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Aggregate green productivity growth in OECD's countries

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Abstract
Most of previous research about Total Factor Productivity (TFP) at the macro level only emphasizes technical effect and technological progress at the country level, but it ignores structural effect for a group of countries at the aggregate level. This paper attempts to measure the green productivity evolution incorporating carbon dioxide emissions based on the Luenberger TFP indicator for a group of 30 OECD countries over the period of 1971−2011. We propose a novel decomposition for green productivity growth at the aggregate level which separates TFP changes into three components: technological progress, technical efficiency change, and structural efficiency change. The structural effect captures the heterogeneity in the combination of input and output mixes among countries that can impact TFP growth at a more aggregate level. In the literature, this effect has not been quantified for a group of nations such as the OECD countries. Our results indicate that the traditional TFP index underestimates green growth which is motivated by the effective and efficient environmental policies of the OECD. The green productivity growth is mainly driven by technology progress which has become a dominant force in the 21st century.

JEL Classification: O44, O47, Q50, D24

Keywords: Undesirable Output; Carbon Dioxide Emissions; Total Factor Productivity; Weak Disposability.

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1. Introduction

For a long time period, income per capita has been considered to be mainly driven by total factor productivity (TFP) changes, but more recently standard of living and welfare have become important factors in regard to green economic growth due to the deterioration in global environmental conditions. Measures of TFP at macro and micro levels have attracted much attention by using different parametric or non-parametric frameworks. In the literature, TFP gain evaluated through output change not explained by input variation. This is initially attributed to the traditional Solow residual interpreted as technological progress (shift of the production frontier). Later a technical efficiency change component (movement to the production frontier) was added to this technical progress to explain TFP change.

Based on the recent literature, our study attempts to measure the green TFP index for a whole group including 30 OECD countries over the period of 1971−2011. Compared to previous studies on productivity growth, the first goal of our research is to measure the green productivity evolution incorporating carbon dioxide emissions. A second goal is to separate TFP changes into three components: technological progress, technical efficiency change, and structural efficiency change. Although the first two elements depend on the capability of a particular country to reach the best technical practices and carry out innovations, the third element covers the heterogeneity in the combination of input intensity and output specialization. The structural efficiency change can be observed as a proxy for an input/output deepening or expanding effect associated with dynamic convergence or divergence of resource reallocation in the economic organization.

The last effect is particularly relevant in the new vision of the role of environment in economic welfare related to global warming and the threat of melting glaciers. Indeed, economists have begun to pay serious attention to the sustainability of economic development and have emphasized savings through environmental protection. Moreover, various international organizations, negotiations, and forums have also been established for enhancing intergovernmental cooperation among regions and countries because pollution control and environmental protection must be negotiated and managed by a global consortium of nations and not only at the national level. Structural efficiency is explicitly related to the adjustments of output and/or input mixes occurring within a group of countries over time. In this way, this element impacts green TFP growth at a worldwide level.

Compared to many other empirical applications which employ the ratio-based Malmquist productivity index, the objective of this paper is to analyze the green TFP growth

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for an aggregation of developed countries (OECD member countries) and to propose a novel decomposition of the difference-based Luenberger productivity index. Beyond the two traditional components, namely technical efficiency change and technological progress, or three components with scale efficiency change (e.g. Kapelko et al., 2015), our decomposition captures a new effect called structural efficiency.

Numerous researches about environmental efficiency and productivity have arisen in the past few decades. Ecologists and economists have both proposed various methods and models to evaluate carbon abatement costs and their effects on TFP evolution. Some previous measurements use a functional form to characterize the production activity including pollution. Färe et al. (1993) and Hailu and Veeman (2000) propose a translog distance function to include bad outputs in an econometric framework. To avoid specifying a functional form of the technology and the inefficiency distribution, data envelopment analysis (DEA) is a non-parametric approach which estimates the best practice frontier by enveloping the data. Since the initial framework was developed by Charnes et al. (1978), DEA has become more and more popular especially because of its capacity to include undesirable outputs through a weak disposable assumption and to decompose the Luenberger productivity index.

