Does international trade improve environmental efficiency? An application of a super slacks-based measurement of efficiency

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Abstract

This study analyzes environmental efficiency, and its determinants, for 98 countries in terms of four typical air pollutants—SO_2, NO_x, particulate matter 10 micrometers or less in diameter (PM10), and CO_2—for the period 1970–2008. For this purpose, I propose a super slacks-based measure and data envelopment analysis (DEA) model with undesirable outputs—which has higher discriminating power than previous DEA efficiency indices, modifying the ones proposed in preceding articles. Furthermore, I analyze the determinants of environmental efficiency in association with the environmental Kuznets curve hypothesis and the pollution haven hypothesis. The panel regression results reveal that there is no Kuznets-type relationship between environmental efficiency and per-capita income. The impact of trade on environmental efficiency depends on relative per-capita income and capital–labor ratio, i.e., the higher the relative income and the lower the capital–labor ratio, the higher the environmental efficiency. Overall, the elasticities of trade openness for NO_x, PM10, and CO_2 are significantly negative for an average country in the sample.

Keywords: Data envelopment analysis · Environmental efficiency · Environmental Kuznets curve· Pollution haven hypothesis· Super efficiency

JEL classification: Q56, Q53, Q54, O13

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1. Introduction

Considerable research has been conducted on the environmental Kuznets curve (EKC) hypothesis since Shafik and Bandyopadhyay (1992) and Grossman and Krueger (1993)[2]. The EKC hypothesis states that there is a U- or N-shaped relationship between environmental pollution per-capita quality and per-capita income. Why does environmental quality improve after a certain turning point? One of the main reasons is that environmental quality is a superior good, whose demand increases with per-capita income.

In addition to economic growth, Grossman and Krueger (1993) also emphasize the role of international trade and decompose the effects of trade openness on the environment into three separate mechanisms: scale, technique, and composition effects. The scale effect refers to an increase in pollution emissions resulting from economic expansion by trade openness. The technique effect refers to a reduction in pollution emissions due to the demand for stricter environmental regulations with rising income. The composition effect refers to a change in the industrial structure through trade openness. In particular, the pollution haven hypothesis (PHH), which asserts that dirtier industries move from developed countries to developing countries, remains controversial. The seminal paper of Antweiler et al. (2001) regresses pollution concentration on representative variables of the above three effects. Their empirical results show a positive scale effect, a negative technique effect, and a negative composition effect. However, the composition effect caused by trade varies across countries depending on relative income and factor abundance (see also Cole and Elliot

[2] See Dinda (2004), Stern (2004), and Kijima et al. (2010).

(2003), Frankel and Rose (2005), and Managi et al. (2009)).

However, the relationships among per-capita pollution emission, per-capita income, and trade openness are a consequence of the production process. Hence, an empirical strategy to regress pollution emissions on income and trade openness fails to understand the underlying production process (Zaim and Taskin, 2000). As long as pollutants are not freely disposable (weak disposability), reducing pollutants involves a transformation of the production process, which requires sacrificing the output and additional inputs. Environmental efficiency allows us to measure and understand the degree to which production processes are environmentally friendly.

Environmental efficiency involving desirable and undesirable outputs has been analyzed by a directional distance function (Chung et al., 1997; Picazo-Tadeo et al. 2005). However, it cannot directly treat input excesses and output shortages, which are termed "slacks." Tone (2001) proposes the slacks-based measurement (SBM) model, which is a non-radial data envelopment analysis (DEA) model. In measuring environmental performance, non-radial efficiency measurement in the SBM model exerts more discriminating power than the radial one in traditional DEA models (Zhou et al., 2006; Wei et al., 2012). Furthermore, the super SBM efficiency model proposed by Tone (2002) has a higher level of discriminating power than the SBM model because it can distinguish between efficient decision making units (DMUs). Honma (2014) applies the super SBM model to measure environmental efficiency of 31 Asia-Pacific countries and regions, treating CO_2 emissions as one of the inputs. Li et al. (2013) construct a super SBM efficiency measurement with undesirable outputs and apply it to China's regional environmental efficiency. However, in their model, the denominator includes a possible expansion rate of undesirable outputs. This yields a misleading efficiency value where a less-polluting DMU receives an undeserved evaluation.

My first question in this paper is whether EKC holds for environmental efficiency. Among the numerous EKC studies, only a few investigate whether environmental efficiency and per-capita income are related. Managi and Jena (2008) find a U-shaped Kuznets-type relationship between environmental productivity and per-capita income in Indian regions. Zaim and Taskin (2000) construct a nonparametric environmental efficiency index based on the production theory and find an N-shaped Kuzunets curve. Halkos and Tzeremes (2009) evaluate environmental efficiency regarding sulphur emissions per capita and conclude that there is no evidence to support an EKC curve. However, Zaim and Taskin (2000) and Halkos and Tzeremes (2009) focus only on the Organization for Economic Cooperation and Development (OECD) countries.

My second and more important question is whether trade is good for environmental efficiency. In environmental efficiency studies, it is not just measuring efficiency, but also exploring its determinants, that matters. As described in the beginning of the Introduction, decoupling economic growth and environmental deterioration in the EKC model would be a spurious phenomenon when we take into account the international transfer of dirtier industries from developed to developing countries. Regarding the trade-induced effect, I focus on the PHH described above. If the PHH holds, although the environment in richer countries can be improved, the environment in poorer countries would be harmed. However, the opposite effect can emerge. Trade raises the income level in developing countries, and in turn, generates demand for better environmental quality and stricter regulations in order to mitigate pollution. This optimistic view is closely related to the EKC hypothesis. Moreover, developing countries acquire state-of-the-art technology from technology transfers through foreign direct investment. Taskin and Zaim (2001) measure environmental efficiency by using a hyperbolic index and investigate its determinants, regressing it on per-capita income, trade openness, trade composition, and share of polluting export. They argue the existence of a U-shaped EKC curve between per-capita income and environmental efficiency. Moreover, they claim that there exists a U-shaped relationship between trade openness and environmental efficiency, i.e., efficiency decreases up to a certain level as trade openness increases, and improves afterward.

This paper proposes a super SBM efficiency model with undesirable outputs, which modifies Li et al.'s (2013) model. I use this index to measure the environmental efficiency of developed and developing countries. This study is the first one to apply the super SBM efficiency measurement for the world dataset in environmental economics.

The purpose of this study is two-fold. The first purpose is to measure a super environmental efficiency index and apply it to 98 countries, including developed and developing countries, for the period 1970–2008 and for four pollutants: SO_2, NO_x, particulate matter 10 micrometers or less in diameter (PM10), and CO_2. The second purpose is to examine the determinants of environmental efficiency in panel data regression analysis, along with the above two questions.

The rest of the paper is organized as follows. Section 2 describes the paper's methodology and data. Section 3 presents the efficiency results. Section 4 investigates the determinants of environmental efficiency in the panel regression. Section 5 concludes the study with a brief summary.

2. Methodology and data

2.1 SBM efficiency without undesirable outputs

This section proposes a super SBM efficiency model modifying Tone (2004) and Li et al.'s (2013) model, in which undesirable outputs can be treated to measure environmental efficiency in the world economy.

