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A metafrontier approach for measuring an environmentally sensitive productivity growth index

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ABSTRACT

This paper presents an alternative environmentally sensitive productivity growth index to incorporate group heterogeneities into a conventional Malmquist–Luenberger productivity growth index. The proposed approach allows the calculation of both efficiency and technical changes, for economic agents operating under different technologies. Moreover, it also enables the computation of changes in the technological gap between regional and global frontier technologies. The proposed index is employed in measuring productivity growth and its decomposed components in 46 countries between 1993 and 2003. The main finding is that Europe has taken the lead in the world frontier technology and that Asia has attempted to move towards the frontier technology. Subsequent policy implications are provided based on some empirical studies.

1. Introduction

As international concerns on climate change and sustainable economic growth increase, global cooperation on environmental regulations, such as the Kyoto Protocol and the Bali Roadmap, has significantly increased. Since the international regulations for emissions of by-products affect economies at the state level as well as the regional level, environmental policies are required to be connected with national and regional economic policies. In order to formulate effective environment-related economic policies, research with different foci has been demanded to measure the relationship between the emissions of by-products and economic growth. This research includes both theoretical approaches and empirical studies.

Among methodologies utilized in examining the relationship between the emissions of by-products and economic growth, the environmentally sensitive productivity growth index has long been regarded as a pioneering tool. Its usefulness originates from the fact that it provides a measure of the economic prosperity, standard of living and environmental amenity of a country. Ever since the seminal work by Chung et al. (1997), the Malmquist–Luenberger productivity growth index (hereafter, ML index) has been used in various research fields for the following reasons: (i) It only requires quantities on the input/output bundles without demanding information on the costs of inputs/outputs; (ii) It does not impose any functional form assumptions on the production function; and (iii) It enables the productivity growth to be decomposed into several components, e. g., efficiency and technical changes. The ML index uses a linear programming technique in calculating the environmentally sensitive productivity growth index, which extends the Malmquist productivity index to incorporate the effect of environmentally harmful by-products. Moreover, the ML index considers by-products as *outputs*, alleviating bias in measuring the environmentally sensitive productivity growth index.[1] Thanks to these methodological merits, the ML index has been frequently utilized, not only at the micro-level but also in macro-level studies.

Regarding empirical studies using the ML index at the micro-level, Chung et al. (1997) is the first one. They analyze productivity growth

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[1] Before the introduction of the ML index, environmentally harmful by-products were often used as inputs.

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and its decomposed sources of Swedish paper and pulp mills for the period 1986–1990. Their empirical result suggests that technical change is the main contributor to productivity growth rather than efficiency change. Using micro-level panel data, Färe et al. (2001) employ the ML index to account for both the marketed output and the output of the pollution abatement activities in the US state manufacturing sectors from 1974 to 1986. Weber and Domazlicky (2001) apply the same methodology to investigate the productivity growth in the US manufacturing sector for the period 1988–1994 in order to incorporate toxic release into the productivity analysis. Pasurka (2006) employs the ML index and decomposes the productivity growth of US coal-fired electric power plants into several factors. By doing this, he calculates the relative importance of factors associated with changes in NO_x and SO_2 emissions. Nakano and Managi (2008) measure productivity in Japanese steam power-generation sector to examine the effects of industrial reforms on the productivity for the period 1978–2003.

Compared to the numerous empirical studies at the micro-level, to our knowledge, only two studies incorporate undesirable outputs into the productivity analysis at the macro-level. Yörük and Zaim (2005) employ both the Malmquist productivity index and the ML index in order to analyze the productivity growth and its decomposed sources in OECD countries for the period between 1985 and 1998. They found that Ireland and Norway were the best performers and that technical change was the main contributor to productivity growth. Kumar (2006) employs the ML index to analyze the environmentally sensitive productivity growth of 41 countries for the period between 1973 and 1992. In his study, Kumar (2006) found that the productivity growth of Annex-I countries are higher than that of the non-Annex-I countries, and that technical change was the main contributor to productivity growth.

In spite of its wide use, the conventional ML index's weakness is that it does not consider *ex ante* heterogeneities among groups when calculating the rate of productivity growth. Instead of including the *ex ante* group heterogeneities when calculating productivity growth, the ML index calculates the productivity growth and then uses the *ex ante* group heterogeneities. However, if they are not included in the calculation of the ML index, the productivity growth rate may be biased for the following reasons. Since heterogeneity among groups leads to different production environments, the production activities of decision making units (DMUs) of one group is different from those of the other groups. That is, each group has its own production technology that determines the production activities of the DMUs in that group. As Battese et al. (2004) indicate, the productivity of the DMUs that operate under a given production technology are not directly comparable to those of the DMUs operating under a different technology. Without taking into account this group heterogeneity, the measured productivity is likely to be biased. Hence, the conventional ML index needs to be revised in order to properly consider group heterogeneity.

To overcome the aforementioned shortcoming of the ML index, in this study we provide an alternative index for measuring environmentally sensitive productivity growth by revising the conventional ML index. The proposed productivity growth index not only deals with the environmentally harmful by-products, but also properly incorporates the *ex ante* group heterogeneities into the process of calculating productivity growth. It also has the aforementioned merits of the conventional ML index. We combine the conventional ML index with the concept of the metafrontier for this methodological development.

The metafrontier is the envelope of the commonly conceived production frontiers, which is introduced by Battese and Rao (2002) and further elaborated by Battese et al. (2004). Battese and Rao (2002) introduced the concept of the metafrontier in order to solve for the incomparability of the performances of various groups. With this concept, they investigated the technical efficiencies of firms in groups that have different technologies. Battese et al. (2004) introduced a modified model assuming a single data-generation process based on Battese and Rao (2002). This framework was employed in analyzing the efficiencies of the Indonesian garment firms in five regions, where they assumed five different production groups.

To our knowledge, the productivity growth index proposed in this study is the first attempt to incorporate group heterogeneities into the environmentally sensitive productivity growth index. Methodologically, this index extends the metafrontier Malmquist productivity index of Oh and Lee (forthcoming) so that it can also incorporate environmentally harmful by-products. The proposed productivity growth index can be decomposed into three individual measures: efficiency change (the catching-up effect), technical change (the innovation effect) and technical leadership change (technological leading effect). Besides incorporating group heterogeneities, one strength of this index is that it provides a measure of the technical leading effect. We named this proposed index “the metafrontier Malmquist–Luenberger productivity growth index” (hereafter, MML index). The parametric metafrontier approach of Battese et al. (2004) is similar to the MML index in that both of the two approaches employ the concept of the metafrontier. However, the former is methodologically different from the latter for the following reasons. First, the parametric metafrontier approach deals with only a single output case. Hence, a multi output case, including undesirable outputs, cannot be considered in the parametric approach in general. Second, in the parametric metafrontier approach assumptions about the functional form are necessary, whereas in the MML index they are not. Third, the parametric metafrontier approach employs an econometric technique, whereas the MML index uses a linear programming technique. This means that the former estimates performance indexes while the latter calculates performance indexes.

The proposed index is employed to measure the environmentally sensitive productivity growth, efficiency change, technical change and technical leadership change of 46 countries over the 1993–2003 period. Data for this empirical investigation were retrieved from the Penn World Table and the World Bank Development Indicators databases. The aim of this empirical study is to investigate the productivity and decomposed components of the production activities originating from the group heterogeneities across continents, by considering CO_2 emissions. Empirical results show the following. First, European countries are good at innovating and creating technologies, indicating that energy- and environment-related technology developments are mainly led by the European countries. Second, Asian countries are good at catching up with frontier technologies by using input factors in an efficient way. Third, Ireland, Hong Kong and Switzerland emerge as global innovative countries. Fourth, environmentally sensitive productivity has diverged between the Americas, Asia and Europe.

The remainder of this paper is organized as follows: Section 2 provides an overview of the methodology; Section 3 describes the data set as well as presents the empirical results; and Section 4 concludes this study.

2. Methodology

The methodology we utilized in this study augments the basic assumptions of the ML index, laid out below. The underlying assumptions are introduced in Section 2.1, followed by the definitions of a directional distance function in Section 2.2. Our MML index, along with the conventional ML index, is presented in Section 2.3. An issue on measuring the MML index is illustrated in Section 2.4.

2.1. The underlying assumptions

Under a panel of $k=1,\dots,K$ countries and $t=1,\dots,T$ time periods, the production technology for countries producing M desirable outputs, $\mathbf{y}\in R_+^M$, and J undesirable outputs, $\mathbf{b}\in R_+^J$, by using N inputs,

$\mathbf{x}\in R^N_+$, is represented by the production possibility set (PPS), **P**. The PPS can be expressed as follows:

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

In order to describe and model production technology in which both the desirable and the undesirable outputs are jointly produced, a number of assumptions are required in the form of axioms. Those axioms are as follows:

$$\text{if } (\mathbf{x},\mathbf{y},\mathbf{b})\in\mathbf{P} \text{ and } 0\le\theta\le1,\ \text{then } (\mathbf{x},\theta\mathbf{y},\theta\mathbf{b})\in\mathbf{P}, \tag{2a}$$

$$\text{if } (\mathbf{x},\mathbf{y},\mathbf{b})\in\mathbf{P} \text{ and } \mathbf{y}'\le\mathbf{y} \text{ then } (\mathbf{x},\mathbf{y}',\mathbf{b})\in\mathbf{P}, \tag{2b}$$

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

The axiom in Eq. (2a) designates that it is costly to reduce undesirable outputs. This condition allows for the reduction of the undesirable outputs only when accompanied by the simultaneous reduction of the desirable outputs. This means that the abatement uses resources that otherwise could have been used to expand the production of the desirable outputs.

