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Measurement of Environmental Efficiency Based on Stochastic Directional Distance Function: A Metafrontier Approach*

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Abstract: This study measures environmental efficiency (EE) based on CO_2 emissions for five groups of countries between 1998 and 2018, using the stochastic metafrontier directional distance function. The model estimates environmental efficiency scores for a panel of 163 countries using data on GDP and CO_2 emissions as economic growth and the consumption of fossil fuels lead to increased CO_2 emissions. Moreover, meta inefficiency and technical gap differences (TGD) are compared, and the findings indicate that most countries have higher mean TGDs than their group's average inefficiency measures. Furthermore, except for the low-income group, the OECD group is closest to the meta environmental frontier, suggesting that the OECD countries have advanced technologies to govern the environment. Alternatively, the findings also showed that upper-middle-income countries have the worst meta efficiency, implying that this group of countries sustain a high pollution growth path. Finally, we compare the difference between the stochastic metafrontier method and the pooling method and show that the pooling approach underestimates the severity of environmental problems.

Key Words: Environmental Efficiency, Stochastic Metafrontier, Directional Distance Function, Technical Gap Difference, Income Group

I. Introduction

Countries have become more cautious about consuming resources that contribute to environmental pollution and global warming in recent decades. The Intergovernmental Panel on Climate Change (IPCC) released its Sixth Assessment Report,1) suggesting that scientists have concluded

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that "human activities are causing climate change" and that human activities have caused global warming and widespread and rapid changes in the climate system. The IPCC report concluded that some of the recent extreme heat events would have been highly unlikely without human influence. Many countries have proposed their own "net-zero plans" and have been developing Carbon Dioxide Removal (CDR).

On the other hand, countries are hesitant to make decisions on CO_2 reduction because of the cost of reducing greenhouse gas emissions and concerns about economic growth. Reducing greenhouse gas emissions requires a shift from existing production technologies to more environmentally friendly ones, which requires a significant increase in human and capital investment. Moreover, limited production resources need to be devoted to reducing emissions. All of this can harm economic growth. Countries have made great efforts to reduce environmental pollution and greenhouse gas emissions and increase productivity in this context. Therefore, measuring the environmental and technology efficiency, evaluating previous efforts, and making recommendations for subsequent developments becomes critical.

In traditional environmental efficiency measures, only desirable outputs (e.g., GDP) are valued, and countries' efforts to reduce undesirable outputs (e.g., CO_2 emission) are ignored. The environmental efficiency measured does not reflect the actual environmental performance. Kopp et al. (1982) pointed out that the efficiency ranking obtained from the frontier production function model can be misleading if differences in environmental constraints are ignored. Murty et al. (2007)

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1) IPCC, 2021, *Climate change 2021: The physical science basis*, (Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change), In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, and S. Berger et al. (Eds.), Cambridge : Cambridge University Press.

proposed that both desirable outputs and pollution reduction or bad outputs must be considered when measuring environmental efficiency.

Therefore, we summarized different methods for measuring undesirable outputs. Atkinson and Primont (2011) summarized the differences among four ways using the distance function.[2)] Chung et al. (1997) extended Shephard's output distance function to an output directional distance function to measure the technical efficiency of increasing desirable outputs and reducing undesirable outputs. Färe et al. (2005) used a quadratic directional output distance function to calculate the technical efficiency using electricity as the desired output and SO_2 as the undesirable output. Kumar and Khanna (2009) estimated the environmental efficiency using the directional output distance function with and without including CO_2 (polluting output), which fully illustrated the importance of CO_2 emissions when analyzing efficiency and productivity change. The directional distance function approach allows for simultaneous expansion of desirable production and reduction of undesirable output. Also, it is specified as if the translog form without the need to take the natural logarithm (Koutsomanoli-Filippaki et al., 2009). It means that this flexible functional form can lessen the potential error of functional specification, and the sample with variables taking a zero value can hold (Huang et al., 2015).

Although directional distance functions present a primary method to study environmental efficiency and undesirable output, these studies treat all DUM's as a homogenous group using the same technology (Yang et al.,

2) Four ways of distance function: using output distance function and given constant input; output distance function and holding undesirable outputs and inputs constant; input distance function keeping the desirable and undesirable outputs constant; input distance function where undesirable outputs are treated like inputs.

2011; Jaraitė and Di Maria, 2012; Song et al., 2013). It is well known that there are significant differences in technology between OECD countries and group countries. If we studied all of the countries as the same technology group, the heterogeneity in the group is ignored, leading to inaccurate estimation of environmental efficiency. Therefore, we believe it is necessary to distinguish different groups' environmental efficiency and find the technical gap between the individual groups and the total frontier. Some studies in China have estimated the environmental efficiency of other regions to address different technologies in different areas (Chang et al., 2013; Wang et al., 2015; Song et al., 2018; Wu et al., 2019; Yue et al., 2021).

Moreover, in this paper, we will apply the metafrontier method. The theoretical framework of Hayami (1969), Hayami and Ruttan (1970) proposes that the meta production function may be considered the envelope of commonly accepted neoclassical production functions. Battese and Rao (2002) have assessed technical efficiency using a stochastic metafrontier model. Battese et al. (2004) and O' Donnell et al. (2008) provide a two-step mixed approach to estimate group efficiency and meta efficiency, solving the technical efficiency scores relative to the different technical groups. However, it has a problem that a nonlinear method is used in the second step. Huang et al. (2014) proposed a new two-step method to solve this problem, and the SFA method was used in both stages. Huang et al. (2015) presented a stochastic metafrontier directional distance function under a stochastic framework that avoids the abovementioned problems.