To begin with, I introduce the SBM DEA models proposed by Tone (2004) and Li et al. (2013). Assume an h DMU having k input, m desirable outputs, and n undesirable outputs. The input and output vectors for DMU $i(i=1,\cdots,h)$ are given by $\boldsymbol{x}_i=(x_{1i,\ldots}x_{ki,})$ and $\mathbf{y}_i=(y^g_{1i},\cdots,y^g_{mi},y^b_{1i},\cdots,y^b_{ni})$, respectively. Then, the inputs, desirable, and undesirable outputs are denoted by $\mathbf{X}=\{x_{ji}\}\in\mathbf{R}^{k\times h}$, $\mathbf{Y}^g=\{y^g_{ji}\}\in\mathbf{R}^{m\times h}$, and $\mathbf{Y}^b=\{y^b_{ji}\}\in\mathbf{R}^{n\times h}$, respectively. Assume $\mathbf{X}>0$, $\mathbf{Y}^g>0$, and $\mathbf{Y}^b>0$. Let $\mathbf{e}=(1,\cdots,1)$. Then, the production possibility set is given by

$$P=\left\{\mathbf{x},\mathbf{y}^g,\mathbf{y}^b \middle| \mathbf{x}\geq X\boldsymbol{\lambda},\mathbf{y}^g\leq Y^g\boldsymbol{\lambda},\mathbf{y}^b\geq Y^b\boldsymbol{\lambda},L\leq\mathbf{e}\boldsymbol{\lambda}\leq U,\boldsymbol{\lambda}\geq\mathbf{0}\right\},$$

where $\boldsymbol{\lambda}=(\lambda_1,\cdots,\lambda_h)$ is the intensity vector, and $L(0\leq L\leq 1)$ and $U(1\leq U)$ are lower and upper bounds for the sum of all elements of $\boldsymbol{\lambda}$, respectively. Next, $L=0$ and $U=\infty$ correspond to constant returns to the scale model and $L=1$ and $U=1$ correspond to variable returns to the scale model[3]. Extending the SBM model in his previous study (Tone, 2001), Tone (2004) proposes an SBM with undesirable outputs

[3] Cooper et al. (2006), pp.150–152.

$$\theta = \min \frac{1 - \frac{1}{k}\sum_{j=1}^{k}\frac{s_j^-}{x_{j0}}}{1 + \frac{1}{m+n}\left(\sum_{j=1}^{m}\frac{s_j^g}{y_{j0}^g} + \sum_{j=1}^{n}\frac{s_j^b}{y_{j0}^b}\right)}$$

$$\text{s.t.} \quad \boldsymbol{x}_i = X\boldsymbol{\lambda} + \boldsymbol{s}^-$$

$$\boldsymbol{y}_i^g = Y^g\boldsymbol{\lambda} - \boldsymbol{s}^g$$

$$\boldsymbol{y}_i^b = Y^b\boldsymbol{\lambda} + \boldsymbol{s}^b$$

$$L \le \mathbf{e}\boldsymbol{\lambda} \le U$$

$$\boldsymbol{s}^-, \boldsymbol{s}^g, \boldsymbol{s}^b, \boldsymbol{\lambda} \ge \boldsymbol{0} \qquad (1)$$

where $\boldsymbol{s}^- \in R^k$, $\boldsymbol{s}^g \in R^m$, and $\boldsymbol{s}^b \in R^n$ denote the input excesses, output shortfalls, and undesirable output excesses, respectively. These are termed as “slacks.” Note that θ takes unity if and only if all slacks are zero.

In order to discriminate the efficient DMUs when undesirable outputs are included, Li et al. (2013) propose a super SBM model with the undesirable outputs SBM model. Before introducing the model, it is useful to define the production set for evaluating a DMU that takes $\theta^* = 1$, as follows:

$$\overline{P} \setminus (\mathbf{x}_0, \mathbf{y}_0) = P(\mathbf{x}_0, \mathbf{y}_0) \setminus (\mathbf{x}_0, \mathbf{y}_0) \cap \{\overline{\mathbf{x}} \ge \mathbf{x}_0, \overline{\mathbf{y}}^g \le \mathbf{y}_0^g, \overline{\mathbf{y}}^b \ge \mathbf{y}_0^b\},$$

where $P \setminus (\mathbf{x}_0, \mathbf{y}_0)$ is defined as a production possibility set spanned by $(\mathbf{X}, \mathbf{Y}^g, \mathbf{Y}^b)$, excluding $(\mathbf{x}_0, \mathbf{y}_0)$, i.e.,

$$P \setminus (\mathbf{x}_0, \mathbf{y}_0) = \{\overline{\mathbf{x}}, \overline{\mathbf{y}}^g, \overline{\mathbf{y}}^b \mid \overline{\mathbf{x}} \ge \sum_{\substack{i=1,\\ i\neq 0}}^{h} \lambda_j \mathbf{x}_j, \overline{\mathbf{y}}^g \le \sum_{\substack{i=1,\\ i\neq 0}}^{h} \lambda_j \mathbf{y}^g{}_j, \overline{\mathbf{y}}^b \ge \sum_{\substack{i=1,\\ i\neq 0}}^{h} \lambda_j \mathbf{y}^b{}_j, L \le \mathbf{e}\boldsymbol{\lambda} \le U, \boldsymbol{\lambda} \ge \mathbf{0}\}.$$

Using the notations in this paper and omitting the constraints, Li et al. (2013) propose the super SBM environmental efficiency

$$\min \frac{\frac{1}{k}\sum_{j=1}^{k}\frac{\bar{x}_j}{x_{j0}}}{\frac{1}{m}\sum_{j=1}^{m}\frac{\bar{y}_j^g}{y_{j0}^g}+\frac{1}{n}\sum_{j=1}^{n}\frac{\bar{y}_j^b}{y_{j0}^b}} \tag{2}$$

for DMU 0, which has unity score in (1). In this equation, however, the less polluting the DMU, the smaller the efficiency value, because the denominator includes "the possible expansion rate" within the production possibility set excluding DMU 0.

This paper proposes a super environmental efficiency with undesirable outputs, as follows:

$$\theta^* = \min \frac{\frac{1}{k}\sum_{j=1}^{k}\frac{\bar{x}_j}{x_{j0}}}{\frac{1}{m}\sum_{j=1}^{m}\frac{\bar{y}_j^g}{y_{j0}^g}+\frac{1}{n}\sum_{j=1}^{n}\left(1-\frac{\bar{y}_j^b-y_{j0}^b}{y_{j0}^b}\right)}$$

$$\text{s.t.}\quad \bar{\mathbf{x}} \ge \sum_{\substack{i=1,\\ i\ne 0}}^{h}\lambda_j\mathbf{x}_j\,,$$

$$\bar{\mathbf{y}}^g \le \sum_{\substack{i=1,\\ i\ne 0}}^{h}\lambda_j\mathbf{y}_j^g\,,$$

$$\bar{\mathbf{y}}^b \ge \sum_{\substack{i=1,\\ i\ne 0}}^{h}\lambda_j\mathbf{y}_j^b$$

$$\bar{\mathbf{x}} \ge \mathbf{x}_0\,,$$

$$\bar{\mathbf{y}}^g \le \mathbf{y}_0\,,$$

$$\bar{\mathbf{y}}^b \ge \mathbf{y}_0$$

$$\bar{\mathbf{y}}^g \ge 0\,,$$

$$L \le \mathbf{e}\boldsymbol{\lambda} \le U$$

$$\boldsymbol{\lambda} \geq 0. \quad (3)$$

Here, I modify the second term of the denominator in (2). The numerator indicates a mean expansion rate of $\mathbf{x}_0$ to $\bar{\mathbf{x}}$, which implies the mixed input superiority of DMU 0. On the other hand, the first term in the denominator indicates a mean reduction rate of $\mathbf{y}_0^g$ to $\bar{\mathbf{y}}^g$. The second term in the denominator indicates a mean of one minus expansion rate of $\mathbf{y}_0^b$ to $\bar{\mathbf{y}}^b$ [4]. Then, the denominator implies the mixed output superiority of DMU 0.