Strong disposability is incorporated in the second axiom shown in Eq. (2b). In this axiom, it is assumed that the desirable outputs may be reduced without the reduction of the undesirable outputs. This also means that the desirable outputs can be freely disposed of.

The third condition posits that no desirable output can be produced unless some negative outputs are also produced. This condition is termed null-jointness.

The PPS, satisfying all the above assumptions, can be depicted in an output space, as illustrated in Fig. 1. Here, a case for one desirable output and one undesirable output is illustrated. Without loss of generality, Fig. 1 assumes that all countries use the same amount of inputs. The horizontal axis represents the undesirable output, and the vertical axis the desirable output. All countries produce desirable and undesirable outputs in the inner area of the solid curve. Countries on the solid curve are assumed to be producing on the production frontier, and they are utilized as the benchmark when calculating the directional distance functions.

In order to consider group heterogeneities in production activities when measuring environmentally sensitive productivity growth, it is assumed that (i) the technology of one group is different from those of the other groups, (ii) there are H different groups in the whole sample.

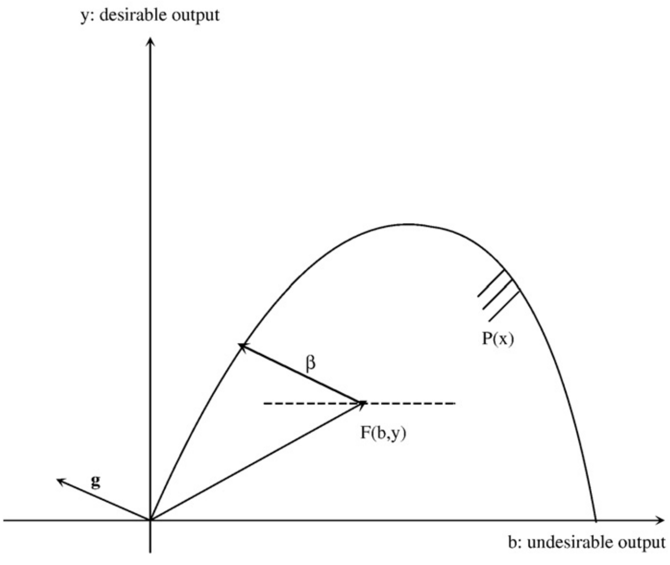

Fig. 1. Distance function and the ML index.

2.2. The directional distance function

The PPS can be elaborated by employing the directional distance function. Let $\vec{g}=(\vec{g}_y,\vec{g}_b)$ be a direction vector, where $\vec{g}\in R^M_+\times R^J_+$. The directional distance function is then defined as follows:

$$\vec{D}\left(\mathbf{x},\mathbf{y},\mathbf{b};\ \vec{g}_y,\ \vec{g}_b\right) = max\left\{\beta : \left(\mathbf{x},\mathbf{y}+\beta\vec{g}_y,\mathbf{b}-\beta\vec{g}_b\right)\in\mathbf{P}\right\} \tag{3}$$

This function seeks the maximal increase of the desirable outputs while simultaneously reducing the undesirable outputs. The direction vector, $\vec{\mathbf{g}}$, determines the direction of the outputs, by which the desirable outputs increase and the undesirable outputs decrease. In the present study, the direction vector was taken as $\vec{\mathbf{g}}=(\mathbf{y},\mathbf{b})$ following Chung et al. (1997).[2]

Since the ML index and MML index require a heavy dose of additional notation, we shall omit the direction vector $\vec{\mathbf{g}}=(\mathbf{y},\mathbf{b})$ when defining and calculating the indices in the remainder of this paper. For example, in all places we replace $\vec{D}(\mathbf{x},\mathbf{y},\mathbf{b};\mathbf{y},\mathbf{b})$ with $\vec{D}(\mathbf{x},\mathbf{y},\mathbf{b})$.

Looking at Fig. 1 again, the direction vector and the directional distance function are depicted for a DMU F. The direction of the directional distance function of the DMU F is represented by an arrow from the origin towards a northwest direction. The directional distance function of the DMU F is represented as β.

2.3. The MML index

In order to define and decompose the MML index, three definitions of benchmark technology sets are essential: a contemporaneous benchmark technology, an intertemporal benchmark technology and a global benchmark technology.

A *contemporaneous* benchmark technology of a group R_h is defined as $\mathbf{P}^t_{R_h} = \left\{\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)|\,\mathbf{x}^t \text{ can produce } \left(\mathbf{y}^t,\mathbf{b}^t\right)\right\}$, where $t=1,\ldots,T$. The contemporaneous benchmark technology constructs a reference production set at time t. This set is made from observations *at that time only* for a group R_h (Tulkens and Vanden Eeckaut, 1995).

An *intertemporal* benchmark technology of a group R_h is defined as $\mathbf{P}^I_{R_h} = \mathbf{P}^1_{R_h}\cup\mathbf{P}^2_{R_h}\cup\cdots\cup\mathbf{P}^T_{R_h}$. The intertemporal benchmark technology consists of a single reference production set made from observations *throughout the whole time period* for a group R_h (Tulkens and Vanden Eeckaut, 1995). There are H distinct intertemporal benchmark technologies. Countries in one intertemporal benchmark technology (i. e.,countries engaged in one group) are assumed to be unable to easily access different intertemporal benchmark technologies.

A *global* benchmark technology of all groups is defined as $\mathbf{P}^G = \mathbf{P}^I_{R_1}\cup\mathbf{P}^I_{R_2}\cup\cdots\cup\mathbf{P}^I_{R_H}$. The global benchmark technology establishes a single reference production set made from observations *throughout the entire time period for all groups* (Tulkens and Vanden Eeckaut, 1995). Contrary to the above two definitions, the global benchmark technology covers all groups, enveloping all intertemporal technologies. For the sake of the analysis, countries are assumed to be able to access the global technology, both theoretically and potentially, although there might be obstacles to accessing other technologies, as described above.

To illustrate the aforementioned three definitions in an output set, Fig. 2 depicts a case for two time periods and two groups. The superscript on **P** represents the time period and the subscript on **P** represents the group. The interior solid lines represent contemporaneous technologies.

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[2] The process of determining the direction vector depends on the purpose of the studies and the policy implications. For example, Arcelus and Arocena (2005) apply three types of direction vectors in examining the effects of environmental regulations on efficiency, assuming that the regulations are represented by the direction vectors. The purpose of this study is not to show the effect of selecting the direction vectors when measuring the environmentally sensitive productivity growth. Due to this reason, we used the direction vector of Chung et al. (1997), which has prevailed in the studies of the environmentally sensitive productivity growth.

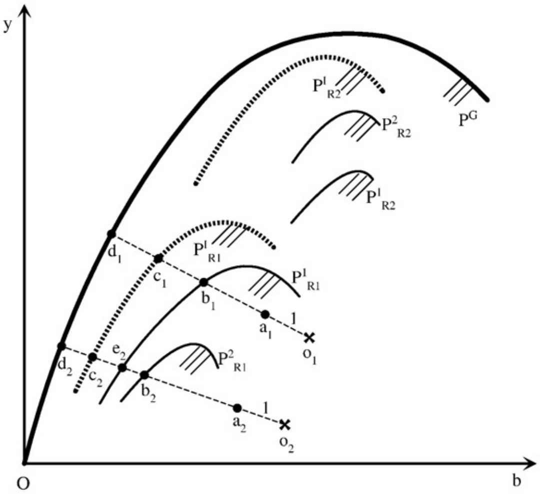

Fig. 2. Concept of the metafrontier Malmquist–Luenberger productivity index.

The interior broken lines represent intertemporal technologies. The interior thick solid line represents global technology. The intertemporal benchmark technology of a specific group envelopes its contemporaneous benchmark technologies, and the global benchmark technology envelopes all the intertemporal benchmark technologies.