Furthermore, most previous studies about the issues of environmental efficiency use the DEA method. Chen et al. (2017) evaluated China's environmental efficiency using the slack-based DEA (SBM-DEA) method, and considering undesirable outputs is introduced to measure the environmental efficiency of different regions. Wei et al. (2021) combined stochastic multicriteria acceptability analysis with DEA to estimate energy and environmental efficiency. The DEA method is a popular method for studying efficiency. This method does not specify a functional form and is more readily applicable to situations where there are multiple inputs and outputs. Among the efficiency study methods in this paper, we prefer a stochastic frontier analysis (SFA). The method can be used to separate random errors from inefficient errors parametrically.

Besides international studies, we also talked about Korean studies. The studies primarily focus on local or specific industries (Kang et al., 2005; Kang, 2010; Yi and Kang, 2018). Chung et al. (2008) estimated the environmental efficiency index under environmental regulation of 20 OECD countries. Kang and Zhao (2013) conducted a study of the efficiency of 83 countries concerning the use of fossil fuels and environmental regulations. Several of these studies utilized Data Envelopment Analysis (DEA). Based on the translog form input distance function, Li and Kang (2021) estimated meta environmental efficiency but did not separate the OECD countries from the rest of the world.

The purpose of this paper is two-fold. First, we hope to use this model to more accurately measure environmental efficiency and provide a better basis for decision-makers. Secondly, we usually think that developed countries have high environmental efficiency and a high level of environmental technology, and we want to verify whether this idea is correct.

In conclusion, we found it difficult to find studies that use stochastic metafrontier models based on directional distance functions to measure environmental efficiency through analysis of the above studies. This approach enables to group 163 countries worldwide by characteristics and to study the technical gaps up to the meta efficiency frontier. In particular, this paper measures technology gap difference (TGD) and meta environmental efficiency (MEE) by a parametric method rather than nonparametric methods in the second step, which is the new point of this paper. This study aims to use the meta stochastic frontier analysis method based on the directional distance function estimating the Environmental Efficiency (EE) of 163 countries from 1998 to 2018. We classified 163 countries into five groups: OECD group, high-income group, upper-middle-income group, lower-middle-income group, and low-income group. We will compare these five groups' environmental inefficiency, meta environmental inefficiency, and technical gap difference.

Section 2 introduces the stochastic metafrontier based on the directional distance function. In Section 3, we present the detailed results of the environmental efficiency measurements for the five groups and identify their trends. In section 4, we offer our conclusions and explain the shortcomings of this study.

Ⅱ. Theoretic Model

1. Theoretic Model

This section will discuss the model based on Huang et al. (2015) to evaluate the group's environmental inefficiency and the technical gap difference between the group and the metafrontier. It is based on a stochastic metafrontier model with a directional distance function.

Following Huang et al. (2015), the stochastic method based on directional distance function (DDF) is used to measure the group inefficiency of each country in the first step. $x=(x_1,\ldots,x_p)'\in R_+^P$ denote the inputs, $y=(y_1,\ldots,y_q)'\in R_+^Q$ indicate the desirable outputs, and undesirable outputs are represented by $b=(b_1,\ldots,b_s)'\in R_+^s$. P, Q, and S are the number of inputs, desirable outputs, and undesirable outputs, respectively. And each number in R_+^P, R_+^Q and R_+^S is a non-negative real number. The DDF for income group z can be defined as:

$$\overrightarrow{D}_T^z(x,y,b:g)=\sup\left\{\beta:(x-\beta g_x,y+\beta g_y,b-\beta g_b)\in T^z\right\} \tag{1}$$

Where $\overrightarrow{D}_T^z(\bullet)$ is the DDF of technology group z. The directional vector is g=(g_x, g_y, g_b) $g_x\in R_+^P$, $g_y\in R_+^Q$, $g_b\in R_+^S$, where g_x, g_y and g_b denote the directional vector of inputs, desirable outputs, and undesirable outputs. $\overrightarrow{D}_T^z(\bullet)$ represents the distance it takes for an actual point to project along the direction (g_x,g_y,g_b) and reach the group's environmental frontier. It is considered as a measure of the group's environmental inefficiency and values in the interval $(0,+\infty)$. The value is equal to 0 for a country that reaches the technical frontier of the group and greater than 0 for countries with technical inefficiencies. The DDF can be estimated using the translation property as follows:

$$\overrightarrow{D}_T^z(x-\psi g_x,y+\psi g_y,b-\psi g_b)=\overrightarrow{D}_T^z(x,y,b:g)-\psi \tag{2}$$

This translation property denotes that if the inputs are decreased by ψg_x undesirable outputs also reduced by ψg_b, and desirable outputs are expanded by ψg_y, then the value of the distance function is reduced by the property ψ. We use the property to transform the DDF into an estimable regression equation. We will choose $\psi = b_1$ 3) and rewrite Eq. (2) as a quadratic function with the stochastic frontier approach:

$$
\begin{aligned}
-b_1 &= \overrightarrow{D}_T^{z^*}(x-b_1, y+b_1, b-b_1)+v-u \\
&= \alpha_0 + \sum_{p=1}^{P}\alpha_p(x_p-b_1)+\sum_{q=1}^{Q}\beta_q(y_q+b_1)+\sum_{s=2}^{S}\lambda_s(b_s-b_1) \\
&+1/2\sum_{p=1}^{P}\sum_{p'=1}^{P}\alpha_{pp'}(x_p-b_1)(x_{p'}-b_1) \\
&+1/2\sum_{q=1}^{Q}\sum_{q'=1}^{Q}\beta_{qq'}(y_q+b_1)(y_{q'}+b_1)+1/2\sum_{s=2}^{S}\sum_{s'=2}^{S}\lambda_{ss'}(b_s-b_1)(b_{s'}-b_1) \\
&+\sum_{p=1}^{P}\sum_{q=1}^{Q}\gamma_{qp}(y_q+b_1)(x_p-b_1)+\sum_{p=1}^{P}\sum_{s=2}^{S}\xi_{sp}(b_s-b_1)(x_p-b_1) \\
&+\sum_{q=1}^{Q}\sum_{s=2}^{S}\rho_{sq}(b_s-b_1)(y_q+b_1)+v-u
\end{aligned} \tag{3}
$$

