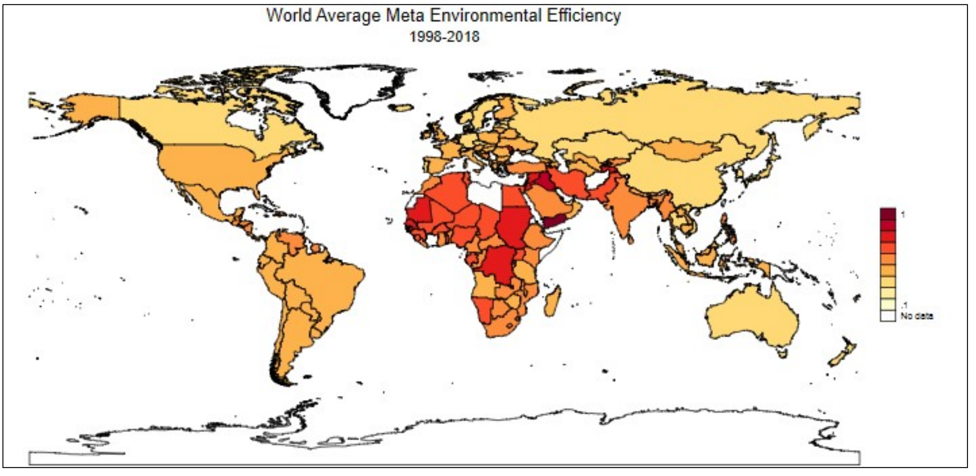
From Figure 4, we can also find that the average MEE of the high-income group and upper-income group is relatively low. In this paper, we use CO_2 emissions as the standard to judge the EE. According to Our World in Data database, the high and upper-middle-income countries emit 86 percent of global emissions. The carbon emissions base of these two groups is too large, and the task of improving EE by reducing carbon emissions is very arduous.

〈Figure 4〉 Time trend of average MEE by income group



For Figure 5, we have drawn the efficiency of countries on the world map. The white areas indicate countries with missing data. We can see that in East Asia countries, the MEE is very low. Furthermore, MEE in West Asia is relatively high. Many countries in the Americas are also less efficient. In Africa, where the economy is less developed, the MEE is higher. Compared with the original data, it is found that Asia has 60% of the population and emits 49% of CO_2, Africa has 16% of the population but emits only 4%. North America emits almost 1/5 of the world's emissions with only 5% of the world population.

〈Figure 5〉 MEE in World Map



IV. Conclusions

This paper estimated the environmental efficiency (EE) of 164 countries for 1998-2018 by using Meta Stochastic Input Distance Function. We divided the countries into four groups by income-level-based classification and used CO_2 emission amount as the standard of EE. Based on our results, increases in energy consumption and GDP lead to an increase in CO_2. The input of labor and capital can effectively reduce CO_2 emissions. Also, we measured Group Environmental efficiency (GEE), Environmental Gap Ratio (EGR), and Meta Environmental Efficiency (MEE). GEE estimation did not consider the environmental gap and tended to be overestimated. The lower-middle-income group has the highest mean value of the EGR, and the average MEE shows a downward trend. The high-income group has the lowest EGR and MEE during this period because they have enormous energy consumption and CO_2 emissions during rapid economic development. The current technology and environmental policies are not enough to solve the current problem of low environmental efficiency.

Based on these results, the following policy implications can be obtained. First, we use CO_2 as the standard to measure the environmental efficiency, and the results show that the EE is relatively low during this period. The primary source of carbon dioxide is fossil energy. To improve EE, we must increase the proportion of clean energy.

Second, although the EGR of the lower-income group is closer to the frontier of environmental efficiency, it shows a downward trend. We need to remind these countries that they must maintain this balance of environmental and economic development. They should not follow “pollution first, treatment afterward” as in the past developed countries. It is vital to strictly formulate pollutant indicators in development and focus on pollution source control. It is also essential to restrict the development of industries with high energy consumption and high pollution. Furthermore, it is necessary to prevent the impact of industrial transfer and carbon transfer on the environment.

Third, both EGR and MEE in high and upper-middle-income countries showed low levels during this period. We do not deny the efforts made by these countries, but due to their large carbon emission base, the current efforts are not enough to improve environmental efficiency. This requires these to increase capital input and reduce the use of fossil energy. They need to find a more effective and rapid reduction of carbon emissions technology while developing through innovation. They also should accelerate the establishment of a low-carbon GDP counting system, unify the performance evaluation with the sustainable development of the economy and environment, and set an excellent example for developing and undeveloped countries.

In future studies, we would like to make the following improvements to the paper. First, due to data limitations, we did not calculate the energy by dividing it into fossil and non-fossil energy, which affects our interpretations of the results. We will remedy this deficiency in future studies. Second, the Battese & Coelli (1992) model we used does not explain the influences that affect inefficiency, and we will add more explanations in future studies.

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