Because this paper analyzes the world dataset, constant returns to scale assumption is inappropriate. Hereafter, I assume variable returns to scale and $L = U = 1$. Using the Charnes–Cooper transformation (Cooper et al., 2006), the fractional problem (3) can be transformed into the following linear programming problem[5]:

$$\theta^{**} = \min t + \frac{1}{k}\sum_{j=1}^{k}\Phi_j$$

$$\text{s.t.} \quad t - \frac{1}{m+n}\left(\sum_{j=1}^{m}\Psi_j^g + \sum_{j=1}^{n}\Psi_j^b\right) = 1$$

$$\sum_{\substack{i=1,\\ i\neq 0}}^{h} x_{ji}\Lambda_j - x_{j0}\Phi_j - x_{j0}t \leq 0 \quad (j = 1, \cdots, k)$$

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[4] When $\bar{y}_{j0}^b$ is very large for some j, the denominator of (2) may take a negative value. In this case, a constraint such as $1 - (\bar{y}_j^b - y_{j0}^b)/y_{j0}^b \geq 0$ should be imposed. However, in my dataset such a problem does not occur.

[5] The above transformation from the fractional problem to the linear programming problem is not shown in Li et al. (2013).

$$\sum_{\substack{i=1,\\ i\neq 0}}^{h} y_{ji}^{g}\Lambda_j + y_{j0}^{g}\Psi_j^{g} - y_{j0}^{g}t \geq 0 \quad (j=1,\cdots,m)$$

$$\sum_{\substack{i=1,\\ i\neq 0}}^{h} y_{ji}^{b}\Lambda_j - y_{j0}^{b}\Psi_j^{b} - y_{j0}^{b}t \geq 0 \quad (j=1,\cdots,n)$$

$$\mathbf{e\Lambda} = t$$

$$\Phi_j > 0 \ (\forall j),\ \Psi_j^{g} \geq 0 \ (\forall j),\ \Psi_j^{b} \geq 0 \ (\forall j),\ \Lambda_j \geq 0 \ (\forall j). \tag{4}$$

The super efficiency is calculated by (4) only if a DMU obtains unity score in (3). Note that the efficiency values in each year are calculated on the basis of the same year data.

2.2 Empirical strategies

What factors influence environmental efficiency? This section investigates the determinants of environmental efficiency along with the EKC and PHH context.

For this purpose, I estimate the following equation[6]:

$$\begin{aligned} EF_{it} &= \beta_0 + \beta_1 I_{it} + \beta_2 I_{it}^2 + \beta_3 (K/L)_{it} + \beta_4 (K/L)_{it}^2 + \beta_5 I_{it} (K/L)_{it} \\ &\quad + \beta_6 T_{it} + \beta_7 T_{it} RI_{it} + +\beta_8 T_{it} RI_{it}^2 + \beta_9 T_{it} \cdot R(K/L)_{it} + \beta_{10} T_{it} \cdot R(K/L)_{it}^2 \\ &\quad + \beta_{11} T_{it} \cdot RI_{it} \cdot R(K/L)_{it} + \varepsilon_{it} \quad , \end{aligned} \tag{5}$$

where i is a country index; t is year; EF is environmental efficiency; I is real

[6] Although Li et al. (2013) calculate the super SBM efficiency, their reason being that the efficiency scores are censored at zero, they apply the Tobit regression model to the results, in which the dataset is treated as a pooling data, in order to seek determinants of efficiency in the second-stage analysis. In general, however, efficiency scores cannot reach zero, at least, when the outputs are positive. There is hardly any need to consider that efficiency scores are censored at zero. Unlike their model, I apply fixed and random effects models as a panel dataset.

GDP per capita; (K/L) is a country's capital–labor ratio; T is trade openness; RI is the relative GDP per capita, which is defined as the ratio of the country's GDP per capita to the world average one in each year; $R(K/L)$ is the relative capital–labor ratio; and ε_{it} is the disturbance term.

The second and third terms on the right-hand side in (5) represent the scale and technique effects. As with Cole and Elliott (2003), we cannot separate the scale and technique effects. The terms including (K/L) capture the *direct* composition effects that are determined by relative capital and labor endowments. According to Cole and Elliott (2003), I refer to this as simply the "composition effects" hereafter. The forth and fifth terms capture that the impact of capital accumulation on environmental efficiency depends on the current capital–labor ratio and per-capita income.

The terms including T capture the trade effects, more specifically the *trade-induced* composition effects we term "trade effects" hereafter. The eighth to twelfth terms present that the impact of trade openness on environmental efficiency depends on a country's per-capita income and capital–labor ratio relative to the world average.

2.3 Data

In my DEA model, there are two inputs—labor and capital stock—and GDP is the sole desirable output. SO_2, NO_x, PM10, and CO_2 emissions are taken as undesirable outputs. Data on GDP, labor, and capital stock are taken from the Penn World Table 8.0. All monetary values are 2005 constant US dollars. Data on the four emissions are obtained from the Emissions Database for Global Atmospheric Research (EDGAR) 4.2 database. The dataset for DEA is a balanced panel data from 1970 to 2008 for 98 countries[7]. The data consist of 30 OECD countries and 68 non-OECD countries. Figure A1 in the Appendix provides a list of the countries.

For the second-stage analysis, data on per-capita income are taken from GDP per capita in PWT 8.0. However, while data on GDP in the first-stage analysis use output-side GDP in PWT 8.0, those in the second-stage regression are calculated by the expenditure GDP divided by the population. Taking data on alternative definitions of GDP will mitigate the endogeneity problem. Trade openness (the sum of export and import values divided by the GDP) is taken as an explanatory variable in the regression, which is obtained from the World Development Indicators 2013 of the World Bank[8]. Table 1 reports the summary of statistics of input and output variables for DEA analysis and the explained and explanatory variables for the regression.

3. Super environmental efficiency results

The environmental efficiency indices for each year are computed by the production possibility set in that year. Note that the efficiency scores in a year are relative comparisons within the same year. Figure A1 in the Appendix provides the SO_2 and CO_2 environmental efficiency scores of 98 countries because these can be considered as the most typical pollutants among the four. Among 3822 (98 countries by 39 years) evaluation scores, 664 observations are efficient and have scores larger than unity.

Figure 1 shows the median environmental efficiency values for SO_2 during the

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[7] Because St. Lucia occupies a unique position in the frontier, its efficiency score is unrealistic beyond 200. Hence, St. Lucia is excluded from the sample, although the data are available.

[8] Data on Taiwan are taken from the Taiwanese government's official site.

sample period[9]. As shown in Figure 1, the median environmental efficiency of the OECD and non-OECD countries slightly increases at almost the same rate until 1978. Since 1979, however, they diverge for the rest of the sample period. The median environmental efficiency of the OECD countries is always larger than that of the non-OECD countries in each year from 1979 to 2008. These features are also the same for NO_x, PM10, and CO_2.

Figures 2 and 3 provide scatter plots of the mean environmental efficiency for SO_2, mean per-capita income, and mean trade openness during the sample period. In the next subsection, the relationships among environmental efficiency, income, and trade are investigated on the basis of EKC and PHH.

4 Determinants of environmental efficiency

First, this section examines whether there is a U-shaped relationship between environmental efficiency and per-capita income according to EKC, excluding the K/L ratio and trade variables. Table 2 presents the empirical results[10]. All coefficients of per-capita income and its quadratic term are statistically significant for all models at 1% significance level. The fixed effects models are preferred to the random effects models, except for the case of CO_2. The suggested turning point income levels are high,

[9] Because mean values are affected by extreme values, I examine median efficiency values.

[10] I also examine the model that adds the cubic term of per-capita income. All three coefficients of linear, quadratic, and cubic terms are statistically significant for each of the four pollutants. Environmental efficiency increases up to US \$46,259-65,653, and then decreases to US \$86,590-101,089, and increases again.

ranging from US \$60,127 to \$68,007. Therefore I conclude that there is no Kuznets-type relationship between environmental efficiency and income. Rather, the estimated coefficients imply that environmental efficiency is a monotone increasing function of per-capita income at a diminishing rate. This may be because the environment is a superior good, because increasing income leads to a more stringent environmental regulation, and because environmental investment to meet it exhibits diminishing returns in terms of technology.