As developed by Chung et al. (1997), the ML index of a country *i* is defined on $\mathbf{P}^s$, where $\mathbf{P}^s = \mathrm{P}^s_{R_1} \cup \mathrm{P}^s_{R_2} \cup \cdots \cup \mathrm{P}^s_{R_H}$ and $s = t, t+1$, as follows[3]:

$$ML^s\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) = \frac{1 + \overrightarrow{D}^s_c\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)}{1 + \overrightarrow{D}^s_c\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)}, \tag{4}$$

where the directional distance functions $\overrightarrow{D}^s_c(\mathbf{x}, \mathbf{y}, \mathbf{b}) = inf\{\beta \mid (\mathbf{x}, \mathbf{y} + \beta\mathbf{y}, \mathbf{b} - \beta\mathbf{b}) \in \mathbf{P}^s\}$, $s = t, t+1$, are defined on the technology set $\mathbf{P}^s$. If a production activity enables more (less) desirable output and less (more) undesirable output, then $ML^s > (<) 1$, resulting in productivity gain (loss). Since $ML^t\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) \neq ML^{t+1}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)$, the ML index is usually redefined as the geometric mean of the ML indices of two adjacent periods. The ML index can be decomposed into components of productivity growth, such as efficiency change (EC) and technical change (TCH). In order to save space, we omit this decomposition process.[4]

The MML index can be defined on the global benchmark technology set as follows:

$$MML\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) = \frac{1 + \overrightarrow{D}^G\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)}{1 + \overrightarrow{D}^G\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)}, \tag{5}$$

where the global directional distance function $\overrightarrow{D}^G(\mathbf{x}, \mathbf{y}, \mathbf{b}) = inf\{\beta \mid (\mathbf{x}, \mathbf{y} + \beta\mathbf{y}, \mathbf{b} - \beta\mathbf{b}) \in P^G\}$, $s = t, t+1$ is defined on the global technology set.

The MML index can also be decomposed into components of productivity growth. The decomposition is as follows:

$$\begin{aligned}
&MML\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) \\
&= \frac{1 + \overrightarrow{D}^G\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)}{1 + \overrightarrow{D}^G\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)} \\
&= \frac{1 + \overrightarrow{D}^t\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)}{1 + \overrightarrow{D}^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)} \\
&\quad \times \frac{\left(1 + \overrightarrow{D}^I\left(x^t, y^t, b^t\right)\right) / \left(1 + \overrightarrow{D}^t\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)\right)}{\left(1 + \overrightarrow{D}^I\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)\right) / \left(1 + \overrightarrow{D}^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)\right)} \\
&\quad \times \frac{\left(1 + \overrightarrow{D}^G\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)\right) / \left(1 + \overrightarrow{D}^I\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)\right)}{\left(1 + \overrightarrow{D}^G\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)\right) / \left(1 + \overrightarrow{D}^I\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right)\right)} \\
&= \frac{TE^{t+1}}{TE^t} \times \frac{BPR^{t+1}}{BPR^t} \times \frac{TGR^{t+1}}{TGR^t} \\
&= EC \times BPC \times TGC,
\end{aligned} \tag{6}$$

where the contemporaneous distance function $\overrightarrow{D}^s(\mathbf{x}, \mathbf{y}, \mathbf{b}) = inf\left\{\beta \mid (\mathbf{x}, \mathbf{y} + \beta\mathbf{y}, \mathbf{b} - \beta\mathbf{b}) \in P^s_{R_h}\right\}$, $s = t, t+1$, is defined on the contemporaneous benchmark technology set $\mathrm{P}^s{}_{R_h}$ of group R_h; the intertemporal distance function $\overrightarrow{\mathrm{D}}^I(\mathrm{x,y,b}) = \inf\{\beta \mid (\mathrm{x,y} + \beta\mathrm{y}, \mathrm{b} - \beta\mathrm{b}) \in \mathrm{P}^I_{Rh}\}$ is defined on the intertemporal benchmark technology set P^I_{Rh} of group R_h; the global distance function $\overrightarrow{D}^G(\mathbf{x}, \mathbf{y}, \mathbf{b}) = inf\left\{\beta \mid (\mathbf{x}, \mathbf{y} + \beta\mathbf{y}, \mathbf{b} - \beta\mathbf{b}) \in \mathbf{P}^G\right\}$ is defined on the global benchmark technology set P^G.

In Eq. (6), TE^s is a measure of technical efficiency at time period *s*.[5] BPR^s is the best practice gap ratio between a contemporaneous benchmark technology and an intertemporal benchmark technology at time period *s*. TGR^s is the technology gap ratio between an intertemporal benchmark technology and a global benchmark technology at time period *s*. It should be noted that all of these measures are gauged in more desirable outputs and fewer undesirable outputs direction through points $(\mathbf{x}^s, \mathbf{y}^s, \mathbf{b}^s)$, $s = t, t+1$.

The efficiency change term, *EC*, is a change in technical efficiency during two periods, capturing how close a DMU moves towards the contemporaneous benchmark technology at time period $t+1$ compared to time period *t*. $EC > (<) 1$ corresponds to efficiency gain (loss), meaning catching up (being lagged behind) relative to the contemporaneous benchmark technology frontier. The best practice gap change, *BPC*, is a measure of a change in the best practice gap ratio during the two periods. $\mathrm{BPC} > (<) 1$ means that the contemporaneous benchmark technology frontier has shifted towards (farther away from) the intertemporal benchmark technology frontier. Technical progress (regress) corresponds to a shift of contemporaneous benchmark technology in more (less) desirable outputs and fewer (more) undesirable outputs direction. Since innovation enables a shift of the frontier, *BPC* is considered as capturing the innovation effect. *TGC* is a change in the technical gap ratio between an intertemporal benchmark technology frontier and a global benchmark technology frontier during the two periods. $TGC > (<) 1$ means that a technical gap between a specific group R_h and the world frontier technology is decreased (increased) by a given country. Hence, *TGC* captures the technical leadership effect of a given country. $MML > (<) 1$ corresponds to productivity gain (loss).

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[3] In their study, Chung et al. (1997) do not include group heterogeneities in defining the ML index.

[4] For further elaboration, readers can refer to Chung et al. (1997).

[5] In previous studies, e. g., Färe et al. (2005), a DMU is regarded as being technically efficient (inefficient) if and only if $\overrightarrow{\mathrm{D}}(\mathbf{x,y,b}) = (>) 0$. Instead of using this definition, $1/(1 + \overrightarrow{\mathrm{D}}(\mathbf{x,y,b}))$ can also be regarded as a measure of technical efficiency. In this case, a DMU is technically efficient (inefficient) if and only if $1/(1 + \overrightarrow{\mathrm{D}}(\mathbf{x,y,b})) = (<) 1$. In the present study, we used the latter definition for technical efficiency.

The decomposition of the MML index is illustrated in Fig. 2. Let us assume that the DMU under our consideration produces outputs at a_1 and a_2 in time periods 1 and 2, respectively. The DMU is assumed to be engaged in group R_1. By using directional distance functions, the MML index can be decomposed as follows:

$$\begin{aligned} MML\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t,\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right) \\ &= \frac{o_1 d_1}{o_2 d_2} \\ &= \frac{o_1 b_1}{o_2 b_2} \times \left\{\frac{o_1 c_1 / o_1 b_1}{o_2 c_2 / o_2 b_2}\right\} \times \left\{\frac{o_1 d_1 / o_1 c_1}{o_2 d_2 / o_2 c_2}\right\}. \end{aligned} \tag{7}$$

The first term in the last line of Eq. (7) measures the efficiency change relative to contemporaneous benchmark technologies. This measures the change in distances between a country and the contemporaneous benchmark technology during two time periods. The second term in the last line of Eq. (7) measures the change in the gap between the contemporaneous benchmark technology and the intertemporal benchmark technology. The third term measures the change in the gap between the intertemporal benchmark technology and the global benchmark technology.

2.4. Calculation of directional distance function

The directional distance function can be calculated in several ways. Färe et al., (2006) specify the directional distance function as a quadratic form and employ linear programming (LP). Färe et al. (2007), Kumar (2006), Lee et al. (2002) and Chung et al., (1997) employ the data envelopment analysis (DEA)-type LP. Both the aforementioned estimation methods are very similar in that they employ LP in the calculation process. However, two main differences between the methods can be distinguished: (i) The advantage of the former approach is that it can easily calculate the shadow prices; however, it requires the assumption on the functional form of the directional distance function and imposes a lot of restrictions on the parameters, (ii) Even though the latter approach does not directly yield the shadow prices, its advantage is that it does not require any functional form of the directional distance function nor does it place any restrictions on the parameters. Since the calculation of the shadow price is not within our research scope in the present study, we employed the latter approach by getting rid of the possibility of the misspecification problem in setting up a functional form of the production function. By choosing this approach, we also secured necessary flexibilities in the calculation process.

In order to calculate and decompose the productivity growth of country k' between t and $t+1$, we need to solve six different linear programming problems: $\overrightarrow{D}^s(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s)$, $\overrightarrow{D}^I(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s)$ and $\overrightarrow{D}^G(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s)$, $s=t,t+1$. The directional distance functions are calculated by using the following equation:

$$\begin{aligned} &\overrightarrow{D}^d\left(\mathbf{x}^{k',s},\mathbf{y}^{k',s},\mathbf{b}^{k',s}\right) = \max\beta \\ &\quad \text{subject to} \\ &\quad \sum_{\text{con}} \lambda^{k,s} y_m^{k,s} \geq (1+\beta) y_m^{k',s}, m = 1,\cdots,M \\ &\quad \sum_{\text{con}} \lambda^{k,s} b_j^{k,s} = (1-\beta) b_j^{k',s}, j = 1,\cdots,J \\ &\quad \sum_{\text{con}} \lambda^{k,s} x_n^{k,s} \leq x_n^{k',s}, n = 1,\cdots,N, \\ &\quad \lambda^k \geq 0, \end{aligned} \tag{8}$$

where the superscript d on $\overrightarrow{D}^d(\cdot)$ represents types of directional distance functions; $\lambda^{k,s}$ is an intensity variable, indicating at what intensity a particular activity may be employed in the construction of a PPS.[6]; the *con* under the Σ represents the condition for constructing a PPS. For the contemporaneous directional distance function, $d \equiv s$ and $con \equiv \{k \in R_h\}$; for the intertemporal directional distance function, $d \equiv I$ and $con \equiv \{k \in R, s \in \tau\}$, where $\tau = \{1,2,\ldots,T\}$; for the global directional distance function, $d \equiv G$ and $con \equiv \{k \in R, s \in \tau\}$, where $\tau = \{1,2,\ldots,T\}$ and $R = R_1 \cup R_2 \cup \cdots \cup R_H$.