Where $v-u$ is the stochastic component. x_p is the pth input, y_q is the qth output, b_s is the sth undesirable output. $\alpha, \beta, \lambda, \gamma, \xi, \rho$ are parameters that need to be estimated. The DDF of Eq. (3) must also satisfy the symmetrical conditions, i.e., $\alpha_{pp'} = \alpha_{p'p}$, $\beta_{qq'} = \beta_{q'q}$, $\lambda_{ss'} = \lambda_{s's}$. v is a random error with a mean of zero and a constant variance σ_v^2, and assumed to be independent of u. Considering the efficiency changes over time, we performed a time-varying efficiency analysis and estimated this error term following Battese and Coelli (1992) method. u is independent

3) Guarda et al. (2013) suggested that this method ($\psi = b_1$) suppressing the directional vectors for notational convenience. Feng and Serletis (2014) suggested that the translation property can transform the DDF into an estimable regression equation in the form of a standard stochastic frontier. Malikov et al. (2016) suggested that the normalization can be performed by setting equal to any of the arguments of the DDF.

of v and assumed to be as a truncated normal distribution $iid \sim (\mu, \sigma_u^2)$. The time-varying environmental inefficiency error takes the form:

$$u_{it} = \exp\{-\eta(t-T)\} \cdot u_i \tag{4}$$

Next, for the second step, the metafrontier DDF can be specified as:

$$\overrightarrow{D}_T^{meta}(x, y, b : g) = \sup\{\beta : (x - \beta g_x, y + \beta g_y, b - \beta g_b) \in T^{meta}\} \tag{5}$$

Where $\overrightarrow{D}_T^{meta}$ is the meta stochastic DDF, which can contain all income groups operating under the metafrontier. And then, we express the metafrontier inefficiency as:

$$\overrightarrow{D}_T^{meta}(x, y, b : g) = \overrightarrow{D}_T^{z}(x, y, b : g) + TGD \tag{6}$$

The metafrontier inefficiency equals the sum of the group inefficiency and the technology gap difference (TGD). As the same with the group inefficiency, TGD values in the interval $(0, +\infty)$. If an income group is technologically advanced and very close to the meta environmental frontier, their TGD has a value of 0.

Since the frontier $\overrightarrow{D}_T^{z}(\bullet)$ for the actual group z is unknown, we utilize the fitted value $\widehat{\overrightarrow{D}}_T^{z*}(\bullet)$ from the estimation via the maximum likelihood estimate method (MLE), which leads to the following Eq. (7):

$$\overrightarrow{D}_T^{z}(x, y, b : g) = \widehat{\overrightarrow{D}}_T^{z*}(x, y, b : g) + v^m \tag{7}$$

v^m is a random error generated by Eq. (3) with a mean of zero and a non-constant variance. Then, we can get the stochastic metafrontier model by substituting $\overrightarrow{D}_T^z(\bullet)$ above into Eq. (6):

$$\overrightarrow{D}_T^{z*}(x, y, b : g) = \overrightarrow{D}_T^{meta}(x, y, b : g) + v^m - u^n \quad (8)$$

Where u^m representing the TGD and also assumed to be as a truncated normal distribution $iid \sim (\mu, \sigma_u^2)$. v^m is the random error. We derived the metafrontier function form based on the combination of Eq. (3) and the translation property of Eq. (2).

2. Data Description

We will describe the variables used and the specific model in this section. The input variables are capital stock per capita (x_1), the number of persons engaged per capita (x_2), fossil energy consumption per capita (x_3), and non-fossil energy consumption per capita (x_4). The desirable output variable is GDP (y_1-Gross Domestic Product). We use CO_2 emission amount (b_1) as an undesirable output. So far, we have seen many papers measuring environmental efficiency but have not found an objective standard to measure it. Carbon dioxide is the main greenhouse gas emitted through human activities and is likely the leading cause of global warming in recent years.[4] So, we use CO_2 as an undesirable output to measure environmental efficiency.

We obtained the original capital stock, the number of engaged persons, total population, and GDP data from the Penn World Table 10.0 databas

4) Pachauri et al. (2014), *Climate change 2014: Synthesis report.*

e.[5] CO_2 emissions data were obtained from the Our World in Data database.[6] Fossil and non-fossil energy consumption data were obtained from the U.S. Energy Information Administration (EIA).[7] Also, to compare the group efficiency, we categorize 163 countries into five groups: the OECD group and the other four groups using the World Bank's classification criteria by income level.[8] OECD countries are generally seen as developed countries, capable of leading global economic development and solving the problems caused by globalization. That is why we separate them from the high-income countries from the upper-middle-income countries. 〈Table 1〉 sorted the variable definitions and units used in the following estimation.

〈Table 1〉 Variables' unit and definition

Variables		Unit	Definition
Desirable Output	y_1–GDP: (GDP/P)	2017 US$ / per capita	Real GDP at constant 2017 national prices per person
Undesirable Output	b_1–C(CO_2/P)	Tonnes / per capita	Annual production-based emissions of carbon dioxide per person
Input	x_1–K: (K/P)	2017 US$ / per capita	Capital stock at constant 2017 national prices per person
	x_2–L: (L/P)	Workers / per capita	The number of persons engaged divided by population
	x_3–F: (F/P)	10^7 BTU / per capita	Consumption of coal, natural gas, petroleum, and other liquids per capita
	x_4–NF: (NF/P)	10^7 BTU / per capita	Consumption of nuclear, renewables, and others per capita

5) The original data has already kept as 2017 constant price, so there is no need to process the data using the depreciation method. Feenstra, R. C., R. Inklaar, and M. P. Timmer, 2015, "The next generation of the Penn World Table," *American Economic Review*, 105, pp.3150-3182.
6) Ritchie, H. and M. Roser, 2020, *CO_2 and greenhouse gas emissions*, Our World in Data.
7) Energy Information Administration of US (EIA), 2020, "International".
8) The World Data Bank's national classification standard by 2018 bank year. World Bank Knowledgebase, 2020, "How does the World Bank classify countries?".