The reminder of the paper is structured as follows: Section 2 offers a recent literature review. Section 3 reviews weakly disposable technology and proposes a green TFP model. By using directional distance functions, this framework is able to conceptualize the aggregate production frontier for the whole set of OECD countries and to split green TFP gain into its three components. Section 4 introduces the data source and comments on the empirical results. Conclusions and future research topics appear in the final section.

2. Literature review

Using a non-parametric approach, Färe et al. (1994) analyze productivity growth in 17 OECD countries over the period of 1979−1988. Their productivity indexes are decomposed of two components, namely, technical changes and efficiency changes, the latter being interpreted as a catching-up effect. Relaxing the constant returns to scale (CRS) assumption for the technology, they further separate the catching-up effect into two terms: one representing a pure technical efficiency change and the other measuring changes in scale efficiency. The authors find that U.S. productivity growth is a little higher than average, while Japan obtains the highest productivity growth rate. Sena (2004) discovers spillover effects of high-tech companies on non-high-tech ones in Italy using the Malmquist index. Hoang and Coelli (2011) study the agricultural TFP among 30 OECD countries during 1990-2003 and they argue that the environmental efficiency and productivity can be improved by changing input combinations.

Empirical research on TFP growth is also available for developing or newly industrialized regions and countries. For instance, Liu and Wang (2008) analyze productivity growth for semiconductor firms in Taiwan to determine whether strategic shift is meaningful. Young (1992, 1994, and 1995) and Kim and Lau (1994) study sources of development for the East Asian economies and find a limited role of TFP growth. Interpreting the above results, Krugman (1994) concludes that East Asian growth has been primarily due to factor accumulation. In opposition to this view, Collins and Bosworth (1997) and Klenow and Rodriguez (1997) evaluate a more significant contribution of TFP growth for some East Asian economies such as that of Singapore. These last conclusions emphasize the role of the assimilation of new technology to explain the growth of the East Asian countries and are in line with the interaction between technological adoption and capital accumulation leading to TFP growth.

Kumar and Russell (2002) re-examine the catching-up mechanism with a methodology which requires no a priori functional form on the world production frontier, nor any assumption about market structure. In addition, it does not specify a particular nation as the world leader, allowing for technical and/or allocative inefficiencies to arise from differences in the countries' abilities to use available technology. They test for the catching-up hypothesis across 57 poor and rich nations, using labor productivity indexes calculated with a nonparametric method. To analyze the evolution of the cross-country distribution of labor productivity, they focus on differences in levels of technology, technological changes over time, and how much of income convergence is due to technological diffusion or to convergence in capital/labor ratios. Their results conclude that there is evidence of technological catch-up, as countries have on the whole moved toward the world production frontier, non-neutrality of technological change and a predominance of capital deepening as opposed to the technological catch-up that contributes to both growth and income divergence of economies.

More recently, Yörük and Zaim (2005) evaluate productivity growth in 28 OECD countries over the period of 1983−1998 by comparing the Malmquist and Malmquist-Luenberger productivity indicators. They incorporate carbon dioxide, nitrogen oxide, and organic water into the Malmquist-Luenberger index, and their results show that the productivity growth is undervalued if we do not consider forms of pollution.

Mahlberg et al. (2011) estimate eco-productivity with the Malmquist indicator for 14 countries from the European Union over the period of 1995−2004. They include greenhouse gas as an undesirable output by dealing with it as a form of input constraint. They argue that growth of the ecological Malmquist TFP is more motivated by environmental improvements. Kerstens and Managi (2012) investigate the Luenberger TFP growth and effect of convexity assumption on convergence issues for U.S. petroleum industry by comparing the convex and non-convex production technologies. Furthermore, Mahlberg and Sahoo (2011) analyze environmental TFP for 22 OECD countries by developing a non-radial decomposition of the Luenberger productivity index. They separate TFP change into efficiency change and technology progress where productivity growth mainly depends on the latter.