The optimal solutions of Eq. (8) are employed in the calculation and decomposition of the MML index.

3. Empirical study

The data used in this empirical study is described in Section 3.1. The two productivity indices, the MML and ML, were computed for each of the sample countries and periods. In analyzing the results, the focus was on the comparison of the productivity and component indices, the innovativeness, and the temporal change of the productivity and the components. In calculating and decomposing the indexes, we used the R version 2.9.0 (R Development Core Team, 2009).[7]

3.1. Description of the data

We obtained the data on the five variables for 46 countries between 1993–2003. Variables included GDP, CO_2 emissions, labor force, capital stock and commercial energy consumption. Of the first two variables, GDP was chosen as a proxy of the desirable output and CO_2 as the proxy of the undesirable output. Labor force, capital stock and commercial energy consumption were chosen as inputs of production technology.

Data on GDP and labor force were collected from the Penn World Table (Mark 6.2). Since the capital stock information of each country is not available in the raw data set for the study period, we estimated the capital stock using investment series in the Penn World Table (Mark 6.2) and the capital stock data of 1970 in the Penn World Table (Mark 5.6), by employing the perpetual inventory method. We assumed that the depreciation rate of the capital stock is 10% per year. GDP and capital stock were transformed to be measured in constant prices and in US dollars corresponding to 2000 purchasing power parities. Data on CO_2 emissions per capita and energy consumption per capita were taken from the World Development Indicators website. These were multiplied by each of the national populations in order to obtain total CO_2 emissions and total energy consumption at the state level.

Our final sample consisted of 46 countries in the Americas, Asia and Europe. The descriptive statistics of the variables used in this study are presented in Table 1. Among all the variables, the mean is quite larger than the median value. This suggests that the distributions of the variables are skewed to the right, indicating that most countries are observed near the left tail of the distribution.

The average level and growth rate of the variables for each country are listed in Table A1 of Appendix. The average annual growth rate in GDP is 3.0% for our sample. Ireland had the highest average annual growth rate in GDP (8.0%), followed by India (6.0%) and Korea (5.1%). The United States ($8899 billion (USD)) had the highest level of GDP, followed by Japan ($2965 billion). The average annual growth rate in CO_2 emissions is 2.4% for our sample. Regarding country-specific CO_2 emissions, Iran had the highest annual growth rate (5.2%), followed by Korea (5.0%) and Thailand (5.0%). Growth rates of CO_2 emissions of Germany (0.2%), the UK (0.5%), Sweden (0.8%) and Switzerland (0.8%) were very low at less than 1.0% per year. The level of CO_2 emissions of the United States (2186.6 billion metric tons) was the highest among the sample countries, followed by Japan (508.7 billion metric tons). The average annual growth rate of energy use is 2.5%. Among our sample countries, Norway (9.2%) showed the highest annual growth

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[6] An activity is equivalent to an observation.

[7] R is a language and environment for statistical computing and graphics. For more information, please visit http://www.r-project.org. The functions the authors wrote for this study are provided in the Appendix of this paper.

Table 1
Descriptive statistics of variables used in this study: 1993–2003.

	Mean	S.D.	Median	Max	Min
GDP (in billion USD)	620.2	1398.2	185.3	10205.1	5.4
CO_2 (in billion metric tons)	126.7	328.1	28.9	2306.6	1.9
Energy (in million KGOE)	306.4	836.9	60.3	5959.8	1.5
Labor (thousands)	24407.4	64021.3	6477.6	466701.6	146.4
Capital (in billion USD)	1100.8	2447.7	311.8	17691.7	10.8

rate in energy use, followed by Honduras (8.2%) and Guatemala (6.3%). Columbia (−1.1%), Luxembourg (−0.9%), Denmark (−0.7%), Ecuador (−0.5%), Germany (−0.5%), the Netherlands (−0.2%) and Switzerland (−0.1%) show the negative growth rate in energy use. The United States (5,607.8 million KGOE) and Japan (1167.3 million KGOE) showed the highest level of energy use among our sample. The average annual growth rates of labor force and the capital stock of our sample were 1.6% and 2.8%, respectively.

3.2. Heterogeneity across continents

It is imperative to determine the number of groups before analyzing a sample under the framework of the MML index. It is also important to decide which country belongs to what group. The process of determining the number of groups and classifying countries may differ from one point of view to another. The difference in categorization may inevitably induce contradicting results. As discussed in the Introduction, the aim of this empirical study is to investigate the heterogeneities inherited in the production activities across similar country groups. Following Oh and Lee (Forthcoming), geographical closeness and national prosperity were chosen as factors for determining the groups.[8]

Based on the above criteria for grouping, the countries were categorized into three groups as follows: the Americas, Asia and Europe.[9] Descriptive statistics of inputs and outputs of the entire period are presented in Table 2. Countries belonging to one group appear to have different production technology from those belonging to other groups. For example, the average annual growth rate in GDP of Asian countries is much higher than those of American or European countries, whereas the average GDP of Asian countries is less than three quarters of that of European countries. The CO_2 emissions of Asian countries have a different pattern from those of the American countries or the European countries. Also, heterogeneities across groups can be found among input factors. For example, the pattern of energy use of European countries is quite different from those of the American or the Asian countries. These differences in patterns of outputs/inputs across groups justify the mechanism inherited in the proposed MML index.

We also explore the heterogeneities in the production activities across the three groups by explanatory data analysis (EDA). Contour plots of the kernel densities estimated from the growth rate of the capital/GDP and the labor/GDP are depicted for each group. As can be seen in Fig. 3, each continent appears to have its own growth patterns. Growth rates in the capital/GDP versus the labor/GDP of the European countries are less dispersed than those of the American and the Asian countries. In Europe, where most countries are advanced countries, heterogeneities in economic prosperity among countries are less than that of the Asian or the American continent. This similarity is reflected in the less-dispersed contour plot of Europe. Another finding is that the average growth rate of the labor/GDP of the American countries seems to center around zero, whereas those of the Asian and the European countries are centered below zero. These group-specific heterogeneities provide another justification for using the concept of a metafrontier in measuring and decomposing productivity growth using the MML index.

3.3. Productivity and decomposition

Average productivity growth, efficiency change, technical change and technical gap ratio change are calculated for the sample countries. These measures are listed in Table A2 in the Appendix. The first four columns provide the results of the MML index and the following three columns provide those of the ML index. For the comparison purpose, we also provide the results of the metafrontier Malmquist productivity growth index Oh and Lee (Forthcoming) and those of the conventional Malmquist productivity growth index Färe et al. (1994), which do not consider the effect of the CO_2 emissions. These results are also listed in Table A2. Recall that index values greater (less) than unity indicate improvement (deterioration) in the relevant performances. The average growth rates of indices are shown at the bottom of Table A2. In analyzing the productivity and decomposition results, we mainly focus on those of the MML index.

Regardless of the methodologies employed, productivity has slightly increased for the study period by around 0.4%. This figure signifies that if factor inputs of an *average* country were fixed for the study period, its GDP could have increased by 0.4% per year while simultaneously reducing CO_2 emissions by 0.4% per year. It should be noted that the productivity growth is distinct from the growth rates of the GDP and the CO_2 emissions discussed in Section 3.1. The former concept incorporates production activities, while the latter does not. Country-specific average annual rates of productivity growth differ considerably between the two methodologies but are of reasonable sizes. Among the sample countries, Iceland (2.4%) was found to be the most productive country, followed by Syria (2.4%) and Ireland (2.1%). Although Iceland was severely affected by the financial crisis in 2008, it showed the highest productivity growth during the study period. This appears to reflect the fact that in booming periods the Icelandic economy gained productivity improvement mainly from less CO_2 emission industries such as the financial sector.

Regarding efficiency change, the average annual growth rate of efficiency is around −0.1%, indicating efficiency deterioration. Economically, this means that the gap between the technology level of an *average* country and frontier technology has been widened. Such efficiency deterioration occurs under the two following conditions: (i) when frontier technology advances, the technical catching-up speed of the *average* country is slower than that of frontier technology advancement; or (ii) when frontier technology deteriorates, the technical deterioration speed of the *average* country is faster than that of the frontier technology deterioration. This deterioration of efficiency needs to be investigated, along with the technical change index. This will be discussed later.