Second, this section presents the results of the full models to examine the composition and trade effects—as well as the scale–technique effects—on environmental efficiency. Because of space limitations, Table 3 presents only the results of the fixed effects models, because the Hausman test prefers the fixed effects model to the random effects model for each of the four pollutants. For the scale–technique effects, while the coefficients of the I term for the four cases remain significantly positive in the full models, those of the I^2 term remain significantly negative for SO_2 and positive for CO_2. The coefficients of the K/L term are significantly positive and the efficients of the $(K/L)^2$ term are significantly negative for SO_2, NO_x, and PM10. This implies that capital accumulation improves environmental efficiency with a decreasing rate.

Regarding trade intensity for SO_2, NO_x, and PM10, the coefficients of T are significantly positive, whereas those of $T\ R(K/L)$ and $T\ R(K/L)^2$ are significantly negative and positive, respectively. This means that a country with a high K/L ratio will experience environmental inefficiency in response to a decreasing rate of trade openness. All coefficients of $T\ RI$ are positive. The impact of trade openness on environmental efficiency varies across countries depending on their income.

High-income countries are generally capital abundant. This is the reason why the impacts of trade on environmental efficiency are not straightforward. The rest of this section examines the elasticities of the scale technique, composition, and trade effects for the OECD and non-OECD countries.

Based on the above results, Table 4 presents elasticities for scale and technique effects (per-capita income based on expenditure), composition effects (K/L ratio), and trade effects (trade intensity) with respect to the four environmental efficiencies. The elasticities for OECD and non-OECD are calculated using each of the sample means. Note that our dependent variable is environmental efficiency, unlike previous PHH studies (Antweiler et al., 2001; Cole and Elliot, 2003; Managi et al., 2009). A positive elasticity for each effect means that the effect is beneficial to the environment.

For scale and technique effects, the magnitude of their elasticities appears plausible. Raising income improves the environmental efficiencies for all pollutants. More interestingly, for each of the three local pollutants, SO_2, NO_x, and PM10, the elasticity of the OECD coutries is greater than that of the non-OECD countries. This means that, for these local pollutants, rising income improves environmental efficiency in the OECD countries more than that in the non-OECD countries. In contrast, for CO_2, the elasticity of the non-OECD countries exceeds that of the OECD ones. This may be because the mean K/L ratio of the OECD countries is larger than that of the non-OECD countries and the coefficients with the K/L ratio are negative.

Almost all composition effect elasticities for SO_2, NO_x, and PM10 are significantly positive. This means that, for example, a 1% increase in the K/L ratio improves the environmental efficiency for NO_x, i.e., 0.644%, 0.363%, and 0.711% for the world, OECD, and non-OECD countries, respectively. As opposed to the local pollutant results, the elasticities for CO_2 are significantly negative for the world, OECD, and non-OECD countries. The difference may reflect the fact that although local pollutants can be removed in plants, carbon capture and storage technologies are not applied at the practical level.

For trade intensity, surprisingly all elasticities except SO_2 for the OECD countries are significantly negative. For the mean countries in the sample, a 1% increase in trade intensity reduces environmental efficiency by 0.117%, 0.149%, and 0.387% for NO_x, PM10, and CO_2, respectively. Note that the elasticities of trade intensity on CO_2 environmental efficiency for the non-OECD countries, −0.415, is absolutely higher than that for the OECD countries, −0.264. This implies that an increase in trade openness causes more environmental inefficiency in the non-OECD than in the OECD countries. Only the elasticity of SO_2 for the OECD countries is significantly positive.

5. Discussion and conclusions

Using a super SBM DEA model with undesirable outputs, this study measures the environmental efficiency of four typical air pollutants—SO_2, NO_x, PM10, and CO_2—for 98 countries for the period 1970–2008. The super SBM DEA efficiency index with undesirable outputs is constructed by modifying Li et al.'s (2013) model. It provides us with more discriminating power than did previous DEA efficiency indices. For the resulting environmental efficiency, the median of the non-OECD countries improves similar to that of the OECD countries untill 1978. However, since 1979, the median of the latter is larger than that of the former.

The environmental efficiency results in the present paper have to be interpreted with care. First, environmental efficiency can be improved even when pollution emissions increase, as long as more outputs are produced. Second, in this paper, an efficiency *impovement* includes a change in the industrial structure from polluting industries to less-polluting industries and that in the technical *impovement* in each industry. Third, because efficiency scores are measured yearly, dynamic efficiency is not taken into account.

In this study, the determinants of environmental efficiency are also examined in association with the context of EKC and PHH. The panel regression results reveal that there is no Kuznets-type relationship between environmental efficiency and per-capita income. Rather, environmental efficiency is a monotone increasing function of income. A 1% increase in per-capita income improves the environmental efficiency for SO_2, NO_x, PM10, and CO_2, 0.398%, 0.313%, 0.347%, and 1.360%, with respect to the mean country in the sample, respectively.

For the composition effect, I find that an increase in the capital–labor ratio improves the environmental efficiency for SO_2, NO_x, and PM10. One reasonable interpretation of this result is that capital accumulation in a country develops capital-intensive, i.e., pollution-intensive industries, but may simultaneously lead to an increase in outputs more than an increase in pollution emissions. As a result, the environmental *efficiency* in that country may improve. In contrast to the local air pollutants described above, the elasticities of the composition effect for CO_2 are negative for both OECD and non-OECD countries. The difference between the impacts of local and global air pollutants on environmental efficiency may arise from the following fact: while local air pollutants can be alleviated by end-of-pipe technology or cleaner production, global air pollutants such as CO_2 cannot be mitigated by existing technology.

Although the impact of trade on environmental efficiency is not straightforward, the elasticity results show that trade openness does not seem to be good for environmental efficiency. The elasticities of trade for NO_x, PM10, and CO_2 are −0.117, −0.149, and −0.387 for all countries, and −0.126, −0.138, and −0.264 for the OECD countries. For the non-OECD countries, CO_2 elasticity is significant as well as negative, −0.415. As a whole, an increase in trade openness tends to reduce environmental efficiency. This may be because an increase in trade openness leads to pollution emissions due to capita-intensive, i.e., pollution-intensive industries in the OECD countries and leads to less-stringent environmental regulation in the non-OECD countries.

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Table 1 Summary of statistics of input and output variables

Variable	Dimension	Obs.	Mean	SD	Min	Max
Real GDP	mil. 2005US$	3822	338,769.200	1,018,679.000	1,206.338	1.31E+07
Real GDP per capita	2005US$	3822	10,545.990	11,845.310	199.208	116423.5
Labor	million	3822	19.877	69.734	0.045	7.72E+02
Capital stock	mil. 2005US$	3822	1,019,600.000	3,225,986.000	1,847.514	4.01E+07
Capital-labor ratio	2005US$/worker	3822	77,730.800	85,428.740	1,131.321	868037.4
Trade openess	%	3518	71.004	52.373	0.703	460.4711
SO_2 emissions	Giga gram	3822	0.973	3.070	0.001	39.903
Nox emissions	Giga gram	3822	0.766	2.186	0.003	20.742
PM10 emissions	Giga gram	3822	0.811	1.881	0.000	19.334
CO_2 emissions	Giga gram	3822	222.401	660.099	0.033	7,809.190

Table 2 Environmental efficiency and GDP per capita (Fixed and random effects models)

	SO_2	NO_x	PM10	CO_2
FE				
C	0.213 ***	0.153 ***	0.171 ***	0.151 ***
I	0.000036 ***	0.0000373 ***	0.0000328 ***	0.0000475 ***
I^2	-2.67E-10 ***	-2.91E-10 ***	-2.52E-10 ***	-3.95E-10 ***
Turning point income 2005US$	67,416	64,089	65,079	60,127
Observations	3,822	3,822	3,822	3,809
RE				
C	0.218 ***	0.158 ***	0.173 ***	0.170 ***
I	0.0000354 ***	0.0000367 ***	0.0000326 ***	0.0000454 ***
I^2	-2.6E-10 ***	-2.86E-10 ***	-2.5E-10 ***	-3.76E-10 ***
Turning point income 2005US$	68,077	64,161	65,200	60,372
Observations	3,822	3,822	3,822	3,809
Hausman	0.603	0.147	0.721	0.014 **

Note) Because of space limitation, t-values are omitted. *p<0.1; **p<0.05; ***<0.01.