However, these previous studies concerning TFP growth or TFP convergence still have room for improvement. First, the initial literature ignores undesirable outputs (such as carbon emissions) in the production process that cannot provide the basis for sustainable economic development. Ananda and Hampf (2015) argue that the influence of including undesirable outputs in productivity measurement is significant. Second, even if more recent papers take into account pollution emissions, they emphasize technical effect and technology progress at the national level but disregard the structural effect at the aggregate level for a group of countries such as all the member countries of the OECD. Third, the shadow prices of undesirable outputs are not constrained in most literature. Berre et al. (2013) investigate the output shadow price for dairy farms, and they find a positive revenue can be attached to nitrogen output if its price is not constrained. Therefore, a constrained model that provides an unambiguous economic interpretation is more appropriate.

Empirical DEA research on dealing with undesirable outputs provides two main alternative approaches: the first one converts the outputs into different transformations while the other maintains the original data but depends on a weak disposability assumption (Zhou et al., 2008). Leleu (2013) argues that the real production process cannot be revealed if the bad outputs are regarded as inputs based on their data transformations.

Distance functions are also usually employed with the weak disposability assumption in seeking a benchmark in terms of desirable and undesirable outputs. Zhou et al. (2014) summarize three main types of distance functions which are commonly used through DEA estimations: Shephard input, Shephard output, and directional distance functions. In these models, undesirable outputs, such as carbon emissions, pollutants, and noise are explicitly

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considered by-products joined to the desirable output. Undesirable outputs should not be considered as freely disposable; hence, the weak disposability defined by Shepard (1970) and Shephard and Färe (1974) provide an alternative way of modeling inputs and outputs. The two key assumptions, namely weak disposability and null-jointness, are usually used together to incorporate undesirable and desirable outputs. The former implies that the abatement of undesirable outputs will be inevitable in affecting the production of desirable outputs, while the latter explains that the only solution to producing pollution is to not produce at all.

Chung et al. (1997) suggest a directional distance function to estimate productivity changes in the Swedish pulp and paper industry from 1986−1990. Färe et al. (2005) measure the technical efficiency of 209 electric utilities from 1993−1997 by employing a quadratic directional output distance function. They use SO2 as an undesirable output and their results show that SO2 emissions can be abated by 4000–6000 tons, and, as a result, the shadow price of SO2 rises during the sample period.

Kumar (2006) measures the Malmquist-Luenberger productivity index in 41 developed and developing countries from 1971−199, using the directional distance functions and decomposing TFP into technical and efficiency changes. Kumar finds that the environmental TFP index value is the same as when carbon emissions are freely disposable. However, his results also show the two components of TFP change, technical change and efficiency change, are not the same in the two measures.

Lin et al. (2013) measure environmental productivity in 70 countries from 1981−2007. They incorporate undesirable output, namely carbon emissions, and find differences in green productivity growth across sample countries, using the directional distance function. They compute the Malmquist productivity index and decompose it into technical efficiency change, technical change, and scale efficiency change. Their results show that developing countries achieve higher growth in their average environmental productivity relative to the convergence growth theory.

Woo et al. (2015) examine the environmental efficiency of renewable energy in 31 OECD countries by using the DEA approach and the Malmquist productivity index from 2004−2011. Their results show a geographical difference in environmental efficiency across the OECD. The group of OECD America has the highest average environmental efficiency, and the group of OECD Europe has the largest standard deviation. They find that global financial crisis affects efficiency change in the United States.

These papers have different features; most of the papers are based on the Malmquist productivity index, while some of the research employs the Luenberger productivity indicator.

