Energy Economics 32 (2010) 1345–1355

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

A sequential Malmquist–Luenberger productivity index: Environmentally sensitive productivity growth considering the progressive nature of technology

Dong-hyun Oh [a,b,*], Almas Heshmati [c,1]

[a] Samsung Economics Research Institute, 29th Fl., Samsung Life Seocho Towe, 1321-15, Seocho 2-dong, Seocho-gu, Seoul, 137-955, Republic of Korea
[b] Centre of Excellence for Science and Innovation Studies, Royal Institute of Technology, Drottning Kristinas väg 30B, 100 44, Stockholm, Sweden
[c] Department of Food and Resources Economics, College of Life Sciences and Biotechnology, Korea University, Anam-dong, Seongbuk-gu, Seoul, 136-701, Republic of Korea

ARTICLE INFO

Article history:
Received 22 February 2010
Received in revised form 2 September 2010
Accepted 3 September 2010
Available online 16 September 2010

JEL classification:
C61
E22
O57
Q43
Q56

Keywords:
Environmentally sensitive productivity growth index
Directional distance function
productivity index

ABSTRACT

This study proposes an index for measuring environmentally sensitive productivity growth which appropriately considers the nature of technical change. The rationale of this methodology is to exclude a spurious technical regress from the macroeconomic perspective. In order to incorporate this in developing the index, a directional distance function and the concept of the successive sequential production possibility set are combined. With this combination, the conventional Malmquist–Luenberger productivity index is modified to give the sequential Malmquist–Luenberger productivity index. This index is employed in measuring environmentally sensitive productivity growth and its decomposed components of 26 OECD countries for the period 1970–2003.We distinguish two main empirical findings. First, even though the components of the conventional Malmquist–Luenberger productivity index and the proposed index are different, the trends of rates of average productivity growth are similar. Second, unlike in previous studies, the efficiency change is the main contributor to the earlier study period, whereas the effect of technical change has prevailed over time.

1. Introduction

In recent decades extensive studies have been made to measure environmentally sensitive productivity growth and its decomposed sources. The expansive development of this research area is in the line with increasing international concerns about climate change and sustainable economic growth. These concerns, in turn, have induced global cooperation in environmental regulations, such as the Kyoto Protocol and the Intergovernmental Panel on Climate Change (IPCC). These international mutual assistance systems for environmental change basically require the assessment of emissions of environmentally harmful by-products through the simultaneous consideration of the environmental, economic as well as technical points of view. This means that the enviro-economic policies, especially those related to climate change, should be made with a multi-facet assessment regarding the features of environmentally harmful by-products.

In order to meet the above prerequisite for the assessment of enviro-economic policies, research with different foci has been demanded to empirically measure the impact of emissions of by-products. This research includes not only theoretical approaches but also empirical studies. Among the range of methodologies in this area, the Malmquist–Luenberger productivity index (hereafter, ML index) has long been widely employed in applied research. Since it only requires the quantities on the input/output bundles without demanding information on costs of inputs/outputs, it has been widely used in applied studies, especially for measuring environmentally sensitive productivity growth in the field of energy and environmental economics. Another favorable aspect is that the ML index does not require any functional form assumptions on the production function. Moreover, the ML index enables environmentally sensitive productivity growth to be decomposed into several components, such as efficiency change and technical change. Thanks to the above methodological merits, the ML index has been frequently utilized not only in micro-level but also in macro-level studies.

With regards to the micro-level, Chung et al. (1997) is the first one. They analyze productivity growth and its decomposed sources of Swedish paper and pulp mills for the period 1986–1990. Their empirical results suggest that technical change is the main contributor

* Corresponding author. Samsung Economics Research Institute, 29th Fl., Samsung Life Seocho Towe, 1321-15, Seocho 2-dong, Seocho-gu, Seoul, 137-955, Republic of Korea. Tel.: +82 2 3780 8093; fax: +82 2 3780 8006.
E-mail addresses: oh@seri.org (D. Oh), heshmati@snu.ac.kr (A. Heshmati).
[1] Tel.: +82 2 3290 3034.

0140-9883/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.eneco.2010.09.003

to productivity growth. Weber and Domazlicky (2001) apply the same methodology to investigate productivity growth in the US manufacturing sector for the period 1988–1994 in order to incorporate toxic release into the productivity analysis. Arocena and Waddams Price (2002) employ the ML index to measure productivity differences of Spanish electricity generators between private and public sectors for the period 1984–1997. 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. Barros (2008) employs the ML index to examine the productivity growth and its components of the hydroelectric energy generating plants in Portugal. Yu et al. (2008) examine the productivity growth of Taiwan's airport sector by studying the 1995–1999 operations of four airports.

The ML index is also employed in measuring environmentally sensitive productivity growth at the macro-level. Yörük and Zaim (2005) employ both the Malmquist index and the ML index in order to analyze 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. Färe et al. (2001) employ the ML index to account for both marketed output and the pollution abatement activities in US state manufacturing sectors from 1974 to 1986. 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 found that the productivity growth of Annex-I countries are higher than that of Non-Annex-I countries, and that technical change was the main contributor to productivity growth. Zhou et al. (2010) employ the ML index to examine CO_2 emission performance of 18 top CO_2 emission countries from 1997 to 2004. Kortelainen (2008) examines environmental performance of 20 EU member states by employing the ML index.

In spite of its wide use, the conventional ML index has a weak point in that it does not appropriately consider the nature of technology. That is, although in general the technology always progresses or at least remains unchanged from the macroeconomic perspective, the conventional ML index often yield long-run technical deterioration when measuring environmentally sensitive productivity growth. Needless to say, as noted by Shestalova (2003), when we consider the features of technology at the industry level, it is not uncommon to observe technical regress in some industrial branches such as the mining sector. Except for those particular branches, it is quite undeniable that in general the technology at least remains unchanged in most industrial sectors. For example, the ratio of CO_2 emissions to energy productions continuously decreases for the period between 1965 and 2005, which reflects that environmental technology progresses or *at least* remains unchanged.[2] Hence, the technology of an economy, being the aggregate of all industrial sectors, should be considered as being in the state of progress or at least as remained unchanged. Especially for the developed countries such as OECD member countries, which will be empirically examined in this study, it is fairly rational to assume that technology progresses or remains unchanged. If we employ the conventional ML index in analyzing data of those countries, it is very frequent to observe technical regress. In Kumar (2006) the half of sample countries showed technical regress, and in Zhou et al. (2010) rates of technical change is negative in almost half of the studied period. Therefore, it is important to adjust the underlying assumptions in the conventional ML index in order to consider the progressive feature of technology.

Recall the necessity of the multi-facet assessment of emissions of by-products. If we employ the conventional ML index in assessing environmentally sensitive productivity growth index, it is obvious that the technical aspect of the three dimensions is left out. Conversely, this means that the feature of technical change is not properly considered in the conventional ML index. Hence, it is necessary to be cautious when assessing the empirical results of the ML index, especially in developing environmental policies. This means that the empirical results obtained by the conventional ML index inherit a likelihood of being biased. Hence, in order to eliminate this dormant bias in the technical change, the conventional ML index needs to be revised.

In this study, we propose an environmentally sensitive productivity growth index which is free from the aforementioned spurious technical regress. We provide this index by augmenting the basic assumptions in the conventional ML index. This measure not only properly reflects the progressive nature of technology but also accordingly yields an unbiased productivity growth index. In developing our methodology, we combine the concept of the successive sequential reference production sets of Tulkens and Vanden Eeckaut (1995) and the concept of the directional distance function (DDF) of Luenberger (1992). We employ the DDF in order to properly deal with environmentally harmful by-products (Färe et al., 2007a). The combination of these two concepts enables us to develop a sequential directional distance function. Our environmentally sensitive productivity growth measure utilizes this sequential directional distance function. We name this environmentally sensitive productivity measure the sequential Malmquist–Luenberger productivity index (hereafter, SML index). Like the conventional ML index, the SML index can also be decomposed into underlying components of productivity growth.[3] It should be noted that, if undesirable outputs are not included in the SML index, the SML index is equivalent to the SM index of Shestalova (2003) and Thirtle et al. (2003). The advantages of using the sequential production possibility sets in calculating the M index are discussed in Shestalova (2003) and Thirtle et al. (2003).

The proposed index is employed in measuring the environmentally sensitive productivity growth, efficiency change and technical change of 26 OECD member countries over the period 1970–2003. Empirical results show that the efficiency change is the main contributor during the earlier part of our study period, whereas technical change is the main contributor during the later part of the study period. Interestingly, this finding is somewhat different from those of the previous studies, in which technical change is the main contributor to productivity growth. Another finding is that the Nordic countries have a higher level of productivity growth among OECD member countries for the study period. For comparison purposes, the result of our methodology is compared with that of the conventional ML index. The result of this comparison

[2] The ratio of CO_2 emissions to energy productions of OECD member countries is as follows: 10.86 kt/ktoe (1965–1975), 7.29 kt/ktoe (1976–1985), 6.12 kt/ktoe (1986–1995), and 6.01 kt/ktoe (1996–2005), where numbers in parentheses are years. We thank an anonymous referee for his/her invaluable comment.