Table 3 Determinants of trade on environmental efficiency (fixed effects models)

	SO_2	NO_x	PM10	CO_2
I	0.0000285***	0.0000198***	0.0000212***	0.0001145***
	[5.181]	[4.748]	[4.408]	[12.194]
I^2	-1.97e-10*	-6.08E-11	-7.79E-11	7.90e-10***
	[-1.888]	[-0.771]	[-0.856]	[4.439]
K/L	8.21e-06***	7.04e-06***	7.09e-06***	-2.40E-06
	[8.694]	[9.870]	[8.615]	[-1.489]
$(K/L)^2$	-2.88e-11***	-1.38e-11***	-1.71e-11***	4.00e-11***
	[-5.808]	[-3.678]	[-3.963]	[4.732]
$(K/L)I$	-5.18E-12	-3.01E-11	-2.78E-11	-6.30e-10***
	[-0.1132]	[-0.870]	[-0.697]	[-8.074]
T	0.0019862***	0.0022154***	0.00203***	0.000251
	[4.626]	[6.826]	[5.434]	[0.339]
$T\ RI$	0.0019553**	0.002944***	0.0018044***	-0.0044343***
	[2.498]	[4.976]	[2.644]	[-3.322]
$T\ RI^2$	0.000263	-7.7E-05	1.82E-06	-0.00029
	[1.523]	[-0.589]	[0.0121]	[-0.997]
$T\ R(K/L)$	-0.0047885***	-0.0071982***	-0.0062283***	-0.00095
	[-5.842]	[-11.617]	[-8.714]	[-0.678]
$T\ R(K/L)^2$	0.0013358***	0.0016265***	0.0015377***	-0.00069
	[4.205]	[6.773]	[5.5508]	[-1.266]
$T\ R(K/L)\ RI$	-0.00052	-0.00048	-0.00033	.0025776***
	[-1.191]	[-1.461]	[-0.850]	[3.442]
Constant	-0.118***	-0.0279	-0.027	0.0519
	[-3.951]	[-1.230]	[-1.036]	[1.013]
R^2	0.195	0.213	0.131	0.083
Observations	3518	3518	3518	3517

Note) *t*-values in parentheses. *p<0.1; **p<0.05; ***<0.01.

Table 4 Scale and technique, composition and trade elasticities

	Effects	SO_2	NO_x	PM10	CO_2
All	Scale and tetchnique	0.398^{***}	0.313^{***}	0.347^{***}	1.360^{***}
OECD		0.405^{***}	0.308^{***}	0.348^{***}	1.095^{***}
Non-OECD		0.377^{***}	0.281^{***}	0.309^{***}	1.409^{***}
All	Composition	0.440^{***}	0.644^{***}	0.597^{***}	-0.351^{***}
OECD		-0.082	0.363^{***}	0.225^{***}	-0.603^{***}
Non-OECD		0.622^{***}	0.711^{***}	0.691^{***}	-0.282^{*}
All	Trade	0.029	-0.117^{***}	-0.149^{***}	-0.387^{***}
OECD		0.059^{**}	-0.126^{***}	-0.138^{***}	-0.264^{***}
Non-OECD		0.083	-0.042	-0.076	-0.415^{***}

Note) *p<0.1; **p<0.05; ***<0.01.

Figure 1 Median environmental efficiency for SO_2.

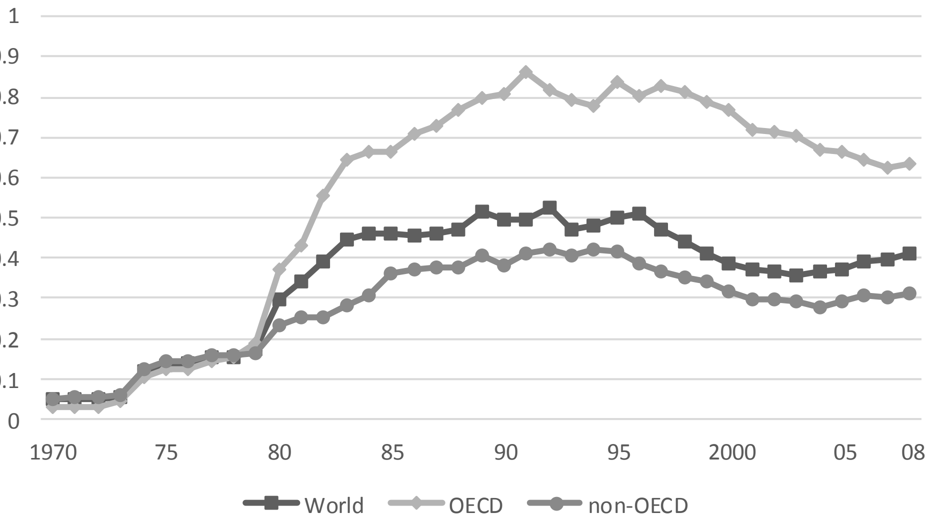
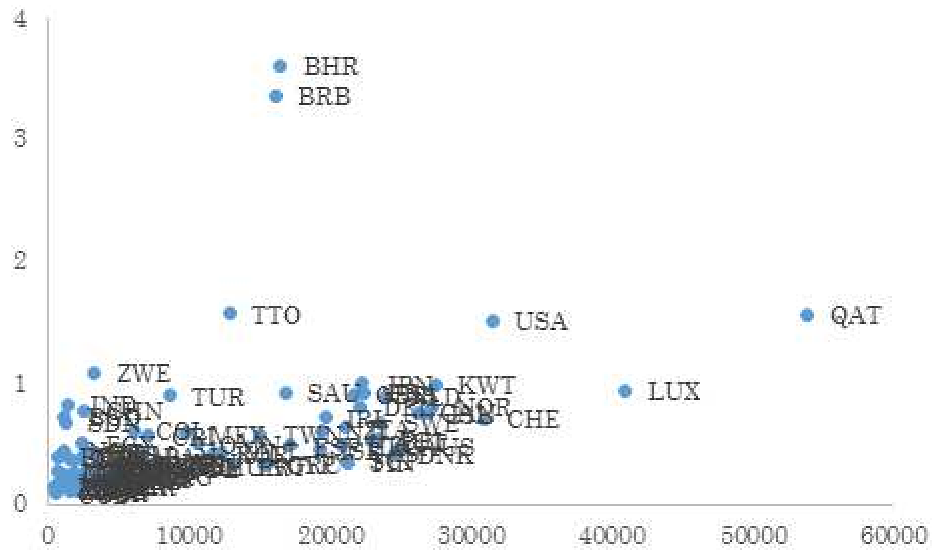
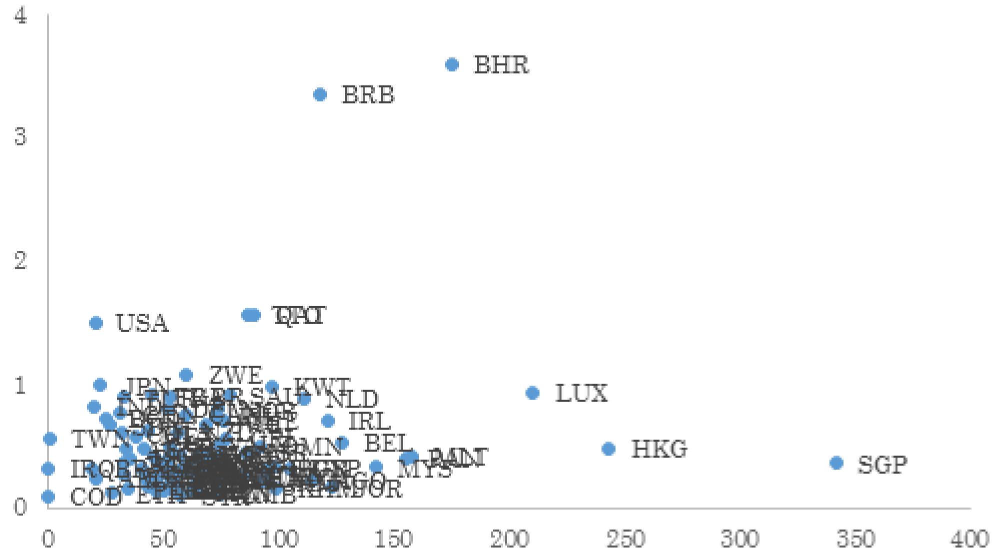