An examination of country-specific efficiency change indices reveals that the two methodologies yield different efficiency change measures. This difference comes from the fact that the MML index considers the contemporaneous technology set within a specific group, whereas the ML index does not incorporate heterogeneities across groups. This difference between the two approaches yields the difference in the two measures. Hence, rank and average growth rate of efficiency change in the two methodologies are quite different. The efficiency change index of the MML index suggests that Iran (1.9%) and Korea (0.9%) are good at catching up with frontier technology.

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[8] Other possibilities of grouping are i) whether a country is a member of OECD countries, ii) whether a country is a member of the International Energy Agency, or iii) whether a country is a developed country, among others. The authors are grateful for this comment from the anonymous referee.

[9] In principal, each country is grouped on the basis of its geographical location which can be retrieved from the Penn World Table (Mark 5.6). However, those *initial* groups are further merged into super-groups in order to increase the discriminating power. Hence, the North, Central and South American countries are merged into the Americas, with the exception of the United States and Canada. The United States and Canada are grouped into European countries following Oh and Lee (forthcoming). Since there were only two Oceanian countries in the sample, New Zealand and Australia were grouped into Asia.

Table 2
Average level and growth rate of inputs and outputs by region: 1993–2003.

Country	GDP (bil. USD)		CO_2 (bil. metric tons)		Energy (mil. KGOE)		Labor (thousands)		Capital (bil. USD)	
	Level	Growth	Level	Growth	Level	Growth	Level	Growth	Level	Growth
America	152.5	2.1	27.4	2.4	71.7	2.5	8991.9	2.7	201.7	2.3
Asia	615.4	3.7	116.0	3.2	285.8	3.8	49533.8	2.1	1164.3	3.5
Europe	890.5	3.0	190.0	1.9	453.3	1.7	17662.0	0.8	1575.2	2.6
Total	620.2	3.0	126.7	2.4	306.4	2.5	24407.4	1.6	1100.8	2.8

Note 1. Growth in every second column represents the growth rate (%) of a corresponding variable.

Interesting is that only ten countries gained efficiency, implying that around 20% of our sample countries attempted to catch up with frontier technology. These countries are Iran (1.9%), Korea (0.9%), Peru (0.8%), Colombia (0.7%), Mexico (0.6%), Ireland (0.5%), Finland (0.3%), Denmark (0.2%), Greece (0.1%) and Israel (0.02%).

The average annual rate of technical change, *BPC*, is 0.38%, indicating technical progress. It appears that recently increasing concerns and policies about energy and environment have fostered advancement in technology. An examination of country-specific *BPC* reveals that Iceland (2.2%) and Belgium (2.1%) had the highest technical change during the study period. *A priori*, one would expect that the European countries would have higher rates of technical change, which is confirmed by our empirical results. Out of ten countries showing the highest rate in *BPC*, eight countries are European countries. These countries are Iceland (2.2%), Belgium (2.1%), the Netherlands (1.7%), Canada (1.7%), Sweden (1.4%), Norway (1.4%), Ireland (1.4%) and the United Kingdom (1.4%).

Now let us investigate the relationship between efficiency *deterioration* and technical *progress*. As discussed in the Methodology, the technical progress corresponds to a shift in the technology frontier in the direction of more GDP and fewer CO_2 emissions. Combining efficiency deterioration with this technical progress, it can be concluded that the *average* country has been lagged behind the technology frontier, as in the first possibility discussed above. Considering that more than half of our sample countries are developing countries, policies encouraging these countries to catch up with frontier technology need to be developed.

The average annual technical gap ratio change, *TGC*, is around 0.15%, indicating that the gap between the global and the regional technology frontiers has been reduced. Despite the *overall* favorable tendency in the technical advance towards global frontier technology, a country-specific examination of the *TGC* reveals that there are distinct heterogeneities across continents. That is, most European countries have a *TGC* greater than unity while most American countries have a *TGC* less than unity. This means that technology is led by European countries, and the technological *levels* of the American countries have deteriorated relative to global technology progress. This unfavorable technological situation of American countries can be solved by prudent and careful regional economic policies for fostering energy- and environment-related technologies.

As already seen in Table 2 and Fig. 3, each continent's own production technology differs from those of other continents. This production heterogeneity across continents affects the productivity growth and its decomposed sources. To examine these heterogeneities between continents, the productivity growth index and its decomposed sources are averaged by each continent. The results are listed in Table 3. The average rate of productivity growth of Europe (0.9%) was the highest and that of America (−0.3%) was the lowest. The rate of productivity growth of Asia is somewhere in-between Europe and America. The average annual rate of technical change in Europe was the highest (0.8% per year), but its average annual rate of efficiency change was the lowest (−0.3%). This indicates that Europe is good at inventing new technology or innovating, rather than squeezing their endowed inputs to catch up with the frontier technology. On the other hand, the efficiency change of the Asian continent was the highest among the three continents, whereas its technical change index was modest. This implies that Asia is good at catching up with the frontier technology, rather than at innovating. America's degrees of catching up was somewhere in-between Asia and Europe. The technical gap ratio change, *TGC*, of the European continent was the highest, indicating that the world frontier technology is mainly led by Europe. As already discussed, the

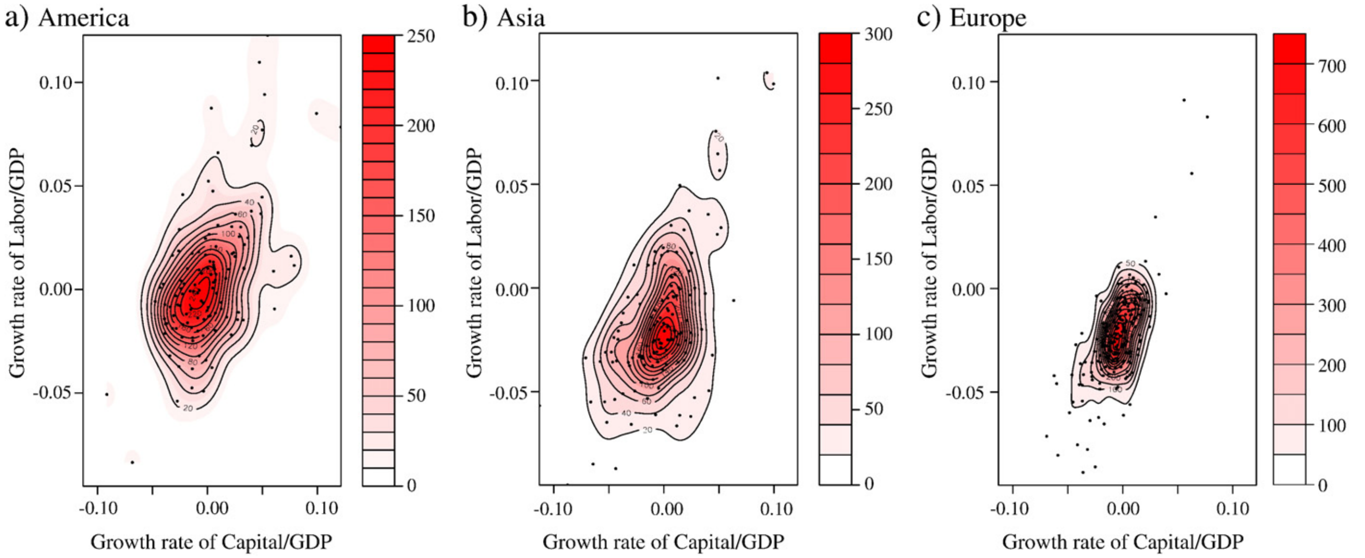


Fig. 3. Contour plot of 2D kernel density estimation by using growth rates of capital/GDP and labor/GDP (whole periods).

Table 3
Decomposition result by region.

Continent	PC	EC	BPC	TGC
America	0.9972	0.9993	0.9985	0.9996
Asia	1.0031	1.0008	1.0022	1.0006
Europe	1.0085	0.9975	1.0079	1.0032
Total	1.0041	0.9989	1.0038	1.0015

technical gap ratio change of the American continent was less than unity, indicating its technological level is deteriorated relative to global frontier technology.

The correlation of productivity growth indexes among the four measures are presented in Table 4. All pairs of measures are positively correlated at the 1% level of significance. The correlation coefficients among the measures are reasonable and within the interval 0.44–0.79. The highest correlation coefficient among the measures is found between the MML and ML indexes (0.79) and the lowest between the MML and M indexes (0.44).

3.4. Innovative countries

Even though the results of the decomposed *TGC* are suggestive for capturing technology leading countries, it does not allow us to clearly determine which countries are innovative countries. This ambiguity in determining the innovative countries by *TGC* comes from the fact that the only information *TGC* gives us is the rate of change in the technical gap between the group-specific technology frontier and the global technology frontier. Hence, processes for capturing innovative countries are needed. In the present study, two processes were made for this purpose. One was to find the regional innovative countries and the other was to find the global innovative countries. Here, global innovative countries are countries that can be considered as innovators without regarding a specific group. The following three conditions help determine regional innovative countries:

$$BPC > 1 \tag{9a}$$

$$\vec{D}^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}\right) < 0 \tag{9b}$$

$$\vec{D}^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) = 0 \tag{9c}$$

As discussed earlier, the first condition designates the contemporaneous technology frontier is shifted in the direction of more GDP and fewer CO_2 emissions. This means that in period $t+1$ it is possible to increase GDP and to decrease the level of CO_2 emissions relative to period *t*. This measures the shift in relevant portions of the contemporaneous technology frontier between period *t* and $t+1$ for a given country when the GDP and the CO_2 emissions are treated asymmetrically. The second condition designates that production in period $t+1$ occurs outside the contemporaneous PPS of period *t*. This means that the technical change has occurred during that period. It also implies that the technology of period *t* is not able to produce the output vector of period $t+1$ with the input vector of period $t+1$. Hence, the value of the directional distance function evaluating input/output vector at period $t+1$ relative to the reference technology of period *t* is less than zero. The third condition indicates that the country should be on the contemporaneous technology frontier in period $t+1$.