[3] It is arguable that the ML index employing the windows analysis is similar with our SML index in that it constructs a production possibility set by using observations of some consecutive years. The ML index with the windows analysis is widely used in previous studies, including Färe et al. (2001), Färe et al. (2007b), Yörük and Zaim (2005), Kumar (2006), Zhou et al. (2010) and Yu et al. (2008). These studies construct production possibility sets by using observations of three or more consecutive years. For example, when measuring directional distance functions at time period t, observations over the period between $t-2$ and t construct a production possibility set. This approach has an advantage that it can solve an infeasibility problem of mixed-period directional distance function, as argued by Färe et al. (2001). Another advantage is that measured directional distance functions are smoothed over the studied period since observations of some consecutive years construct an approximately smoothed surface (Yu et al., 2008). Usage of the ML index with the windows analysis mainly comes from these advantages. This also means that the purpose of the ML index with windows analysis is quite different from the SML index since the initial starting point of the former is not to reflect the progressive nature of technology. In this sense, we see that the SML index is different from the ML index with windows analysis. We thank an anonymous referee for this invaluable comment.

indicates that the developments of productivity between the two methodologies are similar, but the decomposed components are quite different.

The main contribution of this paper to the literature is the provision of the SML index which properly considers the progressiveness of technology. From the empirical perspective, this paper extends the study of Yörük and Zaim (2005) by employing the ML and SML indices. It needs to be emphasized that we investigate the environmentally sensitive productivity growth of OECD member countries with a more recent data set.

The remainder of this paper is organized as follows. A methodological discussion is given in Section 2. A description on the data set and the empirical results are presented in Section 3. This study is briefly concluded in Section 4.

2. Methodology

As stated earlier, the methodology we propose in this study employs an augmentation of the basic assumptions of the ML index. Hence, the underlying assumptions are introduced in Section 2.1, followed by the definitions of the sequential directional distance function in Section 2.2. Then, we present the conventional ML index as well as our SML index in Section 2.3. In Section 2.4, the calculating issue on the SML index is illustrated.

2.1. The underlying assumptions

This section deals with underlying assumptions required for defining the ML and SML indices. The basic assumptions discussed in this section are from Färe et al. (2005).

The production possibility set (PPS) for decision making units (DMUs; countries, in this study) producing M desirable outputs, $\mathbf{y} \in R_{+}^{M}$, and J undesirable by-products, $\mathbf{b} \in R_{+}^{J}$, is represented by the output set $\mathbf{P}(\mathbf{x})$. This set consists of desirable and undesirable outputs vector $(\mathbf{y}, \mathbf{b})$ that is jointly produced from N inputs which is represented by the input vector, $\mathbf{x} \in R_{+}^{N}$. Then, the PPS is expressed as follows:

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

Throughout this study, desirable and undesirable outputs are dealt with asymmetrically. In order to describe and model the production technology in which both desirable and undesirable outputs are jointly produced, a number of assumptions are required in the form of axioms.

First, the PPS is assumed to be compact for the input vector $\mathbf{x} \in R_{+}^{N}$. Inputs are also assumed to be strongly disposable, so that:

$$\text{if } \mathbf{x}' \geq \mathbf{x} \text{ then } \mathbf{P}(\mathbf{x}') \supseteq \mathbf{P}(\mathbf{x}). \tag{2}$$

Eq. (2) suggests that the PPS will not shrink when the inputs used in production activities are increased.

Second, the null-jointness is assumed. This assumption implies that the DMUs should necessarily produce the undesirable outputs when they produce the desirable outputs. The null-jointness is expressed as follows:

$$\text{if } (\mathbf{y}, \mathbf{b}) \in \mathbf{P}(\mathbf{x}) \text{ and } \mathbf{b} = 0, \text{ then } \mathbf{y} = 0. \tag{3}$$

Eq. (3) suggests that the desirable outputs cannot be produced if the undesirable outputs are not produced. This is always true when the assumption of the null-jointness is imposed on the production technology.

Third, a weak disposability assumption needs to be imposed onto the PPS, which is stated as follows:

$$\text{if } (\mathbf{y}, \mathbf{b}) \in \mathbf{P}(\mathbf{x}) \text{ and } 0 \leq \theta \leq 1, \text{ then } (\theta\mathbf{y}, \theta\mathbf{b}) \in \mathbf{P}(\mathbf{x}). \tag{4}$$

This assumption implies that any proportional contraction of the desirable and the undesirable outputs is also feasible if the original combination of the desirable and the undesirable outputs is in the PPS, for a given input $\mathbf{x}$. This assumption also means that the undesirable outputs are costly to dispose of.

Fourth, the strong disposability of desirable outputs is also required, as follows:

$$\text{if } (\mathbf{y}, \mathbf{b}) \in \mathbf{P}(\mathbf{x}) \text{ and } \mathbf{y} \geq \mathbf{y}', \text{ then } (\mathbf{y}', \mathbf{b}) \in \mathbf{P}(\mathbf{x}). \tag{5}$$

This assumption means that some of the desirable outputs can always be disposed of without any additional cost.

The above axioms let us construct the PPS in output spaces, as shown in Fig. 1. The interior piece-wise linear solid line is the PPS.

2.2. The ML and SML indices

In this section, we introduce the ML and SML indices by using the concept of the contemporaneous and sequential PPSes with undesirable outputs. The sequential PPS is constructed by modifying the PPS of Tulkens and Vanden Eeckaut (1995). However, it needs to be noted that undesirable outputs are not considered in Tulkens and Vanden Eeckaut (1995).

Although the PPS presentation is conceptually meaningful, it is not useful from the computational perspective. To overcome this weakness, we use the DDF. Let $\mathbf{g} = \left(\mathbf{g_y}, \mathbf{g_b}\right)$ be a direction vector, where $\mathbf{g} \in R_{+}^{M} \times R_{+}^{J}$. Then, the DDF is defined as follows:

$$\vec{D}\left(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g_y}, \mathbf{g_b}\right) = \max\{\beta : \left(\mathbf{y} + \beta\mathbf{g_y}, \mathbf{b} - \beta\mathbf{g_b}\right) \in \mathbf{P}(\mathbf{x})\}. \tag{6}$$

This function seeks the maximum increase of desirable outputs while simultaneously reducing undesirable outputs. The direction vector, $\mathbf{g}$, determines the direction of outputs, by which desirable outputs increase and undesirable outputs decrease. The process of determining the direction vector is dependent on the purpose of study and policy implications. For example, Arcelus and Arocena (2005) apply three types of direction vectors in analyzing the environmentally sensitive *efficiency* of OECD countries. They examine the effects of environmental regulations which are assumed to be represented by the direction vectors. Since the purpose of this study is not to show the effect of selecting direction vectors when measuring the

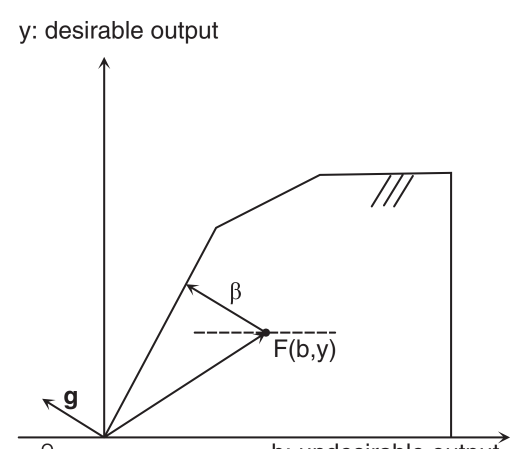

Fig. 1. Distance function and the ML index.

environmentally sensitive productivity growth, the direction vector is chosen following the pioneering work of Chung et al. (1997). Hence, in this study, the direction vector was taken as $\mathbf{g}=(\mathbf{y},\mathbf{b})$.[4]

Looking at Fig. 1 again, the direction vector and the DDF are depicted for a DMU F. Again, the PPS is represented by the inner area of the piece-wise linear line. The direction of the DDF of the DMU F is depicted as an arrow from the origin towards northwest direction, represented as β in Fig. 1.

Since the ML and SML indices require a heavy dose of additional notations, we shall omit the direction vector $\mathbf{g}=(\mathbf{y},\mathbf{b})$ 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 $\vec{D}(\mathbf{x},\mathbf{y},\mathbf{b})$.