Boussemart et al. (2003) argue that the Luenberger productivity indicator is more general than the Malmquist productivity index. In addition, the Malmquist-Luenberger index is also a popular research tool which is proposed by Chung et al. (1997). Its core concept is to use the ratio-based decomposition of the Malmquist index but to replace the Shephard's distance function with a directional one.

3. Methodology

3.1 Weakly disposable technology and directional distance functions

Among methodologies for dealing with undesirable outputs in production activity, the weakly disposable technology becomes more and more popular in literature. Using Shephard's definition of weakly disposable technology (Färe and Grosskopf, 2003), let $\mathbf{x} = (x_1, ..., x_N) \in R_+^N$ denote the vector of the inputs and $\mathbf{v} = (v_1, ..., v_M) \in R_+^M$ and $\mathbf{w} = (w_1, ..., w_J) \in R_+^J$ denote the vectors of the desirable (good) and undesirable (bad) outputs, respectively. The technology and corresponding output set are denoted by T and P:

$$T = \{(\mathbf{x}, \mathbf{v}, \mathbf{w}) : \mathbf{x} \text{ can produce } (\mathbf{v}, \mathbf{w})\} \qquad (1)$$

$$P(\mathbf{x}) = \{(\mathbf{v}, \mathbf{w}) : (\mathbf{x}, \mathbf{v}, \mathbf{w}) \in T\} \qquad (2)$$

Two classical conditions namely weak disposability as introduced by Shephard (1970) and null-jointness proposed by Shephard and Färe (1974) are most often used in modeling good and bad outputs. The assumption of weak disposability (3) allows a proportional evolution between good and bad outputs. The null-joint condition (4) requires that we cannot produce desirable outputs without generating undesirable outputs:

$$\text{If } (\mathbf{v}, \mathbf{w}) \in P(\mathbf{x}) \text{ and } 0 \le \theta \le 1 \text{ then } (\theta\mathbf{v}, \theta\mathbf{w}) \in P(\mathbf{x}) \qquad (3)$$

$$\text{If } (\mathbf{v}, \mathbf{w}) \in P(\mathbf{x}) \text{ and } \mathbf{v} = \mathbf{0} \text{ then } \mathbf{w} = \mathbf{0} \qquad (4)$$

The directional distance function measures the distance between the observed production plans and the frontier and can be interpreted as inefficiency. The directional distance function is defined as follows:

$$D_T(\mathbf{x}, \mathbf{v}, \mathbf{w}; \mathbf{g}_v, \mathbf{g}_w) = \sup_{\delta} \{ \delta \in \Re_+ : (\mathbf{x}, \mathbf{v} + \delta\mathbf{g}_v, \mathbf{w} - \delta\mathbf{g}_w) \in T \}, \qquad (5)$$

where $(\mathbf{g}_v, \mathbf{g}_w)$ is a nonzero vector that means simultaneous adjustments of both desirable and undesirable outputs and δ is the inefficiency score. Besides the static scores, the dynamic evolution of shifting in technology can be measured by relevant productivity indexes.

3.2. The Luenberger productivity index and its decompositions

Chambers (2002) introduce the Luenberger productivity index based on the directional distance functions proposed by Luenberger (1992). We can define the technology at period t:

$$T^t = \left\{(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t) : \mathbf{x}^t \text{ can produce } (\mathbf{v}^t, \mathbf{w}^t)\right\} \qquad (6)$$

The directional distance function is therefore defined as follows:

$$D_T^t(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_\mathbf{v}^t, \mathbf{g}_\mathbf{w}^t) = \sup_{\delta^t}\left\{ \delta^t \in \Re_+ : (\mathbf{x}^t, \mathbf{v}^t + \delta^t \mathbf{g}_v^t, \mathbf{w}^t - \delta^t \mathbf{g}_w^t) \in T^t \right\}, \qquad (7)$$