The three conditions shown in Eq. (9a)–(9c) help us determine the regional innovative countries. Subsequently, adding the following two conditions to the above conditions, the global innovative countries can also be determined.

$$TGC > 1 \tag{10a}$$

$$\vec{D}^{G}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) = 0 \tag{10b}$$

The first condition designates that the gap between the regional technology frontier (intertemporal technology frontier) and the world technology frontier (global technology frontier) is shrunk. The shrinking of the gap means that the technological level of a group under our consideration is progressing towards the world frontier technology. This also means technology convergence towards world frontier technology. The second condition indicates that a given country in period $t+1$ is on the global technology frontier. Needless to say, the regional innovative countries are a subset of the global innovative countries.

Table 5 lists the innovative countries for every year. The regional innovative countries are listed in the first three columns of Table 5. Within the American continents, Argentina, Columbia, Guatemala, Paraguay and Venezuela are found to be innovative countries. Among them, Paraguay is registered five times as an innovative country. Within the Asian continent, only Hong Kong is found to be the innovative country. In the European continent, Austria, France, Ireland, Norway, Sweden, Switzerland, the United Kingdom and the United States are found to be the innovative countries. Ireland is registered eight times as an innovative country, followed by Switzerland (six times).

The global innovative countries are listed in the last column of Table 5. An examination of the global innovative countries reveals that none of the American countries are global innovative countries. Among fifteen regional innovative countries, only three of them are found to be the global innovative countries: Hong Kong, Ireland and Switzerland.

The policy implications deduced from those results are as follows. If policy makers decide to innovate a country within the scope of their continent, regional innovative countries are good nominees for benchmarks. If they make a decision to innovate a country by broadening the scope to world-wide innovators, the global innovative countries can be good benchmarks.

3.5. Temporal changes of productivity and components

The temporal patterns of average productivity change and its decomposed sources are depicted in Fig. 4. The first panel of Fig. 4 shows trends of productivity growth measured by the ML and MML indices. The two productivity growth measures almost coincide. During the periods of 1996–1997 and 1999–2000, the rates of productivity growth are relatively higher than the other years. Trends in the efficiency change measured by the two methodologies do not appear to coincide, as shown in the middle panel of Fig. 4. However, patterns of gaining and losing efficiency from 1995 onwards seem similar. Temporal patterns of indices related with technologies are depicted in the last panel of Fig. 4. The two technical change measures, *BPC* and *TC*, of the two methodologies almost coincide. The technical gap ratio change index seldom appears to change over time. By comparing the productivity growth with technical change index,

Table 4
Correlation coefficients among productivity measures.

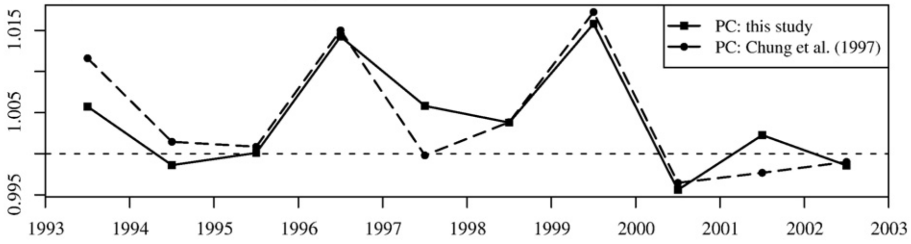
	MML (this study)	ML (Chung et al., 1997)	MM (Oh and Lee forthcoming)	M (Färe et al., 1994)
MML	1.0000 (0.00)			
ML	0.7912 (0.00)	1.0000 (0.00)		
MM	0.7553 (0.00)	0.6954 (0.00)	1.0000 (0.00)	
M	0.4433 (0.00)	0.4611 (0.00)	0.6123 (0.00)	1.0000 (0.00)

Note: The values in parentheses are *p*-values associated with the null hypothesis that the true correlation coefficient is zero.

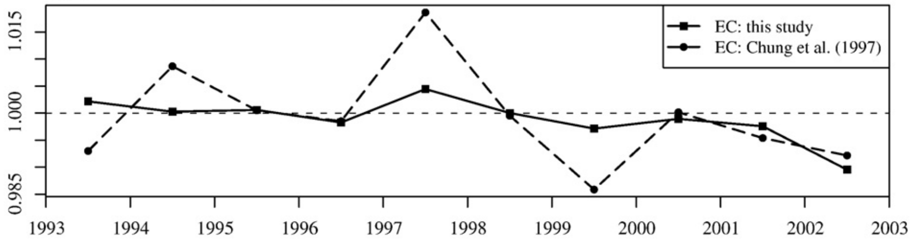
Table 5
Regional innovative countries and global innovative countries.

Year	Within-group innovator			Global innovator
	America	Asia	Europe	
1993–1994	Argentina, Guatemala	Hong Kong	Norway, Switzerland	–
1994–1995	–	Hong Kong	Norway, USA, Switzerland	–
1995–1996	Argentina	Hong Kong	Ireland, Norway, UK	Hong Kong
1996–1997	Paraguay, Venezuela	Hong Kong	Ireland, Norway, UK, USA	–
1997–1998	–	–	Ireland, Norway, USA	–
1998–1999	Colombia, Paraguay	–	France, Ireland, Switzerland	Ireland
1999–2000	Colombia, Guatemala, Paraguay,	Hong Kong	Austria, France, Ireland, Sweden, Switzerland	Switzerland
2000–2001	Paraguay	Hong Kong	Ireland, Sweden	–
2001–2002	Colombia, Guatemala	Hong Kong	France, Ireland, Switzerland	–
2002–2003	Colombia, Paraguay	Hong Kong	France, Ireland, Sweden, Switzerland	–

a) Rate of productivity growth



b) Rate of efficiency change



c) Rates of best practice gap change and technical gap ratio change of the MML index, along with rate of technical change of the ML index.

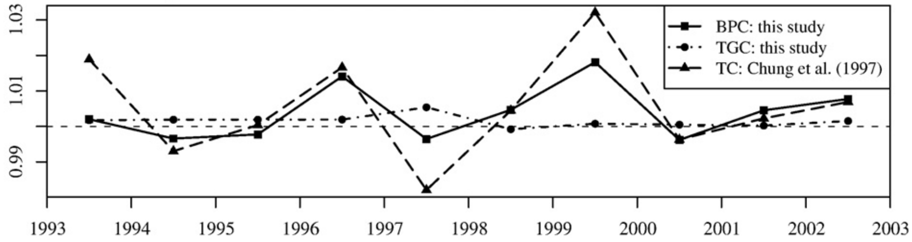


Fig. 4. Temporal developments of productivity growth, efficiency change, best practice gap change and technical gap ratio change, along with the results of the ML index.

productivity growth is mainly attributed to the technical rather than the efficiency change. This finding corresponds to those of Kumar (2006) and Yörük and Zaim (2005).[10]

To demonstrate productivity growth patterns by continent, we included the cumulated MML index in Fig. 5. This was calculated as sequential multiplicative sums of the average annual productivity growth indices. As expected, the cumulated productivity of the Europe was much larger than those of the Asia or the Americas. The productivity of the Americas has slightly decreased over time. This decrease in productivity originates not only from the regional technical regress but also the deepening of the lagging behind the world frontier technology. It also can be found that the cumulated productivity gap has been widened among the three continents during the study period. We also tested the null that productivity growth indexes are the same among the three continents. We failed to reject the null for any pairs of productivity growth indexes at the 1% level of significance. The results of this test support that there existed differences in the cumulative productivity growth among the three continents. This unbalanced productivity cumulation among continents emphasizes the necessity of effective policies for fostering productivity of America and Asia.

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[10] We also tested the null hypothesis that (decomposed) growth indexes of the MML and ML indexes are the same. We used the Wilcoxon test for this test. For the productivity growth and technical change indexes, we failed to reject the null at the 5% level of significance. Test statistics (*p*-value) between productivity growth measures of the MML and ML indexes is 51 (0.9705). Test statistics (*p*-value) between the technical change indexes of the MML and ML indexes is 49 (0.9705). However, in the efficiency change indexes we failed to reject the null, where test statistics (*p*-value) is 49 (0.7394). Note that two identical sets of numbers yield *p*-values of 1.0000 in the Wilcox test.