In defining the SML index, two definitions of the PPS are essential: a contemporaneous PPS and a sequential PPS. The contemporaneous PPS at time period t is defined as $\mathbf{P}^t(\mathbf{x}^t)=\{(\mathbf{y}^t,\mathbf{b}^t)\,|\,\mathbf{x}^t \text{ can produce}(\mathbf{y}^t,\mathbf{b}^t)\}$ with $t=1,\cdots,T$. It constructs a reference production set at each point in time t, made from the observations *at that time only*. The sequential PPS at time period t is defined as $\bar{\mathbf{P}}^t(\mathbf{x}^t)=\mathbf{P}^1(\mathbf{x}^1)\cup\mathbf{P}^2(\mathbf{x}^2)\cup\cdots\cup\mathbf{P}^t(\mathbf{x}^t)$, where $1\le t\le T$. It establishes a reference production set using the observations *from the point in time* 1 *up to time t*. The definition of the sequential PPS defined above may look similar to that of Tulkens and Vanden Eeckaut (1995). However, the two definitions are quite different in the sense that our definition includes the desirable and undesirable outputs, whereas their definition only includes the desirable outputs. Also note that the definition of the sequential PPS is the superset of a single contemporaneous PPS. This favorable feature of the sequential PPS enables us to redefine the environmentally sensitive productivity growth index considering the features of technical change.

By using the definition of the contemporaneous PPS, a contemporaneous ML index (equivalently, the conventional ML index) between time period t and $t+1$ is defined as follows (Chung et al., 1997):

$$ML^s=\frac{\left(1+\vec{D}_c^s\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)\right)}{\left(1+\vec{D}_c^s\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)\right)},\tag{7}$$

where the contemporaneous DDFs, $\vec{D}_c^s(\mathbf{x},\mathbf{y},\mathbf{b})=\max\{\beta:(\mathbf{y}+\beta\mathbf{y},\mathbf{b}-\beta\mathbf{b})\in\mathbf{P}^s(\mathbf{x})\}, s=t,t+1$, are defined on each of the contemporaneous PPS at the time period s. The subscription "c" in the directional distance function represents the "contemporaneous". In order to avoid choosing an arbitrary benchmark technology, a geometric mean form of two consecutive contemporaneous ML productivity indices is typically used, expressed as $ML^{t,t+1}=[ML^t\cdot ML^{t+1}]^{1/2}$. The ML index can be decomposed into the efficiency and technical changes. The decomposition is discussed in details in Chung et al. (1997). We omit the further discussion of this issue in order to save space.

In a similar way, the SML index between time period t and $t+1$ is defined on the sequential PPS, $\bar{\mathbf{P}}^s(\mathbf{x}^s)$, as follows:

$$SML^s=\frac{\left(1+\vec{D}_q^s\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)\right)}{\left(1+\vec{D}_q^s\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)\right)},\tag{8}$$

where the sequential DDFs, $\vec{D}_q^s(\mathbf{x},\mathbf{y},\mathbf{b})=\max\{\beta:(\mathbf{y}+\beta\mathbf{y},\mathbf{b}-\beta\mathbf{b})\in\bar{\mathbf{P}}^s(\mathbf{x})\}, s=t,t+1$, are defined on each of the sequential PPS. The subscription "q" of the sequential distance function represents the *sequential* nature of the index. Since in general $SML^t\neq SML^{t+1}$ without any restrictions on two production technologies, we also use a geometric mean form of these two SML productivity indices to avoid choosing an arbitrary benchmark technology. As a result, the SML index is redefined as:

$$SML^{t,t+1}=\left[\frac{\left(1+\vec{D}_q^t\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)\right)}{\left(1+\vec{D}_q^t\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)\right)}\frac{\left(1+\vec{D}_q^{t+1}\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)\right)}{\left(1+\vec{D}_q^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)\right)}\right]^{1/2}.\tag{9}$$

Obviously, if the contemporaneous PPS at s is contained in the contemporaneous PPS at $s+1$ for all $s\le(T-1)$, then the SML productivity index is equivalent to the contemporaneous ML index.

Proposition 1. *If* $\mathbf{P}^s(\mathbf{x}^s)\subset\mathbf{P}^{s+1}(\mathbf{x}^{s+1})$ *for all* $s\le(T-1)$, *then* $SML^{s,s+1}=ML^{s,s+1}$.

Note that the converse of Proposition 1 is not true.

2.3. Decomposition of the SML index

The geometric mean form of the SML productivity index can be decomposed into two main components as follows:

$$\begin{aligned}SML^{t,t+1}&=\frac{1+\vec{D}_q^t\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)}{1+\vec{D}_q^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)}\\&\quad\times\left[\frac{1+\vec{D}_q^{t+1}\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)}{1+\vec{D}_q^t\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)}\cdot\frac{1+\vec{D}_q^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)}{1+\vec{D}_q^t\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)}\right]^{1/2}\\&=EC^{t,t+1}\times TC^{t,t+1}\end{aligned}\tag{10}$$

where efficiency change component, $EC^{t,t+1}$, represents a movement of a DMU towards the best practice frontier from time period t to $t+1$; the technical change, $TC^{t,t+1}$, measures amount of a shift of frontier between t and $t+1$. The $EC^{t,t+1}$ component measures a catching-up effect and $TC^{t,t+1}$ a technical change effect of the DMU. If there have been no changes in productivity over two time periods, then $SML^{t,t+1}=1$. If there has been an increase (decrease) in productivity then $SML^{t,t+1}>(<)1$.

Changes in efficiency are captured by $EC^{t,t+1}$, which gives a ratio of the distances of the DMU as to their respective frontiers in between the time periods t and $t+1$. If $EC^{t,t+1}>1$, then there has been a catching-up movement or convergence towards the frontier in period $t+1$. It is interpreted as an improvement in efficiency. If $EC^{t,t+1}<1$, then it indicates that the country is further away or diverging from the frontier in $t+1$ compared to t, and hence it has become less efficient.

The technical change component is captured by $TC^{t,t+1}$. The $TC^{t,t+1}$ measures the amount of a shift of the frontier between two time periods t and $t+1$.[5] Note that the technical change index in the SML index is not less than unity since $\vec{D}_q^{t+1}(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s)\ge\vec{D}_q^t(\mathbf{x}^s,\mathbf{y}^s,\mathbf{b}^s),\ s=t,t+1$. If technical change enables more production of desirable outputs and less production of undesirable outputs, then $TC^{t,t+1}>1$, otherwise $TC^{t,t+1}=1$. It should be noted that the technical change component in the ML index can be less than unity, indicating technical regress.

[4] In estimating directional distance functions, a very abnormal observation could be included in a data set. For example, an observation with a large amount of undesirable outputs and a small amount of desirable outputs *could* exist on the frontier. In Fig. 1, those observations *exist* on the right vertical line of the borders of the PPS. Even though those observations are on the frontier, their directional distance functions are not zero, indicating that they are inefficient. This problem does not originate from the conventional ML index or from the SML index. Rather, the directional distance functions bear the essence of the problem. This problem, as far as authors know, has not yet been solved. We believe that new methodological developments in the linear programming could emerge to solve this problem. Also, an investigation of our data set revealed that such abnormal observations are not included, telling us that our empirical examinations are free from this problem. We thank anonymous referees for pointing out this problem.

[5] Although a DMU does not push the frontier outwards, TC could be larger than unity. This occurs when DMUs around the DMU under our consideration push the frontier outwards. To find DMUs that push the frontier outwards, we examined the innovators. The results are provided in Section 3.4. We thank an anonymous referee for this invaluable comment. He/she commented that a correct interpretation of $TC>1$ is 'an environment of technical change under which the DMU plays.' We fully agree with this comment. Following the *convention* of the Malmquist and Malmquist–Luenberger productivity studies, however, we interpreted TC as *technical change*.

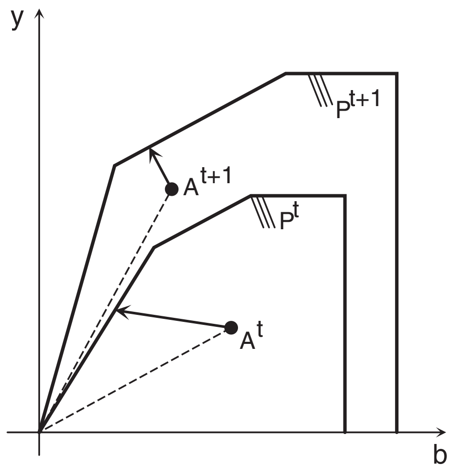

Fig. 2. A graphical exposition of productivity growth, efficiency change and technical change.