Figure 2 Scatter plot of the mean environmental efficiency for SO_2 and mean income per capita during the sample period



Note) The vertical axis presents per capita income and the horizontal axis represents the mean environmental efficiency for SO_2.

Figure 3 Scatter plot of the mean environmental efficiency for SO_2 and mean trade openness during the sample period.



Note) The vertical axis presents trade openness and the horizontal axis represents the mean environmental efficiency for SO_2.

Appendix

The environmental efficiency indices of 98 countries for SO_2 and CO_2

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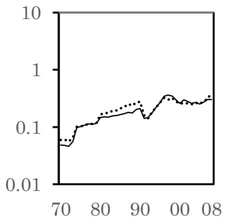
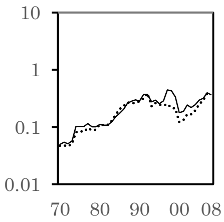
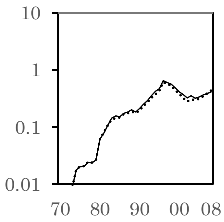


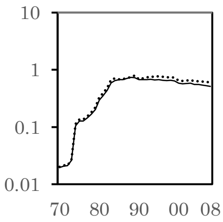
Angola



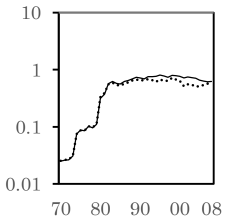
Argentina



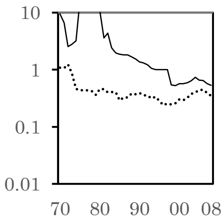
Australia



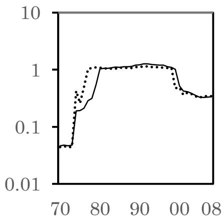
Austria



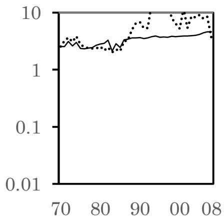
Bahrain



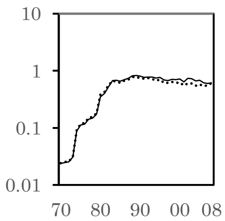
Bangladesh



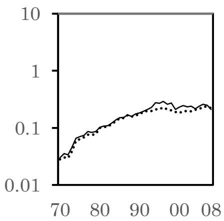
Barbados



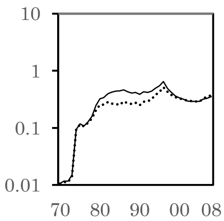
Belgium



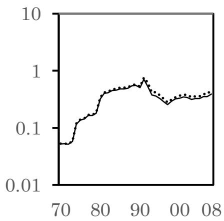
Bolivia



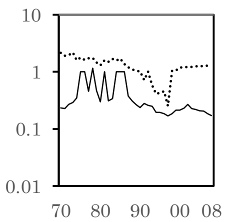
Brazil



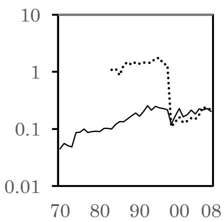
Bulgaria



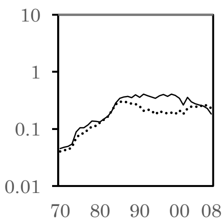
Burkina Faso



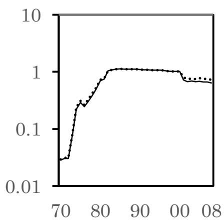
Cambodia



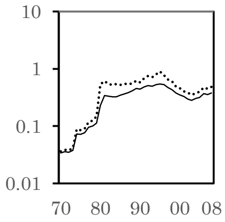
Cameroon



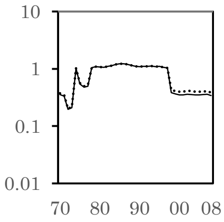
Canada



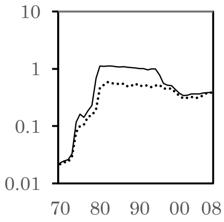
Chile



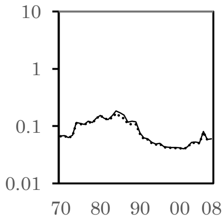
China



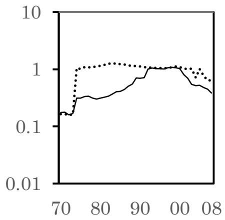
Colombia



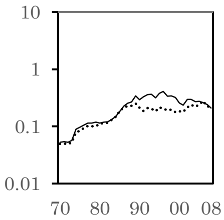
Congo, Dem. Rep.



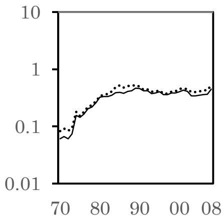
Costa Rica



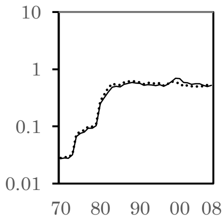
Cote d`Ivoire



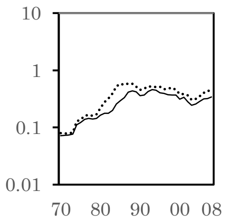
Cyprus



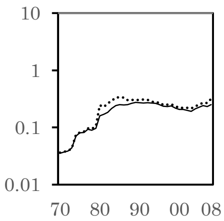
Denmark



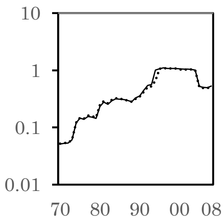
Dominican Republic



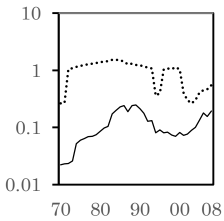
Ecuador



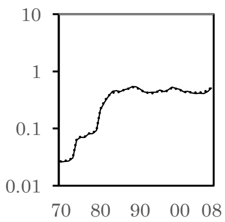
Egypt



Ethiopia



Finland



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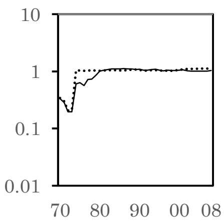

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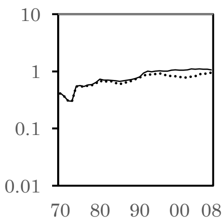

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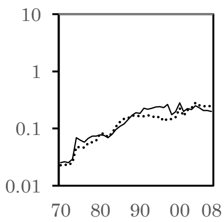