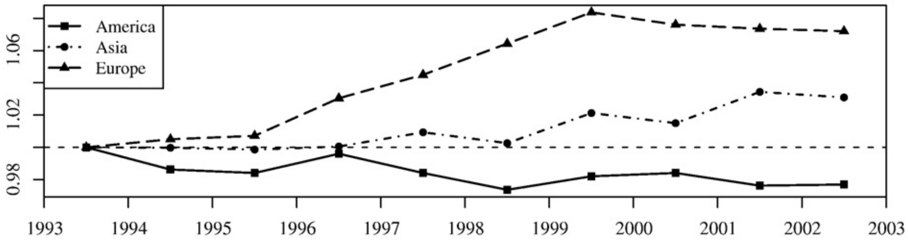

Fig. 5. Cumulative environmentally sensitive productivity growth by region.

4. Conclusion

As environmental concerns have grown in recent decades, classical productivity growth indices such as the Malmquist productivity index have attempted to integrate the effect of environmentally harmful by-products. These attempts have resulted in the creation of an environmentally sensitive productivity growth index by extending the Malmquist productivity growth index. Among these environmentally sensitive productivity growth indices, the ML index has been regarded as an outstanding tool and widely used in the field of energy and environmental studies. Although it integrates the effect of environmentally harmful by-products into productivity growth analysis, its drawback is that it does not incorporate *ex ante* group heterogeneities.

In order to ameliorate the conventional ML index's weakness, we developed an alternative environmentally sensitive productivity growth index, by combining the concepts of the metafrontier and the ML index. We named it the “metafrontier Malmquist–Luenberger productivity growth index” (MML index). With this augmented methodology, we can decompose productivity growth into efficiency change, technical change and technical leadership change.

The MML index is easy to calculate. However, it is unavoidable to recalculate the MML index if time periods are added to a data set. One might argue that the recalculation is a disadvantage of the MML index. The addition of new time periods to the existing data set corresponds to the inclusion of new information to our understanding of the past. Hence, the inclusion of the new time periods enables us to take a look at the past in more informative perspective. In this sense, the recalculation process is not a disadvantage but an advantage.

The proposed methodology was employed in measuring the environmentally sensitive productivity growth of 46 countries in America, Asia and Europe during the 1993–2003 period. Through this empirical study, we found that (i) European countries are good at innovating and the Asian countries are good at catching up; (ii) energy- and environment-related technologies are mainly led by the European countries; (iii) Ireland, Hong Kong and Switzerland are found to be the world innovative countries; and (iv) environmentally sensitive productivity has diverged between America, Asia and Europe.

In addition to presenting an alternative measure, we believe the present paper paves the way for further methodological developments of environmentally sensitive productivity growth measures. Changing the direction vector of the directional distance functions in the MML index would be one example of a methodological development. As Arcelus and Arocena (2005) indicate, changes in environmental policy regimes can be expressed by the change of direction vectors in directional distance functions. Thus, by doing this, we can investigate the effect of regime changes in environmental policies on productivity growth. We believe that this study is a road map for opening up the possibility of expanding the existing environmentally sensitive productivity growth index. Moreover, the results of the empirical studies also have implications for the policymaking related to sustainable growth.

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Appendix A

Table A1
Average levels and growth rates of inputs and outputs by region: 1993–2003.

Country	GDP (bil. USD)		CO2 (bil. metric ton)		Energy (mil. KGOE)		Labor (thousands)		Capital (bil. USD)	
	Level	Growth	Level	Growth	Level	Growth	Level	Growth	Level	Growth
Argentina	398.7	0.8	57.5	1.8	127.4	1.3	14637.9	2.1	513.5	1.6
Australia	460.5	3.9	103.9	2.0	323.6	0.7	9444.1	1.4	882.9	3.9
Austria	204.8	2.1	29.0	2.4	61.4	2.4	3735.6	0.2	414.3	2.1
Belgium	238.3	2.2	56.3	1.6	102.3	0.2	4200.0	0.4	456.6	2.2
Bolivia	22.4	3.2	4.3	3.4	8.5	3.1	3182.3	2.3	17.6	2.7
Canada	746.8	3.7	241.1	1.7	538.2	3.8	16132.3	1.1	1458.3	3.2
Colombia	229.8	2.6	28.2	−0.1	60.4	−1.1	16308.6	2.6	236.1	2.0
Denmark	138.2	2.5	20.3	0.7	54.4	−0.7	2941.5	−0.0	258.2	2.7
Ecuador	54.8	1.8	7.9	4.4	21.9	−0.5	4760.5	3.2	86.1	1.4
Finland	106.1	3.8	32.8	2.5	57.7	2.7	2599.3	−0.0	237.4	0.4
France	1385.3	2.3	253.7	1.2	360.5	0.3	26424.7	0.6	2715.6	1.9
Germany	1963.3	1.5	346.1	0.2	823.9	−0.5	40572.1	0.0	4066.1	1.0
Greece	145.3	3.4	26.1	2.8	85.0	2.6	4672.4	1.0	273.3	2.3
Guatemala	45.2	3.6	6.3	4.1	8.5	6.3	4374.5	3.5	25.5	1.8
Honduras	13.4	2.4	3.1	3.2	4.6	8.2	2162.5	3.2	16.5	4.7
Hong Kong	180.3	3.0	15.5	1.8	34.3	1.0	3594.9	2.6	327.8	5.0
Iceland	6.5	3.5	2.8	4.1	2.1	0.9	155.2	1.2	12.1	2.6

(*continued on next page*)

Table A1 (*continued*)

Country	GDP (bil. USD)		CO2 (bil. metric ton)		Energy (mil. KGOE)		Labor (thousands)		Capital (bil. USD)	
	Level	Growth	Level	Growth	Level	Growth	Level	Growth	Level	Growth
India	2363.9	6.0	426.9	3.3	1059.2	4.5	422633.8	2.0	1875.7	5.4
Iran	370.1	3.3	108.2	5.2	319.6	6.0	21577.3	2.9	783.1	0.3
Ireland	80.2	8.0	13.1	3.5	38.1	2.8	1538.5	2.1	112.1	6.4
Israel	115.0	3.3	17.9	3.5	58.0	4.7	2370.7	2.7	217.6	4.3
Italy	1237.4	1.7	165.6	1.9	416.3	1.4	25306.6	0.2	2374.9	1.3
Jamaica	12.1	0.3	3.6	2.6	9.9	2.4	1289.3	1.2	16.8	1.7
Japan	2965.0	1.0	508.7	1.1	1167.3	1.3	67561.5	0.3	7969.9	1.4
Korea	671.5	5.1	170.6	5.0	399.2	3.6	23094.3	1.6	1599.9	6.1
Luxembourg	18.0	4.7	3.7	0.9	8.8	−0.9	179.5	1.1	33.3	4.4
Mexico	730.6	2.6	145.0	1.9	419.2	0.7	39268.1	2.6	1067.2	3.1
Nepal	31.9	4.4	7.5	3.3	2.6	7.0	11185.0	2.3	39.7	5.3
Netherlands	383.5	2.5	75.1	1.4	146.0	−0.2	7288.6	0.5	705.1	2.1
New Zealand	74.4	3.4	16.8	1.4	29.5	3.1	1861.5	1.3	132.8	3.0
Norway	138.2	3.3	25.1	1.2	47.3	9.2	2288.0	0.8	292.4	2.1
Panama	20.7	3.2	2.4	3.3	5.4	3.8	1137.6	2.2	28.0	5.1
Paraguay	26.8	1.8	3.9	1.9	3.9	3.4	1985.9	3.2	27.2	0.9
Peru	106.7	4.1	11.6	1.4	25.8	1.3	9651.9	3.0	155.0	3.1
Philippines	265.4	3.4	37.9	3.9	70.0	4.0	31453.7	2.7	310.0	2.4
Portugal	163.4	2.5	23.0	3.1	53.9	2.2	5128.9	0.6	293.7	3.8
Spain	734.4	3.4	114.1	3.8	258.1	4.0	17534.2	1.2	1410.4	3.2
Sri Lanka	70.2	4.4	7.2	3.5	8.0	7.4	8347.9	1.8	64.9	2.8
Sweden	206.9	2.8	50.6	0.8	49.1	0.9	4796.5	0.3	372.2	1.3
Switzerland	197.2	1.2	26.1	0.8	40.7	−0.1	3769.3	0.4	510.8	0.8
Syria	30.4	4.1	15.9	2.9	46.1	0.7	4836.3	4.0	19.5	2.5
Thailand	401.8	3.2	71.5	5.0	197.4	5.5	35978.0	1.4	912.5	2.8
Turkey	356.8	2.4	69.0	3.2	193.1	3.2	30435.7	2.4	450.1	4.2
UK	1350.1	3.0	228.9	0.5	573.6	0.3	29156.4	0.4	2042.0	3.0
USA	8899.0	3.2	2186.6	1.2	5607.8	1.5	142045.8	1.2	14590.8	4.1
Venezuela	168.1	−0.9	54.9	1.1	165.0	0.8	9143.4	2.7	231.0	−0.5
Total	620.2	3.0	126.7	2.4	1100.8	2.5	306.4	1.6	24407.4	2.8

Table A2

Averaged productivity change, efficiency change, best practice gap change, and technical gap ratio change, along with results of the approach of Chung et al. (1997), Oh and Lee (Forthcoming) and Fare et al. (1994): 1993–2003.