In order to provide the meanings of PC, EC and TC in a graphical way, one simple example is depicted in Fig. 2. In this example only two time periods are considered, t and $t+1$. It is assumed that the same quantity of input factors are used in producing desirable and undesirable outputs. Now we focus on the observation A for these periods, i.e., A^t and A^{t+1}. A productivity gain occurs (i.e., $PC>1$) between two time periods since time period $t+1$ yields more desirable output and less undesirable output than time period t. Positive efficiency change (i.e., $EC>1$) also occurs since the distance between the frontier at $t+1$ and A^{t+1} is less than the distance between the frontier at t and A^t. Technology also progresses (i.e., $TC>1$) since the frontier moves outwards following the direction vector, making the size of the PPS increase. The examples of $PC<1$, $EC<1$ and $TC<1$ are skipped to save space.

2.4. Calculation of directional distance functions

The DDF can be calculated in several ways. Färe et al. (2006) and Färe et al. (2005) specify the directional distance function as a quadratic form and employ a linear programming (LP) approach. Other studies by Färe et al. (2007a), Kumar (2006), Lee et al. (2002) and Chung et al. (1997) employ a data envelopment analysis (DEA)-type linear programming approach. The above two estimation methods are very similar in that they employ a linear programming in the calculation process. However, two main differences between the two methods can be distinguished: (i) the former approach has an advantage that it can easily calculate the shadow prices, whereas it requires an assumption of the functional form of the directional distance function and imposes lots of restrictions on parameters, and (ii) even though the latter approach does not directly yield the shadow prices, it has advantages in that it requires neither any functional form of the directional distance function nor any restrictions on the parameters.[6] Since the calculation of the shadow price is not within our research scope in this study, we employed the latter approach. One might argue that this deterministic approach is not free from *being deterministic* since it does not allow statistical noise in calculating DDFs. This weakness can be overcome by integrating the stochastic frontier analysis into estimation of DDFs, as used in Färe et al. (2005) and Kumar and Managi (2009). In doing so, a parametric functional specification of a DDF should be determined *before* the estimation process, bearing possibilities of misspecification of the functional form. This means that, if misspecified, the estimated DDFs are likely to be biased. For this reason, we chose the deterministic approach.[7] By choosing this approach, we can secure necessary flexibilities in the estimation process.

Let us assume that there are $k=1,\cdots,K$ DMUs of inputs and outputs $(\mathbf{x}_k^\tau,\mathbf{y}_k^\tau,\mathbf{b}_k^\tau)$ for time period $\tau=1,\cdots,T$. Using this data, the sequential PPS can be established as follows:

$$\begin{aligned}\overline{\mathbf{P}}^s(\mathbf{x}) = \{(\mathbf{y},\mathbf{b})\Big| &\sum_{\tau=1}^{s} \mathbf{Y}^\tau\mathbf{z}^\tau \geq \mathbf{y},\\ &\sum_{\tau=1}^{s} \mathbf{B}^\tau\mathbf{z}^\tau = \mathbf{b},\\ &\sum_{\tau=1}^{s} \mathbf{X}^\tau\mathbf{z}^\tau \leq \mathbf{x},\\ &\mathbf{z}^\tau \geq 0\},\end{aligned} \tag{11}$$

where $\mathbf{Y}^\tau$ is a $(M\times K)$ matrix of desirable outputs, $\mathbf{B}^\tau$ is a $(J\times K)$ matrix of undesirable outputs, and $\mathbf{X}^\tau$ is a $(N\times K)$ matrix of inputs for time period τ, respectively; $\mathbf{y}$, $\mathbf{b}$ and $\mathbf{x}$ are a $(M\times 1)$ vector of desirable outputs, a $(J\times 1)$ vector of undesirable outputs, and a $(N\times 1)$ vector of inputs, respectively; $\mathbf{z}^\tau$ is a $(K\times 1)$ vector which represents intensities assigned to each observation in constructing the sequential PPS.

In order to calculate and decompose the SML productivity index of country k between time period t and $t+1$, we need to solve four different LP problems. Two of them utilize the same time period for observations and a sequential PPS, while the remaining two utilize the mixed time period for observations and a sequential PPS: $\vec{D}_q^t\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)$, $\vec{D}_q^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)$, $\vec{D}_q^t\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)$ and $\vec{D}_q^{t+1}\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)$. By using the empirical PPS shown in Eq. (11), the first sequential DDF of the country k, $\vec{D}_q^t\left(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t\right)$, can be calculated by solving the following LP problem:

$$\vec{D}_q^t\left(\mathbf{x}_k^t,\mathbf{y}_k^t,\mathbf{b}_k^t\right) = \max\beta \tag{12}$$

$$\begin{aligned}\text{s.t.} &\sum_{\tau=1}^{t} \mathbf{Y}^\tau\mathbf{z}^\tau \geq (1+\beta)\mathbf{y}_k^t,\\ &\sum_{\tau=1}^{t} \mathbf{B}^\tau\mathbf{z}^\tau = (1-\beta)\mathbf{b}_k^t,\\ &\sum_{\tau=1}^{t} \mathbf{X}^\tau\mathbf{z}^\tau \leq \mathbf{x}_k^t,\\ &\mathbf{z}^\tau \geq 0.\end{aligned}$$

The computation of $\vec{D}_q^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)$ is almost the same as Eq. (12), except that the superscript t is substituted for superscript $t+1$ of variables.

The remaining two distance functions used in construction of the SML productivity index require mixed-period information. The first of these, $\vec{D}_q^t\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1}\right)$, is computed for the country k as:

$$\vec{D}_q^t\left(\mathbf{x}_k^{t+1},\mathbf{y}_k^{t+1},\mathbf{b}_k^{t+1}\right) = \max\beta \tag{13}$$

$$\begin{aligned}\text{s.t.} &\sum_{\tau=1}^{t} \mathbf{Y}^\tau\mathbf{z}^\tau \geq (1+\beta)\mathbf{y}_k^{t+1},\\ &\sum_{\tau=1}^{t} \mathbf{B}^\tau\mathbf{z}^\tau = (1-\beta)\mathbf{b}_k^{t+1},\\ &\sum_{\tau=1}^{t} \mathbf{X}^\tau\mathbf{z}^\tau \leq \mathbf{x}_k^{t+1},\\ &\mathbf{z}^\tau \geq 0.\end{aligned}$$

[6] The shadow price can be obtained if dual linear programming is employed.

[7] We thank an anonymous referee for providing this invaluable comment.

Table 1
Summary statistics of inputs and outputs of 26 OECD countries: 1970–2003.

Variable (unit of measurement)	Mean	Std. dev.	Median	Maximum	Minimum
GDP (in millions USD)	6,799.9	13,440.2	2,005.4	102,051.2	22.7
CO_2 (in metric mega tons)	403.1	944.2	102.2	5,959.8	1.4
Labor (in thousands)	17.2	25.8	5.1	150.4	0.1
Capital (in millions USD)	1,193.4	2,291.6	357.4	17,701.9	1.3

In Eq. (13), the reference technology which is evaluated at by $\left(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{b}_k^{t+1}\right)$ is constructed from all observations over the period from 1 to t. The last LP problem we need to solve, $\overrightarrow{D}_q^{t+1}\left(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t\right)$, is also a mixed-period problem. It is specified as in Eq. (13), but the superscript t and $t+1$ are transposed.

3. Empirical study

As part of the empirical study, the data is described and the two productivity indices, ML and SML, are computed for each of the sample countries and periods. In analyzing the results, the focus is on comparison of the productivity indices, country heterogeneity and their innovativeness.

3.1. Description of the data

We obtained the data on five variables namely, GDP, CO_2, labor force, and capital stock for 26 OECD countries over the periods 1970–2003 from Penn World Tables and World Development Indicators. The Czech Republic and Slovakia are excluded from the empirical analysis since these two countries lack data for the period 1970–1995; Hungary and Poland were also excluded from the analysis due to the unavailability of capital stock information over the study period. Among the first two variables, GDP is chosen as a proxy of the desirable output, and CO_2 is a proxy of the undesirable output. Labor force, and capital stock are chosen as the inputs of production technology.

Data on GDP, labor force, and capital stock are obtained by merging the Penn World Table (Mark 5.6) and the Penn World Table (Mark 6.2). The capital stock for the period 1990–2003 is not available for all countries. The capital stock series is estimated using the capital stock definition stated in the Penn World Table (Mark 5.6) and gross investment information in the Penn World Table (Mark 6.2) by employing the perpetual inventory method. In doing so, we assumed 10% of a depreciation rate. GDP and capital stock are transformed and are measured in 2000 US dollars. Data on CO_2 emissions per capita per capita are taken from the website of World Development Indicators. These are multiplied by each national population in order to get the total emissions of CO_2 at the country level.