This study used 3,423 observations spanning 21 years, from 1998 to 2018, across 163 countries. 〈Table 2〉 describes the basis of statistics, and we can see that there are significant differences between the different groups and within some groups. We divided each variable by the total population to compare environmental efficiency across countries objectively. This can solve the problem that the magnitude of different country variables may affect environmental efficiency. As a particular group, OECD countries have low average carbon dioxide emissions with high GDP and capital stock. From the data on non-fossil energy, we can see that the average consumption of non-fossil energy is highest in the OECD group. The high-income group has the highest GDP per capita of the four groups at $43,676. This group also has the highest capital stock per capita and fossil energy consumption per capita. Per capita fossil energy consumption in low-income countries is less than one-fiftieth of that in high-income countries. As expected, high-income countries have high GDP, high fossil energy consumption, and CO_2 emissions. Therefore, we hope them to make more efforts for environmental management.

〈Table 2〉 Summary of the data

Variables	Group	Obs.	Mean	Std.	Min.	Max.
GDP	OECD	798	37,063	16,703	8,469	92,975
	High	357	43,676	26,791	10,889	120,748
	Upper-middle	903	12,469	5,967	355	46,640
	Lower-middle	819	5,090	2,528	1,255	14,641
	Low	546	1,911	1,786	580	13,138
C	OECD	798	8.751	4.495	1.297	26.439
	High	357	14.876	12.711	1.362	67.015
	Upper-middle	903	4.119	3.023	0.401	17.448
	Lower-middle	819	1.260	1.623	0.119	20.348
	Low	546	0.272	0.500	0.016	3.306
L	OECD	798	0.462	0.065	0.292	0.736
	High	357	0.466	0.089	0.274	0.763
	Upper-middle	903	0.377	0.088	0.159	0.574
	Lower-middle	819	0.363	0.084	0.139	0.575
	Low	546	0.365	0.067	0.177	0.540
K	OECD	798	196,912	90,982	26,192	450,888
	High	357	198,946	132,674	25,072	723,042
	Upper-middle	903	50,496	26,162	7,127	132,802
	Lower-middle	819	23,003	26,215	2,610	173,426
	Low	546	7,077	11,316	1,118	81,230
F	OECD	798	12.612	6.948	1.894	41.536
	High	357	30.967	23.899	2.075	112.725
	Upper-middle	903	5.594	4.612	0	31.791
	Lower-middle	819	1.726	1.959	0.108	11.750
	Low	546	0.408	0.784	0.030	5.113
NF	OECD	798	5.085	8.017	-0.507[1)]	52.700
	High	357	0.395	0.765	-0.057	3.629
	Upper-middle	903	0.911	1.153	-0.200	7.113
	Lower-middle	819	0.440	0.988	0	7.614
	Low	546	0.142	0.423	0	2.537

Note: 1) Some countries have negative figures for non-fossil energy. According to the IEA data rules, the energy consumption for each country also includes net electricity imports (electricity imports – electricity exports) and net coke imports (coke imports – coke exports)

After this, we bring these variables into Eq. (3) in the theoretical model, and Eq. (3) becomes next:

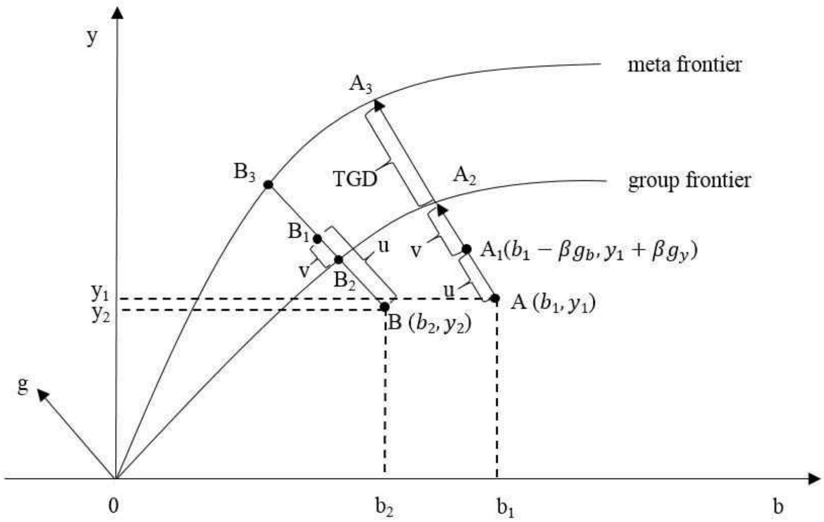
$$
\begin{aligned}
-C_{it} &= \alpha_0 + \alpha_1(L_{it} - C_{it}) + \alpha_2(K_{it} - C_{it}) + \alpha_3 NF_{it} + \beta_1(GDP_{it} + F_{it}) + \lambda_1(F_{it} - C_{it}) \\
&+ 1/2\alpha_{11}(L_{it} - C_{it})^2 + 1/2\alpha_{22}(K_{it} - C_{it})^2 + 1/2\alpha_{33}NF_{it}^2 + 1/2\beta_{11}(GDP_{it} + C_{it})^2 \\
&+ 1/2\lambda_{11}(F_{it} - C_{it})^2 + \alpha_{12}(L_{it} - C_{it})(K_{it} - C_{it}) + \alpha_{13}(L_{it} - C_{it})NF_{it} + \alpha_{23}(K_{it} - C_{it})NF_{i} \\
&+ \gamma_{11}(GDP_{it} + C_{it})(L_{it} - C_{it}) + \gamma_{12}(GDP_{it} + C_{it})(K_{it} - C_{it}) + \gamma_{13}(GDP_{it} + C_{it})NF_{it} \\
&+ \xi_{11}(F_{it} - C_{it})(L_{it} - C_{it}) + \xi_{12}(F_{it} - C_{it})(K_{it} - C_{it}) + \xi_{13}(F_{it} - C_{it})NF_{it} \\
&+ \rho_{11}(F_{it} - C_{it})(GDP_{it} + C_{it}) + v_{it} - u_{it}
\end{aligned} \tag{9}
$$