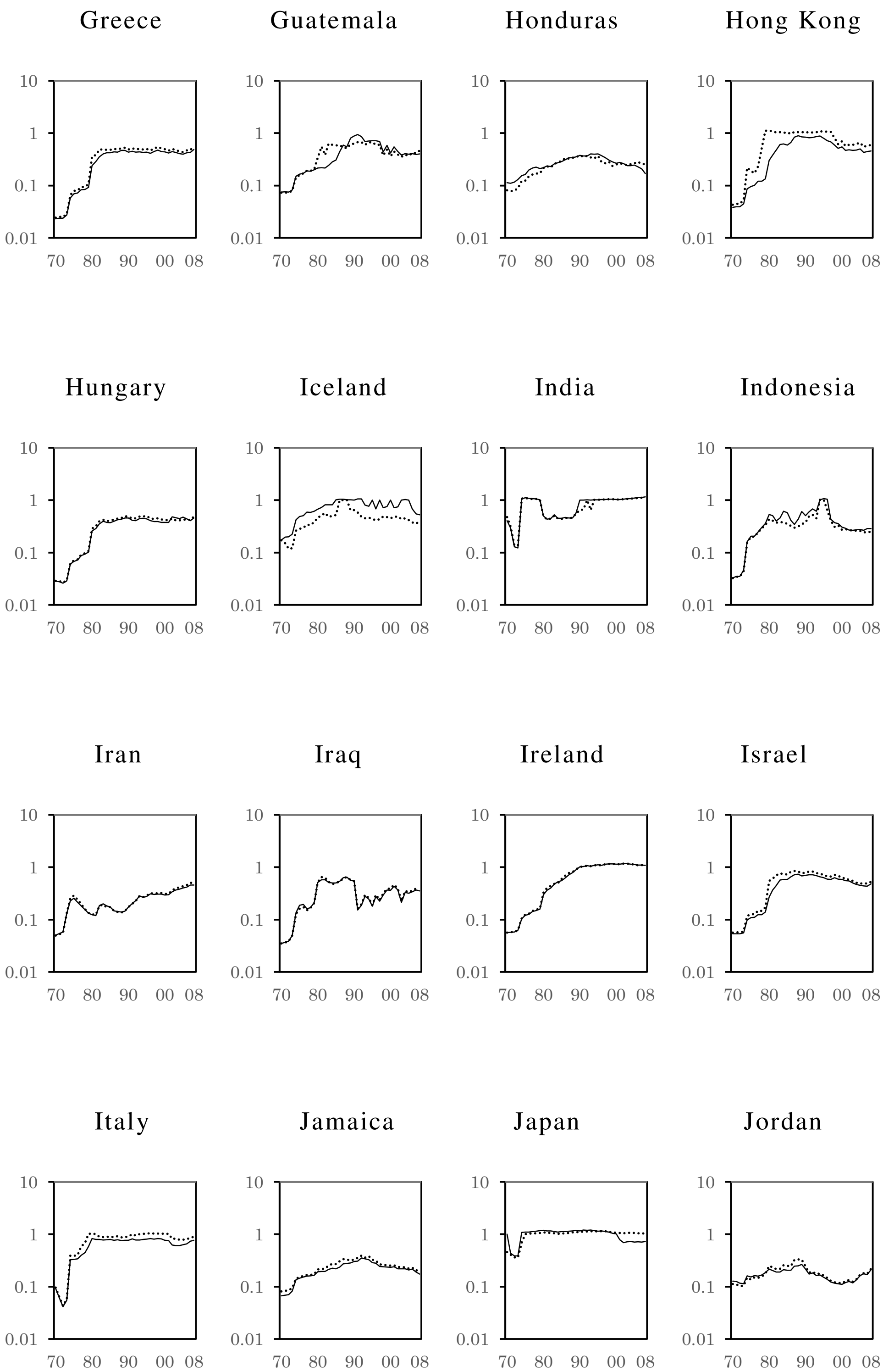
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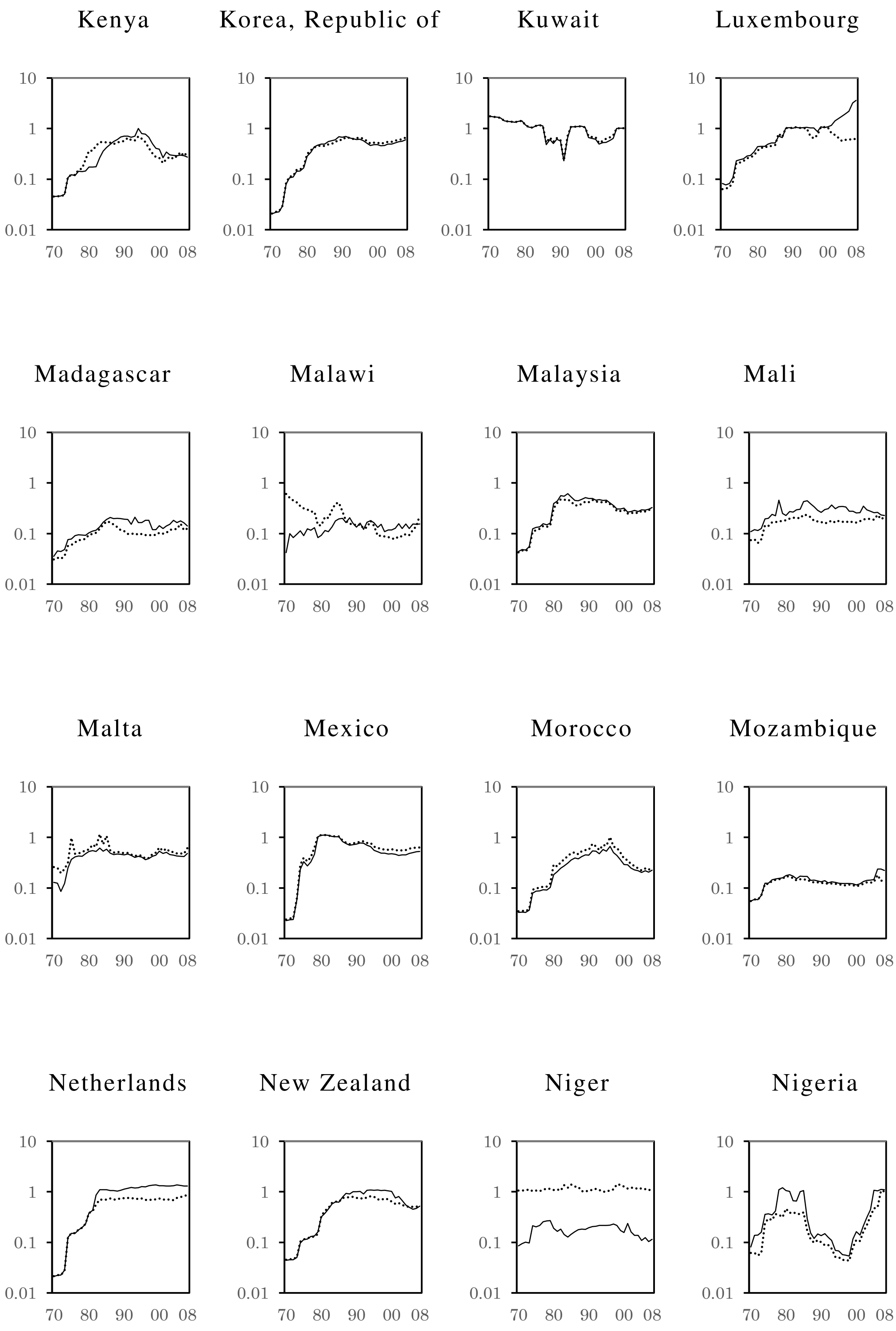
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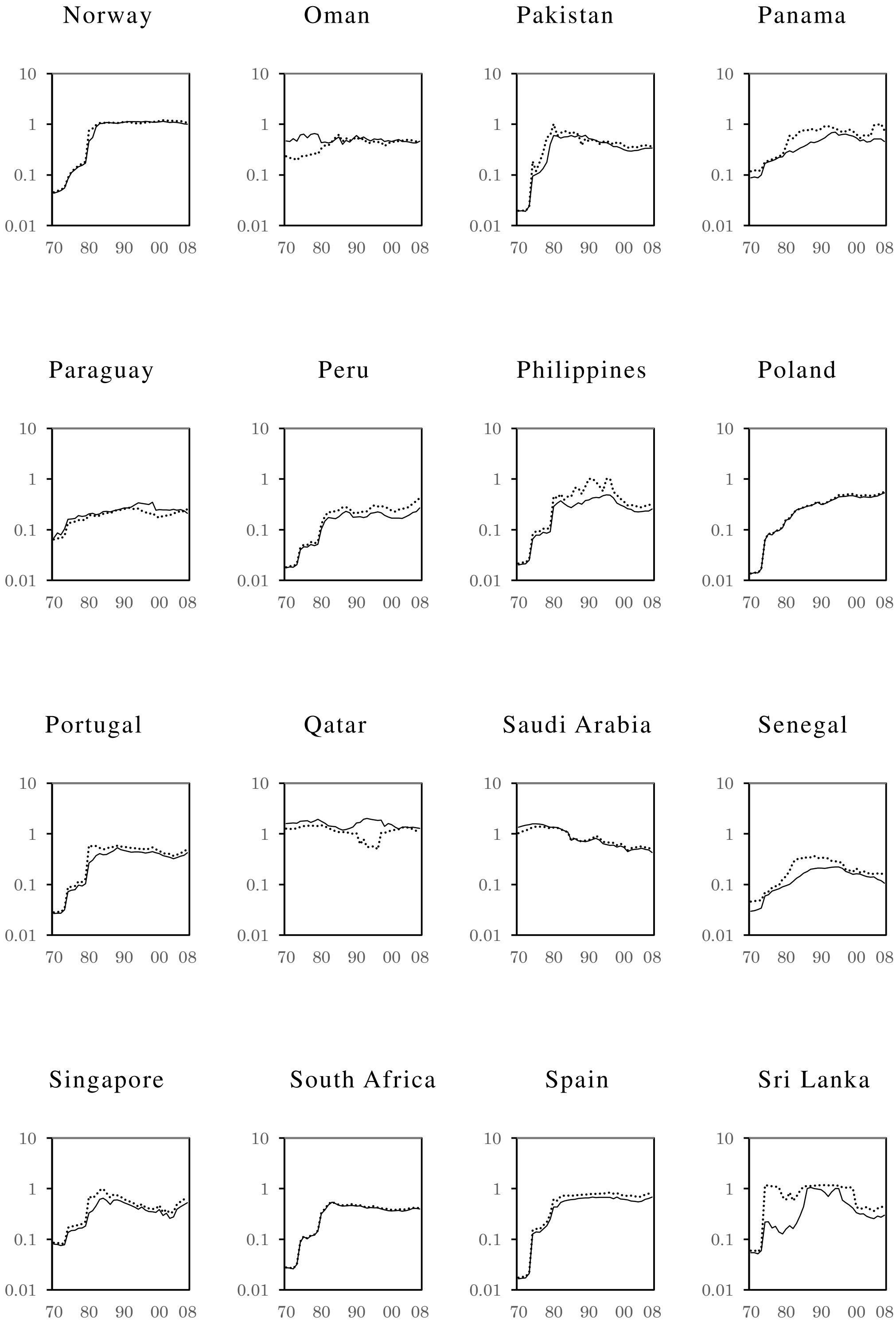
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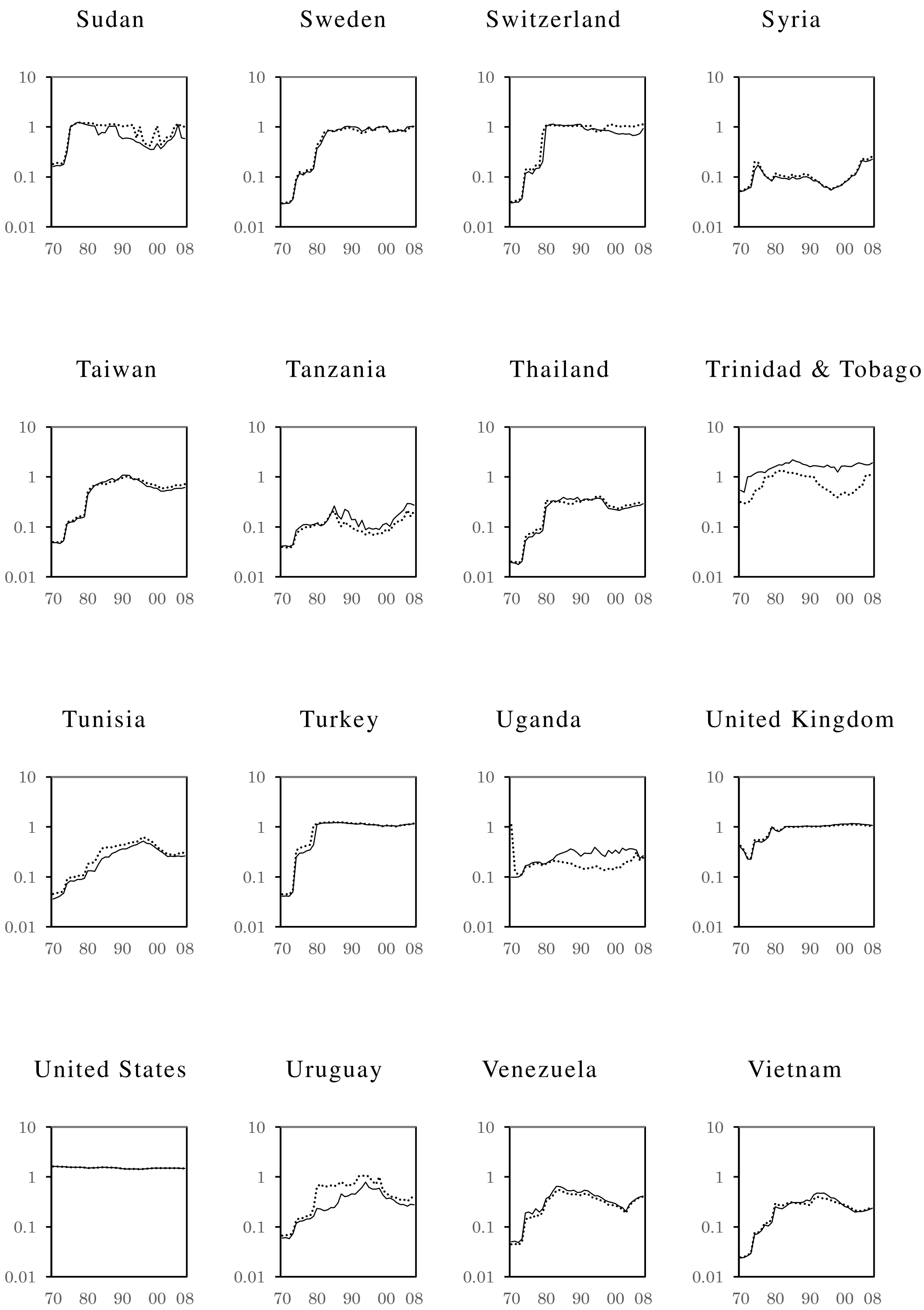
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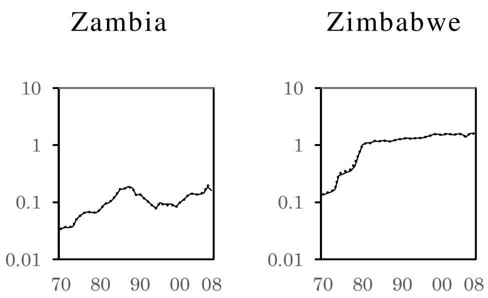

Note) Solid and dotted lines present environmental efficiency for SO_2 and CO_2, respectively. Note that the vertical axis is is a logarithmic axis for visualazation. CO_2 environmental efficiency scores of Cambodia for 1970–1982 are not presented because of non-existence of solutions for the linear programming problem.