Summary statistics of variables used in this study are shown in Table 1 and 2. The average level of annual GDP of our sample is 6,799 million USD. The largest GDP is observed in the USA (64,715 million USD), followed by Japan (22,508 million USD). Iceland (50 million USD) and Luxembourg (115 million USD) are ones showing the smallest GDP. The average growth rate of GDP of our sample is 3.02% per year. The highest growth rate of GDP was observed in the Republic of Korea (6.97%), followed by Ireland (4.84%), Luxembourg (4.13%) and Turkey (3.93%). Switzerland (1.42%), Sweden (1.88%) and Denmark (1.88%) show the slowest GDP growth rate during the study period.

As regards CO_2 emissions, the annual emissions are 403 metric mega tons for our sample. The USA (4890 metric mega tons) and Japan (999 metric mega tons) are the biggest emitters, and Iceland (1.9 metric mega tons) and Luxembourg (10.1 metric mega tons) are the smallest emitters. The annual growth rate of our sample is around 1.68%. The Republic of Korea, recorded as the fastest growing economy, is found to be the highest CO_2 emitter (6.57%). This figure is around four times as much as the mean rate of our sample. Turkey (5.01%), Portugal (4.34%), Mexico (4.24%) and Greece (4.18%) are also found to be major emitters. Interestingly around one quarter of our sample had a negative growth rate of CO_2 emissions. Those countries are Sweden

Table 2
Average growth rate of input and output variables used in this study: 1970–2003.

Country	GDP (in millions USD)		CO_2 (in metric mega tons)		Labor (in thousands)		Capital (in millions USD)	
	Level	Growth	Level	Growth	Level	Growth	Level	Growth
Australia	3302.8	3.27	244.1	2.41	7.8	1.83	609.0	5.03
Austria	1585.6	2.62	57.3	1.03	3.5	0.56	294.1	6.02
Belgium	1896.7	2.36	111.3	-0.62	4.0	0.51	336.1	4.49
Canada	5578.5	3.19	438.6	2.01	13.5	1.96	1006.6	5.28
Denmark	1121.7	1.88	56.6	−0.39	2.8	0.65	200.6	4.41
Finland	862.4	2.50	51.3	1.60	2.5	0.53	199.4	3.73
France	10967.1	2.48	401.2	−0.41	24.5	0.69	2000.9	5.01
Germany	15668.2	2.05	950.3	−0.69	38.6	0.42	3075.0	4.79
Greece	1188.6	2.67	62.5	4.18	4.1	1.14	228.5	5.35
Iceland	49.5	3.67	1.9	1.35	0.1	1.91	8.9	7.29
Ireland	500.7	4.84	29.8	2.39	1.3	1.28	75.6	6.67
Italy	9961.5	2.29	373.2	1.38	23.6	0.61	1827.7	4.87
Japan	22508.2	2.89	999.0	1.55	61.6	0.77	5362.8	6.63
Korea, Republic of	3683.3	6.97	224.0	6.57	18.4	2.26	782.8	10.35
Luxembourg	115.0	4.13	10.1	−0.97	0.2	1.13	20.6	5.86
Mexico	5456.4	3.53	318.8	4.24	28.5	3.32	757.4	5.45
Netherlands	2974.0	2.33	138.2	0.35	6.3	1.36	527.7	5.13
New Zealand	591.0	2.34	22.5	2.50	1.5	1.77	100.7	4.42
Norway	991.2	3.36	36.4	3.60	2.0	1.21	226.2	3.73
Portugal	1196.2	3.30	35.9	4.34	4.6	1.34	188.7	7.62
Spain	5539.7	3.08	205.8	3.15	15.4	1.17	968.5	6.79
Sweden	1715.6	1.88	62.9	−1.71	4.4	0.82	297.2	3.73
Switzerland	1687.8	1.42	40.6	0.06	3.4	0.85	402.7	3.35
Turkey	2439.7	3.93	125.4	5.01	23.9	2.18	264.7	5.72
U.K.	10501.3	2.38	591.2	−0.30	27.6	0.51	1465.2	5.02
U.S.A.	64715.1	3.11	4890.4	1.02	122.0	1.56	9801.8	5.32
Average	6799.9	3.02	403.1	1.68	17.2	1.24	1193.4	5.46

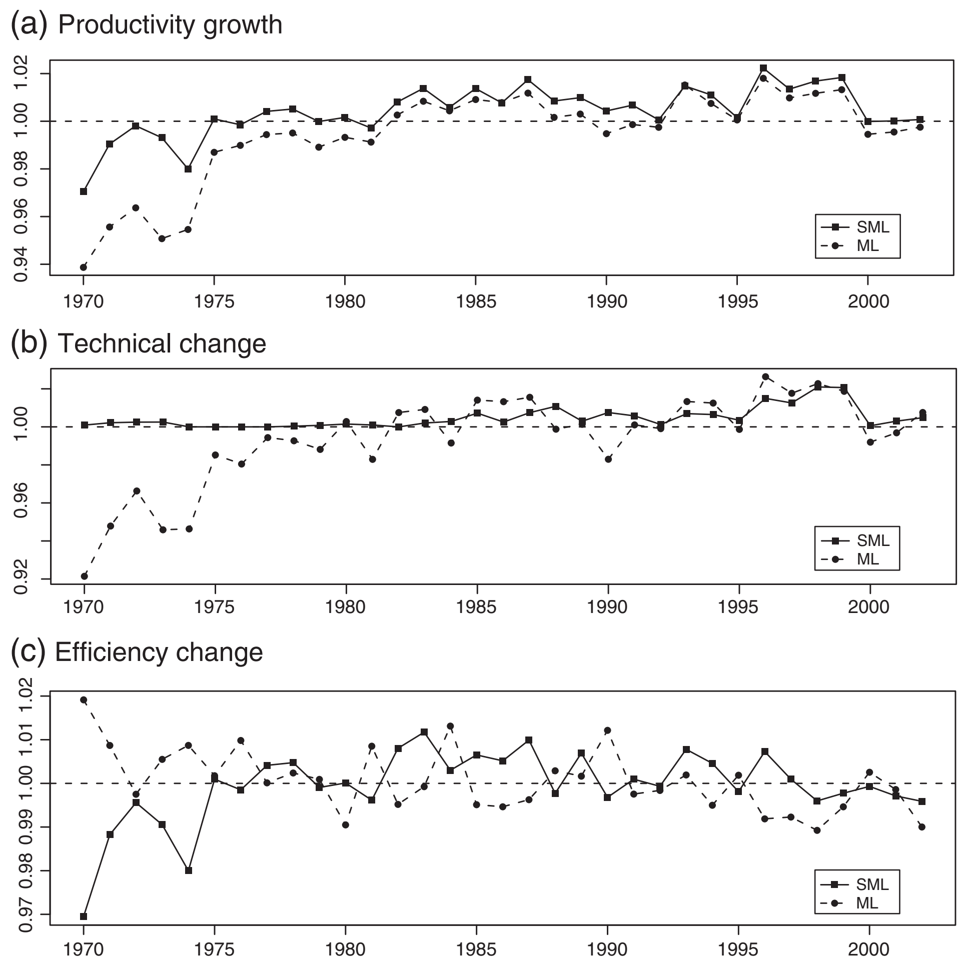

Fig. 3. Developments of average SML and ML productivity growths, technical change and efficiency change indices of 26 OECD countries, 1970–2003.

(−1.71%), Luxembourg (−0.97%), Germany (−0.69%), Belgium (−0.62%), France (−0.41%), Denmark (−0.39%) and UK (−0.30%).

The average growth rates of labor and capital stock of our sample are around 1.24% and 5.46%.

3.2. A comparison of the ML and SML indices

The approach described in the Methodology section constructs the best practice sequential technology frontier from the data. First, we report the average productivity growth and its decomposed components including efficiency change and technical change calculated by the two methodologies. These are shown in Fig. 3. The rates of productivity growth, efficiency change and technical change are shown in the upper panel, middle panel and lower panel of Fig. 3, respectively. In this figure, solid lines and dotted lines are productivity (component) indices calculated from the SML index and ML index, respectively. Recall that the index number larger (smaller) than unity corresponds progress (deterioration).[8]

As can be seen in panel (a) of Fig. 3, the rates of productivity growth of the two measures show very similar trends, signifying that the productivity measures calculated by the two methodologies are similar. The correlation coefficient between the SML and the ML indices is quite high, 0.914. We also tested the null hypothesis that the two productivity growth measures have the same rank by using the Wilcoxon rank sum test. We failed to reject the null at the 1% level of significance, indicating that the ranks of the two productivity growth measures can be regarded as being identical. Based on those two test statistics, it is inferred that the productivity growth indices computed based on the two methodologies in aggregate form are not statistically different. It should also be noted that, although Shestalova (2003) does not include emissions of CO_2 in estimating productivity growth OECD countries, the result of the high correlation between the SML and the ML indices is consistent of her result.[9]

A priori, one would expect that the development of technical change measured by the SML framework is different from that of the ML framework, which is confirmed by the trends of technical changes shown in panel (b) of Fig. 3. In the technical change measure of the ML index, a total of fifteen years of technical deterioration is observed, especially during 1970–1981. However, as discussed in the Introduction, this technical change measure is considered as being biased since such a long-run technical regress is not possible from the macroeconomics perspective. In the technical change of the SML index this spurious technical regress is not observed. Trends of technical change components of the two methodologies are different when the rate of technical change of the ML index is less than unity, but they show a similar pattern when the ML index is larger than unity. We can observe this similarity in particular at the end of the sample period.