Here we need to clarify that we do not impose negative directional weight on the NF (non-fossil energy) consistent with other inputs. We want to reduce the use of fossil energy to decrease CO_2 emissions, not reduce the use of non-fossil energy. The subscript "it" means the i^{th} country in the t^{th} year.

Figure 1 shows the stochastic metafrontier based on the directional distance function. The observed point A or B relative to the projected metafrontier point A_3 or B_3 consists of three components: the technology gap difference (A_3A_2 or B_3B_2), the random error (A_1A_2 or B_1B_2), and the country's environmental inefficiency between points (AA_1 or BB_1). We can also get the relationship next:

$$A_3 - A = TGD + u + v \tag{10}$$

〈Figure 1〉 Stochastic metafrontier based on the directional distance function



Ⅲ. Empirical Analysis and Results

1. Coefficient Estimates of Group Frontiers

To validate the use of the meta stochastic frontier method, it is crucial to test the null hypothesis that income groups undertake the same technology. If the hypothesis is not rejected, there is no need to establish a meta model. The statistic of the LR test is calculated by $L = -2[L(H_0) - L(H_1)]$.[9] $L(H_0)$ =8182.072 is the log-likelihood value of the pooled regression ignoring the group technological heterogeneity, $L(H_1)$ =8871.105 is the sum of all groups' estimation log-likelihood. The value of the LR test is L=1378.156, and the hypothesis is rejected at the 1% level of significance with 80 degrees of freedom.[10] Thus, we can conclude technological heterogeneity across

9) By following Battese et al. (2004), the threshold value is a value of 1% significance level.

income groups by testing the above hypothesis.

〈Table 3〉 shows the estimates of stochastic metafrontier based on the directional distance function by the MLE method. Model (1) – Model (5) offers the group estimation. In Eq. (3), we can see that CO_2 is a dependent variable with a negative sign. Therefore, we should reverse the interpretation of its estimation results. We find that fossil energy and capital stock are positively related to CO_2. As expected, to reduce CO_2 emissions, it is necessary to reduce the use of fossil energy and reduce unnecessary investments. At the same time, increasing labor will reduce CO_2. This may be because increasing the labor to replace the energy-intensive mechanical production effectively reduces CO_2 emissions. We also find that non-fossil energy consumption in OECD countries is proportional to CO_2 emissions. This result is different from what we expected. It is usually assumed that clean energy can appropriately reduce CO_2 emissions. However, excessive use may also cause emissions to increase. This is also possible due to the immature production technology of non-fossil energy sources, which produces large amounts of CO_2 and causes the opposite effect. The eta (η) shows the form of time variation of the group inefficiency. The group inefficiency of the environment increased slightly with time. This indicates a continued decline in group environmental efficiency and further deterioration of environmental problems. Since the distribution of environmental inefficiency error terms are $iid \sim (\mu, \sigma_u^{\,2})$ as the truncated normal distribution, the distribution u is symmetric at about μ = 0.126, 0.389, 0.749, 0.296, and 0.049 at the interval of zero or more.

10) By following Battese et al. (2004) and Zhang and Wang (2015), the difference between the number of pooled regression coefficients and the sum of the five groups' coefficients is the degree of freedom (Here, the critical value is 101.88).