Country	This study				Chung et al. (1997)			Oh and Lee (forthcoming)				Fare et al. (1994)		
	PC	EC	BPC	TGC	PC	EC	TCH	PC	EC	BPC	TGC	PC	EC	TCH
Argentina	0.9935	1.0000	0.9937	0.9996	0.9935	0.9920	1.0015	0.9925	1.0000	0.9916	1.0008	1.0099	0.9917	1.0178
Australia	1.0094	1.0000	1.0084	1.0011	1.0108	1.0009	1.0103	1.0074	1.0154	1.0042	0.9884	1.0396	0.9933	1.0468
Austria	1.0055	0.9959	1.0041	1.0055	1.0077	0.9970	1.0116	1.0059	0.9925	1.0130	1.0006	1.0212	0.9966	1.0255
Belgium	1.0092	0.9903	1.0210	0.9985	1.0116	0.9952	1.0169	1.0107	0.9909	1.0223	0.9982	1.0224	0.9988	1.0241
Bolivia	1.0006	0.9995	1.0007	1.0003	1.0001	0.9984	1.0018	1.0062	0.9899	1.0184	1.0000	1.0328	0.9896	1.0461
Canada	1.0084	0.9912	1.0166	1.0010	1.0130	0.9970	1.0162	1.0112	0.9914	1.0201	1.0000	1.0376	0.9967	1.0412
Colombia	1.0088	1.0067	1.0014	1.0007	1.0082	1.0067	1.0016	1.0081	1.0089	0.9986	1.0008	1.0267	1.0057	1.0214
Denmark	1.0099	1.0017	1.0068	1.0015	1.0121	1.0099	1.0028	1.0123	0.9946	1.0200	0.9981	1.0256	1.0044	1.0216
Ecuador	0.9920	0.9875	1.0024	1.0025	0.9919	0.9898	1.0025	1.0020	1.0051	0.9961	1.0018	1.0186	0.9990	1.0208
Finland	1.0151	1.0026	1.0024	1.0105	1.0235	1.0108	1.0128	1.0311	1.0064	1.0220	1.0026	1.0388	1.0175	1.0218
France	1.0182	1.0000	1.0110	1.0072	1.0188	1.0025	1.0168	1.0138	1.0000	1.0149	0.9990	1.0234	1.0061	1.0181
Germany	1.0078	0.9979	1.0076	1.0024	1.0084	1.0017	1.0072	1.0116	0.9923	1.0212	0.9985	1.0150	1.0017	1.0136
Greece	1.0080	1.0009	1.0020	1.0052	1.0082	1.0095	0.9992	1.0126	0.9973	1.0139	1.0015	1.0344	1.0023	1.0324
Guatemala	1.0003	1.0000	1.0000	1.0002	1.0017	1.0000	1.0017	1.0005	1.0000	1.0003	1.0003	1.0369	1.0000	1.0369
Honduras	0.9937	0.9932	1.0007	0.9998	0.9946	0.9913	1.0034	0.9789	0.9821	0.9967	1.0000	1.0252	0.9804	1.0460
Hong Kong	0.9994	1.0000	0.9983	1.0010	1.0087	1.0000	1.0087	0.9965	1.0000	0.9974	0.9986	1.0306	1.0001	1.0305
Iceland	1.0244	1.0000	1.0216	1.0027	1.0091	1.0000	1.0091	1.0143	0.9975	1.0176	0.9995	1.0354	1.0165	1.0192
India	1.0102	1.0000	1.0065	1.0038	1.0104	1.0086	1.0018	1.0061	1.0000	1.0073	0.9988	1.0623	0.9876	1.0757
Iran	1.0026	1.0188	0.9938	0.9912	1.0014	1.0010	1.0007	1.0242	1.0343	0.9929	0.9978	1.0342	1.0181	1.0161
Ireland	1.0212	1.0047	1.0140	1.0023	1.0282	1.0109	1.0173	1.0233	1.0057	1.0149	1.0025	1.0836	1.0111	1.0722
Israel	0.9984	1.0002	0.9974	1.0011	0.9964	0.9944	1.0026	0.9924	1.0056	0.9967	0.9907	1.0341	0.9791	1.0562
Italy	1.0056	0.9982	1.0015	1.0060	1.0067	1.0014	1.0061	1.0076	0.9908	1.0168	1.0004	1.0175	1.0010	1.0173
Jamaica	0.9919	0.9909	1.0010	1.0001	0.9918	0.9909	1.0010	0.9886	0.9897	0.9996	0.9999	1.0032	0.9832	1.0207
Japan	1.0022	0.9938	1.0137	0.9966	1.0032	0.9968	1.0073	0.9997	1.0005	1.0065	0.9938	1.0098	0.9872	1.0240
Korea	0.9987	1.0091	0.9891	1.0011	0.9979	1.0018	0.9965	1.0014	1.0080	0.9900	1.0039	1.0533	0.9940	1.0594
Luxembourg	1.0009	1.0000	1.0009	1.0000	1.0045	1.0000	1.0045	1.0152	1.0000	1.0152	1.0000	1.0486	1.0000	1.0486
Mexico	0.9997	1.0057	0.9959	0.9987	1.0003	0.9988	1.0015	0.9969	1.0050	0.9930	0.9999	1.0270	0.9926	1.0346
Nepal	0.9957	1.0000	0.9956	1.0000	0.9932	1.0000	0.9932	0.9940	1.0000	0.9940	1.0000	1.0451	1.0000	1.0451
Netherlands	1.0129	0.9958	1.0168	1.0005	1.0167	1.0071	1.0098	1.0154	0.9960	1.0219	0.9978	1.0260	1.0069	1.0191
New Zealand	1.0055	1.0000	1.0042	1.0015	1.0095	0.9994	1.0105	1.0058	1.0177	0.9888	1.0000	1.0347	1.0032	1.0317
Norway	1.0087	0.9911	1.0143	1.0032	1.0117	0.9899	1.0218	0.9976	0.9767	1.0141	1.0072	1.0338	0.9790	1.0568
Panama	0.9948	1.0000	1.0004	0.9946	0.9965	0.9975	0.9992	0.9931	1.0055	0.9954	0.9959	1.0328	0.9964	1.0383
Paraguay	0.9961	1.0000	0.9974	0.9987	1.0050	1.0000	1.0050	0.9946	1.0000	0.9946	1.0000	1.0178	1.0000	1.0178
Peru	1.0119	1.0077	1.0050	0.9997	1.0122	1.0099	1.0024	1.0141	1.0215	0.9923	1.0007	1.0422	1.0174	1.0246
Philippines	0.9994	0.9946	1.0054	1.0000	1.0005	0.9955	1.0050	1.0057	0.9929	1.0159	0.9971	1.0351	1.0081	1.0267
Portugal	0.9943	0.9958	1.0012	0.9977	0.9951	0.9994	0.9963	0.9951	0.9826	1.0092	1.0037	1.0256	0.9999	1.0261
Spain	1.0042	0.9954	1.0030	1.0061	1.0031	1.0047	0.9993	1.0043	0.9854	1.0171	1.0022	1.0347	1.0053	1.0300

Table A2 (*continued*)

Country	This study				Chung et al. (1997)			Oh and Lee (forthcoming)				Fare et al. (1994)		
	PC	EC	BPC	TGC	PC	EC	TCH	PC	EC	BPC	TGC	PC	EC	TCH
Sri Lanka	1.0001	1.0000	1.0001	1.0000	0.9838	1.0000	0.9838	0.9993	1.0000	1.0002	0.9990	1.0453	1.0000	1.0453
Sweden	1.0203	1.0000	1.0144	1.0057	1.0081	1.0002	1.0079	1.0175	1.0000	1.0173	1.0003	1.0288	1.0198	1.0101
Switzerland	1.0124	1.0000	1.0025	1.0098	1.0162	1.0003	1.0163	1.0100	1.0000	1.0089	1.0010	1.0122	1.0005	1.0125
Syria	1.0240	1.0000	1.0131	1.0104	1.0082	1.0000	1.0082	1.0174	1.0000	1.0158	1.0015	1.0428	0.9987	1.0443
Thailand	0.9952	0.9933	1.0029	1.0000	0.9946	0.9933	1.0023	1.0046	1.0081	1.0002	0.9963	1.0333	1.0037	1.0298
Turkey	0.9938	1.0000	0.9911	1.0027	0.9948	0.9928	1.0022	0.9906	1.0000	0.9869	1.0034	1.0259	0.9852	1.0413
UK	1.0070	0.9949	1.0139	0.9985	1.0122	0.9967	1.0159	1.0074	0.9930	1.0144	1.0001	1.0305	0.9965	1.0344
USA	0.9914	0.9919	0.9995	1.0000	0.9914	0.9919	0.9995	1.0014	0.9877	1.0139	1.0000	1.0331	0.9877	1.0462
Venezuela	0.9833	1.0000	0.9830	1.0006	0.9818	0.9792	1.0028	0.9876	0.9943	0.9938	1.0007	0.9924	0.9841	1.0086
Total	1.0041	0.9989	1.0038	1.0015	1.0043	0.9992	1.0053	1.0049	0.9992	1.0064	0.9996	1.0043	0.9992	1.0053

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.eneco.2009.07.006.

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