8 Percentage change can be calculated multiplying hundred after subtracting unity from an index. For example, the SML index of 1.028 corresponds to a productivity growth rate of 2.8%.

9 If not stated, the results of comparing the SML and the ML are highly consistent with the results of Shestalova (2003).

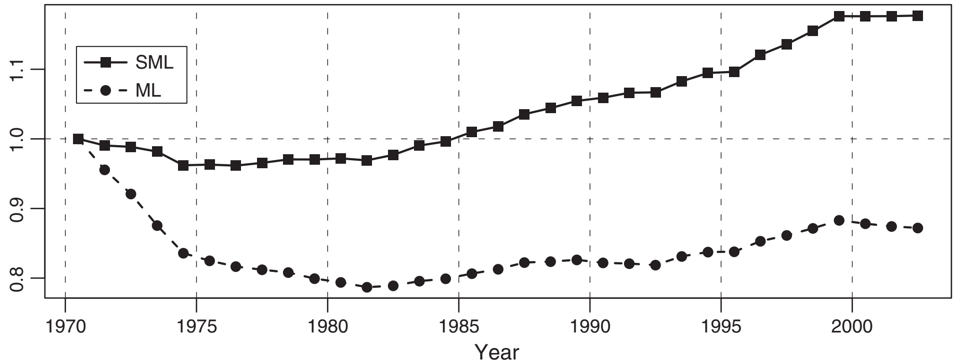

Fig. 4. Cumulative SML and ML productivity growth indices, 1970–2003.

This appears to indicate that innovatory technology related with energy and carbon dioxide emissions has emerged during this period.

Another interesting fact deduced from panel (b) of Fig. 3 is that the technical change measure of the ML index shows much more volatility than the sequential one. This is because it classifies each change in the productivity of countries that belong to the frontier as technical change. On the contrary, the technical change measure in the SML index registers only those changes that lead to the expansion of the PPS. Those differences can be found around the two oil crises of 1973 and of 1979. These oil crises caused lagged overall fall in productivity. These oil crises affect the declines in the technical change measure of the ML index, whereas they have no impact on that of the SML index.

Compared to the similarity in the patterns of productivity growth between the two methodologies, the development of efficiency of the SML index is very different from that of the ML index. Not only the correlation coefficient is negative (−0.514), but also the Wilcoxon rank sum test statistics is not statistically significant (p-value is 0.929), indicating inconsistency between the two indices. This dissimilarity in the efficiency change needs to be investigated through the simultaneous examination of the behavior of the PPS and our assumptions imposed when constructing the PPS. Before discussing this dissimilarity, it should be noted again that the efficiency change captures the speed at which a country moves towards the world technology frontier. Recall that efficiency change index measures a catching-up effect. It is obvious that the efficiency gain occurs if the PPS does not change and an input/output bundle of a country moves closer towards the world technology frontier. Even when the PPS expands, the efficiency gain can occur if the convergence speed is faster than the speed of PPS expansion.

It is indisputable that a country catches up the world frontier when the above two conditions are satisfied. If the PPS contracts, however, a very different story unfolds. That is, the efficiency of a country increases even when it does not attempt to squeeze its endowed inputs to catch up the world frontier technology *only if* the PPS contradicts. In this case the country's distance from the world technology frontier is automatically shortened by the contraction of the PPS. This *counterfeit catching-up effect* can be seen as merely the resultant effect of a *free lunch* which is prepared by the temporary technological deterioration of the world frontier countries. In other words, the country, although it does not do anything, is recorded as having caught up the world frontier technology if we allow the temporal contraction of the PPS. This is one of the drawbacks of the ML index. As a result, during the period 1970–1980 this *counterfeit catching-up* effect is observed many times especially during 1970–1980. Considering that during the same period the technology is *spuriously* measured as being deteriorated for a long time period, this *counterfeit catching up* originates from the assumption imposed when constructing the PPS of the ML index.

Contrary to the efficiency change measure of the ML index, that of the SML index is free from this *counterfeit catching-up effect* problem. Because the temporal contraction of the PPS is absorbed by the previous PPS under the framework of the SML index, the abnormal catching up cannot occur. In this sense, the catching-up effect measured by the SML index can be seen as being the *genuine* catching-up effect compared to that of the ML index.

The two components of the productivity growth measure, i.e., efficiency change and technical change, contribute to the development of productivity. In many previous studies such as Chung et al. (1997), Yörük and Zaim (2005) and Kumar (2006), it is reported that productivity growth is mainly attributed to technical change rather than efficiency change. This is true if we only look at the result of the ML index as investigated in the previous studies. That is, the trend of productivity growth is quite similar to that of the technical change under the framework of the ML index, as can be seen in panels (a) and (b) of Fig. 3. The correlation coefficient between the ML productivity growth index and the technical change index of the ML index is 0.973, while the one between the ML productivity growth and the efficiency change of the ML index is −0.602. This correlation test supports the argument that the rate of technical change is the main contributor to productivity growth under the framework of the ML index approach.

Looking at the result of the SML index, however, it is easily induced that this argument is not *always* true. In the earlier years of the study period, where the technology rarely changes, the productivity growth is mainly attributed to the efficiency change. Nonetheless, the influence of technical change becomes more attributable to the productivity growth over time. This increasing influential pattern of technical change appears to reflect recent technological development related to energy and environment. The recent increasing frequency of policies and protocols launched related to energy and the environment, such as the sustainable growth policies, may be attributed to this trend.

The cumulative productivity growth measure is also economically meaningful since it gives us information about how much productivity is accumulated over time. The cumulative productivity growth indices of our sample using the two productivity indices are depicted in Fig. 4. In this figure, the productivity growth indices of the first year are adjusted to unity so that the developments of the two measures are easily compared. Even though temporal developments of productivity growth measured by the two methodologies are similar to each other, as discussed earlier, their cumulative versions are apparently different in the following two aspects. First, the productivity measures diverge over time. The cumulative productivity growth for the study period measured by the SML index is 14.2% and the one measured by the ML index is −18.1%. Second, the cumulative productivity of the SML index becomes larger than unity from 1986, whereas that the ML index is less than the unity for the whole study period. Reconsidering the recently increasing concerns and policies about energy and environments, the positively cumulated productivity growth of the SML index appears to reflect recent changes better than that of the ML index.

Table 3
Productivity growth, efficiency change, and technical change of 26 OECD countries: 1970–2003.