〈Table 3〉 Estimation of stochastic meta directional distance function

GROUP	(1) OECD	(2) High	(3) Upper-Middle	(4) Lower-Middle	(5) Low	(6) TGD	(7) Pooled
L	1.013***	1.003***	0.998***	0.968***	0.869***	1.003***	1.002***
K	-3.30E-08	-7.3e-07***	5.60E-07	-1.6e-06***	4.4e-06*	-5.6e-07***	-5.0e-07***
F	-0.003	-.0058***	-.011***	0.006	-0.074	-0.002***	-0.003***
NF	-0.005***	-0.012	0.003	0.013	-0.113**	0.006***	.005***
GDP	-2.7e-06***	2.9e-06**	1.30E-06	-1.90E-06	1.30E-05	-1.80E-07	-9.5e-07**
L^2	4.0e-04*	-1.40E-04	-4.90E-04	-0.005***	-0.273***	-6.80E-05	-4.70E-05
K^2	4.1e-12***	7.00E-13	-2.6e-11***	-1.20E-11	7.20E-11	2.8e-12***	2.6e-12***
F^2	5.9e-04***	1.5e-04***	-9.4e-04***	.0046**	-0.178***	-4.20E-06	2.60E-05
NF^2	9.9e-05**	0.011	0.002	-1.30E-04	0.108	-1.3e-04**	-5.90E-05
GDP^2	8.5e-11***	-4.60E-11	-7.30E-11	9.5e-10**	-1.1e-08*	2.00E-11	2.60E-11
LK	-1.7e-08*	5.70E-09	-5.10E-08	1.8e-07*	-3.40E-06	1.1e-08**	1.2e-08***
LF	-3.2e-04*	-9.1e-05**	-8.3e-04**	7.90E-04	0.019	-8.7e-05***	-8.4e-05***
LNF	-2.6e-04**	0.002	-0.001	0.002	0.169**	1.60E-04	2.6e-04*
LGDP	7.10E-08	-8.7e-08*	2.00E-07	1.0e-06*	-4.5e-05**	-6.4e-08**	-5.6e-08*
KF	-4.70E-09	1.8e-08***	1.7e-07***	1.10E-07	3.6e-06*	6.6e-09*	6.3e-09*
KNF	-5.80E-09	1.2e-06***	3.70E-08	7.7e-07***	-2.90E-06	2.8e-08***	2.3e-08***
KGDP	-1.5e-11***	-5.70E-13	2.9e-11*	1.1e-10***	-3.0e-09***	-7.0e-12**	-5.6e-12**
FNF	1.10E-04	0.002	-0.003*	9.10E-04	-0.056	-5.10E-06	2.90E-06
FGDP	-1.40E-07	-8.2e-08**	-3.9e-07***	-2.3e-06***	3.1e-05*	-3.00E-08	-3.4e-08*
NFGDP	3.40E-08	-5.9e-06***	-2.70E-07	-5.8e-06***	6.5e-05***	-1.0e-07*	-9.4e-08*
_cons	-0.176***	--2)	0.329	-0.075*	-0.261***	--2)	-0.028
μ	0.126***	0.389***	0.749*	0.296***	0.049	0.707***	0.329***
η	-0.011***	-0.008***	-0.004*	-0.008***	-0.015***	-0.005***	-0.004***
σ^2	0.0036	0.0052	0.0075	0.0086	0.0037	0.0922	0.0062
γ	0.9575	0.8875	0.95	0.9794	0.933	0.9956	0.9392
LLR	2263.839	781.752	2152.945	2242.437	1430.132	7830.428	8182.072
Obs.	798	357	903	819	546	3423	3423
country	38	17	43	39	26	163	163

Note:
1) *: P-value ≤0.1, **: P-value ≤0.05, ***: P-value ≤0.01
2) We found that model (2) and (6) fit better when there are no constant terms
The absence of a constant term means they are not truncated at x=0

To compare the group inefficiency, we make the kernel density of each group in ⟨Figure 2⟩. We can see that the group inefficiencies are very concentrated in OECD and low-income countries, while they are dispersed in high, upper-middle, and lower-middle-income countries (have a long tail). It indicates significant differences in environmental inefficiencies among countries within these three income groups. It is also evident from Table 1 that the standard variance of these three groups are immense values and are higher than the standard variance of the low-income group. The middle-income countries may include better-developed nations such as China, with more advanced science and technology than other countries and a high level of concern for environmental pollution. Similarly, the World Bank classification criteria that we use change from year to year, and certain countries have reached the tipping point of the grouping. These factors contribute to the relatively large disparities within the groupings of these groups. In the future, we will also investigate more scientific methods for grouping.

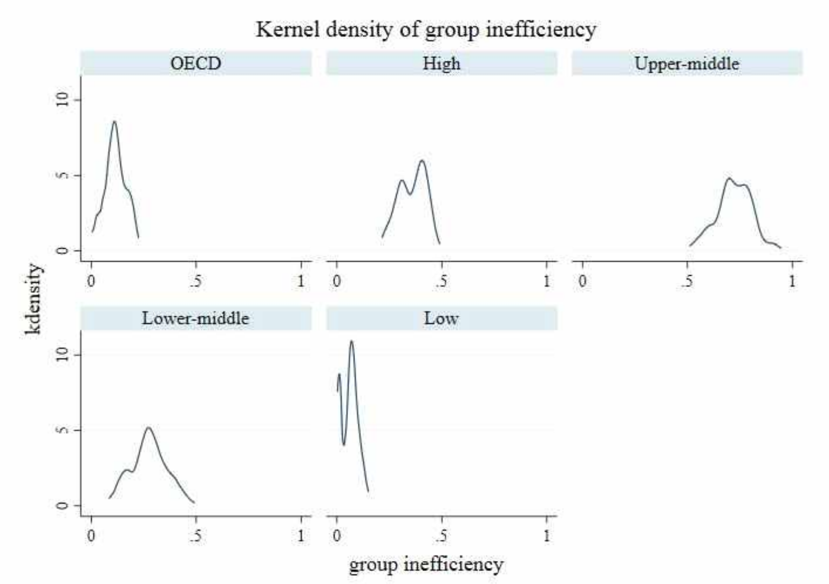
⟨Table 4⟩ summarizes group inefficiency, TGD, meta inefficiency, and pooled inefficiency.[11] By reducing inputs usage by 11.5 percentage points, increasing outputs by 11.5 percentage points, and decreasing undesirable output by 11.5 percentage points, the OECD countries can reach its efficient frontier. Similarly, the mean group inefficiency of the income groups of the highest, middle, lower-middle, and low income can be interpreted as 0.358, 0.723, 0.274, and 0.060, respectively. This inefficiency score cannot be compared across income groups since it is estimated using group-specific efficient frontiers.

11) Due to space limitations, we do not present group inefficiencies, technology differences and meta inefficiencies for each country; please contact the author for detailed inefficiency values if needed.