Country	SML (This study)			ML (Chung et al., 1997)			SM (Shestalova, 2003)			M (Fäare et al., 1994)		
	PC	EC	TC	PC	EC	TC	PC	EC	TC	PC	EC	TC
Australia	1.0046	0.9989	1.0057	1.0004	0.9993	1.0013	1.0049	0.9974	1.0076	1.0024	0.9983	1.0044
Austria	1.0019	0.9987	1.0032	0.9909	0.9990	0.9920	1.0013	0.9923	1.0091	0.9903	0.9931	0.9974
Belgium	1.0099	1.0033	1.0066	1.0018	1.0040	0.9982	1.0076	0.9989	1.0088	1.0017	0.9999	1.0022
Canada	1.0028	0.9972	1.0056	0.9951	0.9974	0.9980	1.0025	0.9960	1.0066	0.9909	0.9967	0.9944
Denmark	1.0032	1.0001	1.0031	0.9953	1.0004	0.9950	1.0015	0.9950	1.0066	0.9938	0.9958	0.9983
Finland	1.0050	1.0030	1.0020	1.0056	1.0030	1.0026	1.0140	1.0046	1.0094	1.0104	1.0054	1.0052
France	1.0061	1.0036	1.0025	0.9981	1.0035	0.9947	1.0053	0.9968	1.0087	0.9972	0.9977	0.9999
Germany	1.0050	1.0006	1.0044	0.9950	1.0009	0.9943	1.0034	0.9949	1.0086	0.9955	0.9956	1.0000
Greece	0.9960	0.9946	1.0014	0.9950	0.9962	0.9991	0.9986	0.9944	1.0042	0.9863	0.9991	0.9871
Iceland	0.9999	0.9978	1.0021	0.9834	0.9979	0.9855	0.9964	0.9907	1.0058	0.9823	0.9918	0.9904
Ireland	1.0113	1.0081	1.0031	0.9961	1.0081	0.9886	1.0126	1.0082	1.0043	0.9923	1.0086	0.9842
Italy	1.0017	0.9991	1.0026	0.9955	0.9995	0.9962	1.0043	0.9962	1.0082	0.9952	0.9968	0.9986
Japan	1.0019	0.9993	1.0026	0.9942	0.9995	0.9949	0.9997	0.9908	1.0091	0.9864	0.9913	0.9951
Korea, Republic of	1.0028	1.0010	1.0018	0.9836	1.0016	0.9828	1.0006	0.9981	1.0025	0.9797	1.0005	0.9816
Luxembourg	1.0376	1.0001	1.0375	1.0068	1.0000	1.0068	1.0230	1.0002	1.0229	1.0185	1.0000	1.0185
Mexico	0.9969	0.9962	1.0007	0.9857	1.0040	0.9826	0.9890	0.9890	1.0000	0.9845	1.0087	0.9774
Netherlands	1.0019	0.9977	1.0042	0.9977	0.9981	0.9997	1.0013	0.9923	1.0091	0.9966	0.9932	1.0037
New Zealand	0.9974	0.9961	1.0013	0.9925	0.9966	0.9960	0.9993	0.9939	1.0055	0.9911	0.9966	0.9950
Norway	1.0079	1.0012	1.0067	1.0057	1.0020	1.0038	1.0194	1.0022	1.0178	1.0189	1.0034	1.0164
Portugal	0.9978	0.9947	1.0032	0.9794	0.9959	0.9835	0.9882	0.9858	1.0024	0.9676	0.9899	0.9777
Spain	0.9977	0.9958	1.0019	0.9858	0.9959	0.9900	0.9951	0.9901	1.0050	0.9772	0.9905	0.9866
Sweden	1.0079	1.0046	1.0033	0.9982	1.0047	0.9938	1.0035	0.9976	1.0059	0.9941	0.9997	0.9949
Switzerland	1.0070	0.9999	1.0071	1.0042	1.0000	1.0042	1.0038	0.9859	1.0186	1.0032	0.9867	1.0172
Turkey	0.9965	0.9963	1.0003	0.9884	1.0075	0.9817	0.9899	0.9899	1.0000	0.9877	1.0160	0.9752
U.K.	1.0004	0.9983	1.0021	0.9847	0.9984	0.9863	1.0002	0.9961	1.0041	0.9826	0.9982	0.9847
U.S.A.	1.0054	0.9965	1.0090	0.9887	1.0008	0.9879	1.0040	0.9964	1.0077	0.9942	0.9971	0.9972
Average	1.0041	0.9993	1.0048	0.9941	1.0005	0.9938	1.0027	0.9951	1.0076	0.9931	0.9981	0.9955

SML, ML, SM and M represent the sequential Malmquist–Luenberger index, the Malmquist–Luenberger index (Chung et al., 1997), the sequential Malmquist index (Shestalova, 2003) and the Malmquist index (Färe et al., 1994), respectively.

3.3. Country heterogeneity

Average productivity growth, efficiency change and technical change are calculated for the sample countries. These measures are listed in Table 3. For comparison purposes, we also calculated the sequential Malmquist productivity growth index (SM) of Shestalova (2003) and the conventional Malmquist productivity growth index (M) of Färe et al. (1994), shown in the last six columns of Table 3.[10] Recall again that index values greater (less) than unity indicate improvement (deterioration) in the relevant performance. As expected from the aforementioned result, the two methodologies yield different measures and decompositions. The number of countries having productivity deterioration is seven in the SML index, while the corresponding number in the ML index is twenty. This large discrepancy between the two methodologies is caused by the different assumptions imposed in constructing the PPS. Compared with the aggregate level, non-aggregated productivity growth shows significant differences between the two methodologies. Regardless of selection of the methodologies, Australia, Belgium, Finland, Luxembourg, Norway and Switzerland have positive rate of productivity growth; while Greece, Iceland, Mexico, New Zealand, Portugal, Spain and Turkey show a negative productivity growth for both measures.

In order to examine the relationship among the three performance (efficiency change, technical change and productivity growth) measures, a scatter plot is depicted with x-axis of an efficiency change index and y-axis of a technical change index, as shown in Fig. 5. The size of the circle in this figure gives us information about the average annual growth rate of productivity.

Our sample countries can be classified into several groups in accordance with the following categorization rule. The countries are categorized into a specific group based on their performance in the rates of technical change and efficiency change. If the technical change index of a country is larger (smaller) than the average technical change of our sample, its innovative ability can be considered as being better (worse) than the *virtual* average country. Likewise, if the efficiency change index of a country is larger (lesser) than unity, it is considered as being in the state of catching up (lagging behind) the world frontier technology, as discussed in the Methodology section. Hence, in the present study the criterion of our categorization is set as the average technical change of our sample and a unit efficiency change. Through this categorization rule, we can divide the OECD member countries into four groups: more innovative and catching-up countries (Group I), more innovative but lagged countries (Group II), less innovative but catching-up countries (Group III) and less innovative and lagged countries (Group IV).

In Fig. 5, those country groups are placed in the northeast, northwest, southeast and southwest spaces. Belgium, Luxembourg and Norway are categorized as Group I countries; Australia, Canada, Switzerland and the USA are categorized as Group II; Denmark, Finland, France, Germany, Ireland, Korea and Sweden are categorized as Group III countries; and finally Austria, Greece, Iceland, Japan, Mexico, New Zealand, Portugal, Spain, Turkey and UK are categorized as Group IV countries. In the Group IV, it is worth noting that more than half the countries have negative productivity growth. Another interesting fact deduced from Fig. 5 is that, except for Iceland, the Nordic countries are categorized as high productivity growth countries. For example, Norway is good at innovating as well as catching up the world frontier technology; Finland and Sweden are also good at catching up the world frontier technology. This favorable state of the Nordic countries can be considered as a benchmark for a successful sustainable economic growth policy.

3.4. Innovative countries

The technical change index for any one particular country between two consecutive years, if not on the frontier, is not necessarily an index of the shift in the world technology frontier. Hence, a value of

[10] We are grateful to the anonymous referees for providing this invaluable comment.

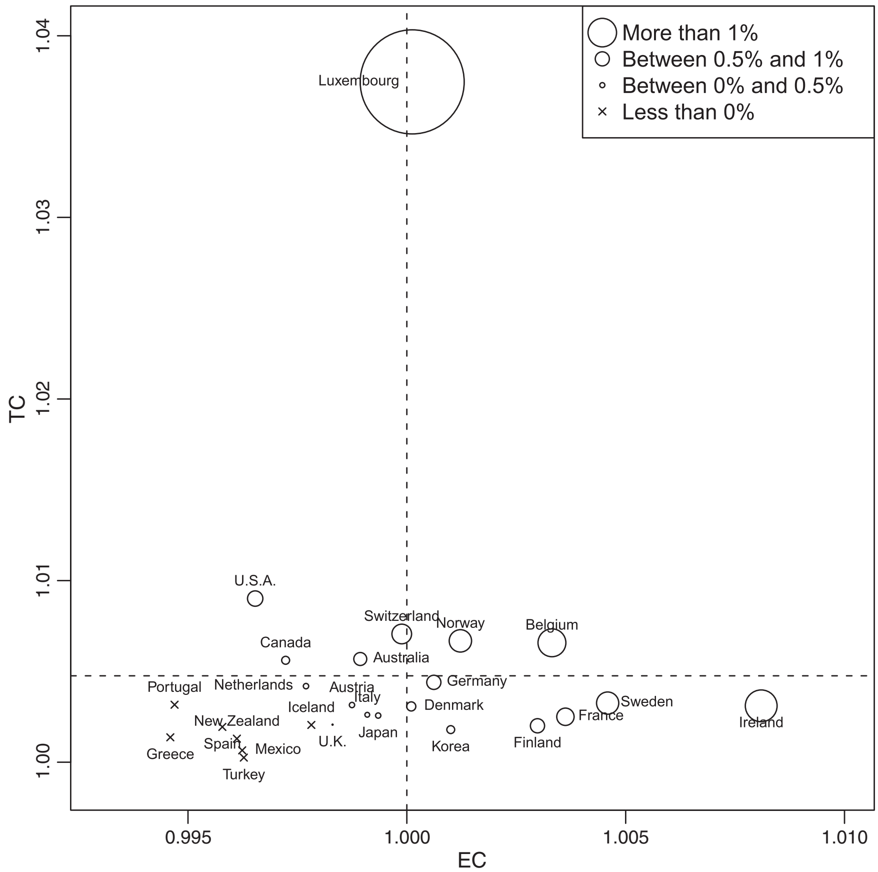

Fig. 5. Average efficiency change and technical change of OECD countries by means of the SML index, 1970–2003.

this factor greater than unity does not necessarily imply that the country under consideration actually pushes the world technology frontier outwards. This means that additional information needs to be investigated in order to determine which countries are the world innovators. The following three conditions help us determine this issue:

$$TC^{t,t+1} > 1 \tag{14a}$$

$$\vec{D}_q^t\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) < 0 \tag{14b}$$

$$\vec{D}_q^{t+1}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}\right) = 0 \tag{14c}$$

As discussed earlier, the first condition indicates that the world technology frontier is shifted in more good outputs and fewer bad outputs direction. 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 the relevant portions of the frontier between period t and $t+1$ for a given country when the good and bad outputs are treated asymmetrically. The second condition indicates that production in period $t+1$ occurs outside the PPS of period t. This means that technical change has occurred during the transition period. It implies that technology of period t cannot 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 world technology frontier in period $t+1$. In should be noted that, since our sample countries contain all advanced countries, we are confident that the estimated frontier represents the world frontier technology.

Table 4 lists the innovative countries for every five-year period from 1970 to 2003. Out of 26 OECD countries, eight countries are recorded as the innovative countries. Those countries are France, Ireland, Luxembourg, Norway, Portugal, Sweden, Switzerland and the USA. Some countries are innovators only for a short period, e.g., Portugal and the USA, whereas others are innovators covering almost the entire study period, e.g., Luxembourg and Switzerland. As expected, low CO_2 emitters coupled with high GDP growth, such as Luxembourg and Switzerland, are recorded as innovative countries. High CO_2 emitting countries, such as Korea and Turkey, are not found to be innovators in spite of the fact that their rate of GDP growth is quite high. Interestingly, only two of the Nordic countries (Norway and Sweden), which are among high productive economies, are recorded as the innovators during the period 1990–2000. Although not all of them are the innovators, the Nordic countries appear to be good at following the world frontier technology closely and are only slightly lagged by the top innovators.

Table 4
Innovative countries classified by the SML index, 1970-2003.

Period	List of innovative countries
1970–1975	Luxembourg, Portugal, and Switzerland
1975–1980	Switzerland
1980–1985	Luxembourg, Switzerland, and USA
1985–1990	Luxembourg, Switzerland, and USA
1990–1995	Luxembourg, Norway, and Switzerland
1995–2000	France, Luxembourg, Norway, Sweden, and Switzerland
2000–2003	France, Ireland, Luxembourg, Sweden, and Switzerland

4. Conclusion

Although productivity is not the only determinant of economic growth and welfare, it does provide an indirect measure of the economic prosperity, as well as of the standard of living and of the degree of competitiveness of a country. As the environmental concern has remarkably grown during recent decades, the classical productivity growth indices such as the Malmquist productivity index have attempted to integrate the effect of environmentally harmful by-products. Those attempts have resulted in the creation of the environmentally sensitive productivity index by expanding the classical productivity index, such as the Malmquist–Luenberger index. Although this productivity measure considers the environmental and economic perspectives of the relationship between the desirable and undesirable outputs, it fails to appropriately integrate the features of technology.

In order to overcome this weakness of the conventional ML index, we proposed the substitute index for measuring environmentally sensitive productivity growth. It was done by combining the two concepts of the directional distance function and the successive sequential reference production set. We named it the sequential Malmquist–Luenberger productivity index (SML index). With this augmented methodology, the components of the productivity growth, such as the efficiency change and technical change indices, are properly measured without bias by eliminating the possibility of the contraction of the production possibility set.

The proposed methodology was employed in measuring the environmentally sensitive productivity growth of 26 OECD countries over the period 1970–2003. The empirical results show that: (i) although the developments of the productivity calculated by the ML and SML index are similar to each other, the components of the productivity indices are quite different, (ii) unlike the previous studies, the efficiency change is found to be the main contributor of the productivity growth in the earlier study period, whereas the effect of technical change prevails over time, (iii) by categorizing OECD countries, Belgium, Luxembourg and Norway are found to be good at innovating as well as catching up the world frontier technology, (iv) Luxembourg and Switzerland are found to be innovative countries for most of the study period, and (v) the environmentally sensitive productivity growth of the Nordic countries are on average higher than that of the rest of the OECD member countries.

Beyond presenting the SML index, the present paper is believed to pave the way for further methodological development related to the needy environmentally sensitive productivity growth measure. A combination of the concept of the metafrontier (Hayami, 1969) and the SML index would be a good nominee of those methodological developments in order to facilitate the investigation of group heterogeneity among the sub-samples. We believe that this study will be a roadmap for opening up the possibility of expanding the existing environmentally sensitive productivity growth index. We also believe that the results of the empirical study will have implications for policy-making related to sustainable growth.

References

Arcelus, F.J., Arocena, P., 2005. Productivity differences across OECD countries in the presence of environmental constraints. The Journal of the Operational Research Society 56 (12), 1352–1362.

Arocena, P., Waddams Price, C., 2002. Generating efficiency: economic and environmental regulation of public and private electricity generators in Spain. International Journal of Industrial Organization 20 (1), 41–69 1.

Barros, C.P., 2008. Efficiency analysis of hydroelectric generating plants: a case study for Portugal. Energy Economics 30 (1), 59–75.

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. Journal of Environmental Management 51 (3), 229–240.

Färe, R., Grosskopf, S., Noh, D.-W., Weber, W., 2005. Characteristics of a polluting technology: theory and practice. Journal of Econometrics 126 (2), 469–492.

Färe, R., Grosskopf, S., Norris, M., Zhang, Z., 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. The American Economic Review 84 (1), 66–83.

Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2001. Accounting for air pollution emissions in measures of state manufacturing productivity growth. Journal of Regional Science 41 (3), 381–409.

Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2007a. Environmental production functions and environmental directional distance functions. Energy 32 (7), 1055–1066.

Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2007b. Pollution abatement activities and traditional productivity. Ecological Economics 62 (3-4), 673–682 5.

Färe, R., Grosskopf, S., Weber, W.L., 2006. Shadow prices and pollution costs in U.S. agriculture. Ecological Economics 56 (1), 89–103.

Hayami, Y., 1969. Sources of agricultural productivity gap among selected countries. American Journal of Agricultural Economics 51 (3), 564–575.

Kortelainen, M., 2008. Dynamic environmental performance analysis: a Malmquist index approach. Ecological Economics 64 (4), 701–715 2.

Kumar, S., 2006. Environmentally sensitive productivity growth: a global analysis using Malmquist–Luenberger index. Ecological Economics 56 (2), 280–293.

Kumar, S., Managi, S., 2009. Energy price-induced and exogenous technological change: assessing the economic and environmental outcomes. Resource and Energy Economics 31 (4), 334–353 11.

Lee, J.D., Park, J.B., Kim, T.Y., 2002. Estimation of the shadow prices of pollutants with production/environment inefficiency taken into account: a nonparametric directional distance function approach. Journal of Environmental Management 64 (4), 365–375.

Luenberger, D.G., 1992. Benefit functions and duality. Journal of Mathematical Economics 21 (5), 461–481.

Nakano, M., Managi, S., 2008. Regulatory reforms and productivity: an empirical analysis of the Japanese electricity industry. Energy Policy 36 (1), 201–209.

Shestalova, V., 2003. Sequential Malmquist indices of productivity growth: an application to OECD industrial activities. Journal of Productivity Analysis 19 (2), 211–226.

Thirtle, C., Piesse, J., Lusigi, A., Suhariyanto, K., 2003. Multi-factor agricultural productivity, efficiency and convergence in Botswana, 1981–1996. Journal of Development Economics 71 (2), 605–624 8.

Tulkens, H., Vanden Eeckaut, P., 1995. Non-parametric efficiency, progress and regress measures for panel data: methodological aspects. European Journal of Operational Research 80 (3), 474–499 (Aug).

Weber, W., Domazlicky, B., 2001. Productivity growth and pollution in state manufacturing. The Review of Economics and Statistics 83 (1), 195–199.

Yörük, B.K., Zaim, O., 2005. Productivity growth in OECD countries: a comparison with Malmquist indices. Journal of Comparative Economics 33 (2), 401–420.

Yu, M.-M., Hsu, S.-H., Chang, C.-C., Lee, D.-H., 2008. Productivity growth of Taiwan's major domestic airports in the presence of aircraft noise. Transportation Research Part E: Logistics and Transportation Review 44 (3), 543–554.

Zhou, P., Ang, B.W., Han, J.Y., 2010. Total factor carbon emission performance: a Malmquist index analysis. Energy Economics 32 (1), 194–201.