〈Table 4〉 Summary of the inefficiency estimation

Group	Group inefficiency	TGD	Meta inefficiency	Pooled inefficiency
OECD	0.115	0.482	0.597	0.321
High	0.358	0.693	1.052	0.291
Upper-middle	0.723	1.063	1.786	0.306
Lower-middle	0.274	0.623	0.897	0.318
Low	0.060	0.422	0.482	0.332

〈Figure 2〉 Kernel density of group inefficiency



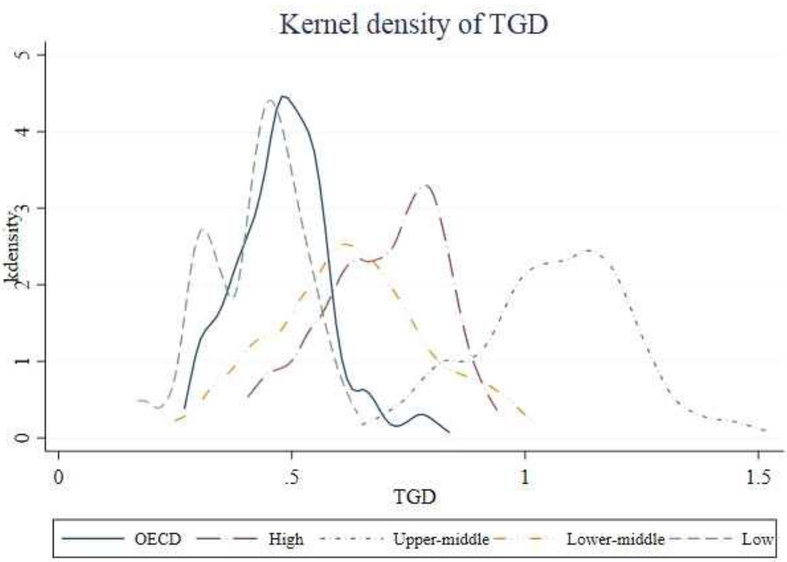
2. Technology Gap Difference (TGD) and Meta Environmental Inefficiency

We first illustrate the essential parameters gamma (γ), mu (μ), and eta (η) in the model (6). The interval of gamma value is from zero to one, and the larger it is indicated that the environmental inefficiency error accounts for a larger proportion of the total error. A gamma value of 99.6%

means that most errors consist of environmental inefficiency errors. The eta (η) indicates the direction and magnitude of change of environmental inefficiency over time. The inefficiency gap of the environment increased slightly with time. The distribution u is symmetric at about μ = 0.707 at the interval of zero or more. If there is no environmental inefficiency, we will use the ordinary least square (OLS) method for measurement instead of the MLE method. L, K, and NF show a negative (-) relationship with CO_2, and fossil energy and GDP show a positive (+) relationship with CO_2. This shows that L, K, and NF do not contribute to CO_2 increase as they substitute fossil energy for 163 countries as a whole. On the other hand, due to the economic growth of each country, fossil energy, GDP, and CO_2 show a chain-like rise.

〈Figure 3〉 reports the TGD of each group. We can see that the TGD is more concentrated in OECD and low-income groups, with the most pronounced in upper-middle-income countries. As we mentioned in part 2, the smaller value of TGD, the more advanced technology an income group undertakes, and closer to the metafrontier. We find a surprising result that low-income countries have the smallest inefficiency values and are most relative to the meta-frontier. However, we do not think they have reached a truly technologically advanced level. There are two reasons for this interesting result: the first is that these countries have low fundamental CO_2 emissions, making their environmental self-purification very high. Secondly, it may be because the advanced countries transfer their advanced technologies and industries. The TGD scores of the OECD group are more concentrated on the left of the distribution except for the low-income group. This shows that OECD countries do have a high level of environmental technology. We anticipate that OECD countries are closer to the frontier and lead to high levels of environmental technology because even though OECD countries have high CO_2 emissions in proportion to their highest energy consumption, their CO_2 reduction is high. We can see that the other high and upper-middle-income countries have not yet found better technology to solve their environmental problems while developing rapidly.

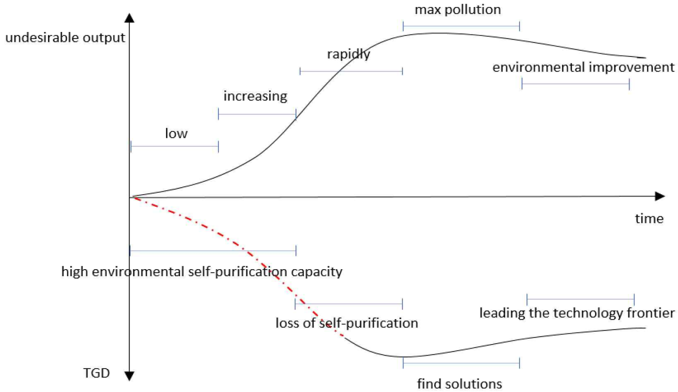
〈Figure 3〉 Kernel density of TGD



From 〈Table 4〉 above, we can see that the mean TGD for the OECD group is 0.482. Furthermore, we can see that the difference between groups' TGD is enormous, showing a significant gap between groups regarding environmental protection and treatment technology. We hope that OECD countries will continue to lead the technological frontier and transfer advanced technologies to other groups to face global environmental issues together. Every country is suggested to adopt innovations swiftly to enhance their environment protection technology in such a way as to be able to produce on the metafrontier.

In ⟨Figure 4⟩, we label the stages of environmental pollution and TGD changes for each period of economic development. The curve above represents the trend of environmental change with economic growth. From a small amount of environmental pollution at the beginning of low-speed economic development to the environmental deterioration caused by a gradually growing and high-speed economy, recognizing the seriousness of the environmental problems, and finally finding ways to improve the environment. The curve below represents the TGD calculated in this paper. With a small amount of environmental pollution, the environmental self-purification capacity can effectively solve the environmental problems. As the economy grows, the self-purification capacity reaches its maximum. The self-purification capacity is no longer able to reduce environmental pollution effectively. We indicate this part with a dashed line, a false high-tech level phenomenon. As countries reach a particular stage of development and realize the seriousness of environmental pollution, they begin to develop environmental technology and strive to reach the environmental frontier.

⟨Figure 4⟩ The stages of environmental pollution and TGD changes



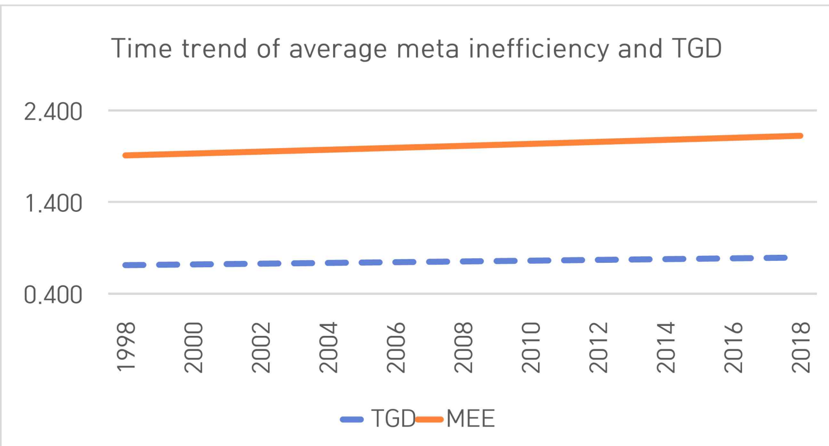
Furthermore, it is noticeable that most countries have higher mean TGDs than their average group inefficiency measures. Our sample countries' inefficiencies are most likely caused by their inability to utilize potential technology instead of managerial inadequacies. Every country should swiftly adopt innovation to improve their environmental protection technology to produce on the metafrontier. Their GDP could increase dramatically in this way, resulting in a reduction in pollution output and input (except for non-fossil fuels).

Based on the above analysis, we report the meta inefficiency scores for countries. The low-income group showed the lowest inefficiency in meta-efficiency, while the high-income and upper-middle-income groups showed the highest inefficiency. The low inefficiency of the OECD group appears to be the result of efforts to reduce CO_2 emissions through the climate change agreement, etc. On the other hand, the low inefficiency of the low-income group seems to be because most of the countries of the low-income group are not yet economically developed, so CO_2 emission is small. The high-income and upper-middle groups' meta inefficiency is higher than other groups, with a mean value of 1.052 and 1.786, respectively. We believe this is due to two main reasons. First, from Eq. (6) above, the meta inefficiency is the sum of group inefficiency and TGD. These groups have higher group inefficiency and also high TGD. This requires high-income and upper-middle-income countries to develop technology while improving the management of their environment. Second, the "Jevons paradox"[12] proposes that increasing technological efficiency does not reduce total resource consumption but instead increases the consumption of coal, iron, and other resources in the production process. Increasing fossil energy consumption will lead to

12) Alcott, B., 2005, "Jevons' paradox," *Ecological Economics*, 54(1), pp.9-21.

a continuous increase in CO_2 emissions. A database maintained by Our World in Data estimates that 86 percent of global emissions come from OECD, high-, and upper-middle-income countries. Furthermore, during 2009-2018, the proportion of carbon dioxide damage costs[13] in Gross National Income (GNI) increased from 1.5% to 2.1%. Because the carbon emission base of the OECD, high, and upper-middle-income countries is too large, it is challenging for them to improve environmental efficiency by reducing fossil energy emissions and carbon emissions. Although they have made many efforts to improve environmental efficiency, they have not found the essential methods and technologies to change environmental problems. Figure 5 shows the time trend of average meta inefficiency and TGD during 1998-2018, and both of these indicators increased slightly. Again, this indicates that we still have not found effective ways to curb environmental degradation despite our efforts.

〈Figure 5〉 Time trend of meta inefficiency and average TGD



13) World Bank Databank, 2020, “Adjusted savings: Carbon dioxide damage (% of GNI)”.

3. Comparing with a Pooled Frontier

As mentioned before, previous studies calculated the inefficiency with a pooled frontier method, which ignores technological heterogeneity and assumes all countries are using the same technology. Using pooled stochastic frontiers, we examine how inefficiency estimates vary with the income group. As shown in Table 4, the last column lists the technical inefficiencies derived from the pooling method.[14] Compared to the meta frontier method, pooled inefficiency underestimates technical inefficiency levels. In connection with the hypothesis test described above, we can show that the meta frontier method is more suitable for our study than the pooled method.

Ⅳ. Conclusions

This study compared the environmental efficiency of five groups with the directional distance function (DDF), using a stochastic metafrontier model. The DDF is better for estimating environmental efficiency since it can calculate the efficiency under reducing input, undesirable output, and expansion of outputs. Also, in conjunction with the DDF, the stochastic meta frontier model enables us to evaluate the meta inefficiency of five income level groups, taking into account the divergences in adopting the potential technology available to environmental protection.

Our study shows that the OECD group has the smallest value of TGD except for the low-income group, which means near to the environmental frontier and has the advantage in technology in environmental protection.

14) Estimated by model (7) in 〈Table 3〉.

Furthermore, most countries have higher mean TGDs than their average group inefficiency measures. This implies that governments need to increase their research on environmental science and technology than on managing their own countries. The high-income and upper-middle-income groups also have a high value of group inefficiency, which places higher demands on these two groups to set strict limits on their pollution and emissions and lead to the development of new environmental technologies that contribute to the global environment. We also found that the relatively high meta inefficiency of the high-income and upper-middle-income groups is due to their large fossil energy and carbon emissions base and that despite their strong efforts, they need to find better ways to address environmental issues. Each country can produce more GDP and less CO_2, respectively, and use less fossil energy and capital stock to reach the meta environmental frontier. In particular, governments need to increase non-fossil energy use and develop CDR technology to reduce carbon dioxide emissions.

In future research, we will study the factors that affect environmental inefficiency. In addition, in this paper, we use a single desirable output variable (GDP) and a single undesirable output variable (CO_2). We will collect more data and hope to measure environmental efficiency more comprehensively.

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