Following Chambers (2002), the Luenberger TFP indicator over the time period t and t+1 can be traditionally decomposed for a country as follows:

$$TFP^{t,t+1} = EC^{t,t+1} + TP^{t,t+1}$$

where:

$$TFP^{t,t+1} = \frac{1}{2}[D^t(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^t(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1}) +$$
$$D^{t+1}(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_\mathbf{v}^t, \mathbf{g}_\mathbf{w}^t) - D^{t+1}(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1})]$$

$$EC^{t,t+1} = D^t(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^{t+1}(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1}) \qquad (8)$$

$$TP^{t,t+1} = \frac{1}{2}[D^{t+1}(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_\mathbf{v}^t, \mathbf{g}_\mathbf{w}^t) - D^t(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_\mathbf{v}^t, \mathbf{g}_\mathbf{w}^t) +$$
$$D^{t+1}(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_\mathbf{v}^{t+1}, \mathbf{g}_\mathbf{w}^{t+1}) - D^t(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1})]$$

In other words, the TFP indicator at a national level is the sum of efficiency change (EC) and technology progress (TP). Although this decomposition captures EC and TP at individual levels, it still ignores the structural effect for the whole group of countries at the aggregate level.

More precisely, as illustrated in Figure 1, we can see the case of countries A and B which are technically efficient at individual plan levels, but are inefficient at the aggregate plan level (A+B). This component, namely structural inefficiency, is due to the heterogeneity of input allocations between countries A and B and the convexity of the isoquant curve. This lack of coordination can be seen as a market inefficiency. As a result, variations of the output and input mix among countries over time, impacting TFP growth of the aggregate production plan via structural inefficiency changes. The more the countries converge to similar output and input mixes, the less important is the inefficiency of the aggregate production plan. As a result, the TFP level at the whole group level increases. This effect is of particular importance for the impact on the environment on a worldwide level.

Figure 1 about here

To estimate the technical inefficiency at a group level of K countries, we employ the aggregate output vector as this direction: $(\mathbf{g}_v^t, \mathbf{g}_w^t) = (\sum_{k=1}^{K} \mathbf{v}_k^t, \sum_{k=1}^{K} \mathbf{w}_k^t)$ using a CRS technology. As mentioned before, technical inefficiency for an aggregation of countries takes into account a structural component, but also includes eventual technical inefficiency observed for individual countries. This aggregate inefficiency is defined as the overall inefficiency which can be split into two components: technical inefficiency which is the sum of individual countries' technical inefficiencies and structural inefficiency. According to the chosen direction, these inefficiency scores are expressed in percentages of the total group output.

The overall efficiency change (OE) reveals the evolution between overall inefficiency scores in periods t and t+1. Therefore, the Luenberger TFP index at an aggregate level based on a CRS technology can be defined as the sum of OE and TP:

$$TFP^{t,t+1} = OE^{t,t+1} + TP^{t,t+1}$$

where:

$$TFP^{t,t+1} = \frac{1}{2}[D^t(\sum_{k=1}^{K}\mathbf{x}_k^t, \sum_{k=1}^{K}\mathbf{v}_k^t, \sum_{k=1}^{K}\mathbf{w}_k^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^t(\sum_{k=1}^{K}\mathbf{x}_k^{t+1}, \sum_{k=1}^{K}\mathbf{v}_k^{t+1}, \sum_{k=1}^{K}\mathbf{w}_k^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1}) +$$
$$D^{t+1}(\sum_{k=1}^{K}\mathbf{x}_k^t, \sum_{k=1}^{K}\mathbf{v}_k^t, \sum_{k=1}^{K}\mathbf{w}_k^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^{t+1}(\sum_{k=1}^{K}\mathbf{x}_k^{t+1}, \sum_{k=1}^{K}\mathbf{v}_k^{t+1}, \sum_{k=1}^{K}\mathbf{w}_k^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1})]$$

$$OE^{t,t+1} = D^t(\sum_{k=1}^{K}\mathbf{x}_k^t, \sum_{k=1}^{K}\mathbf{v}_k^t, \sum_{k=1}^{K}\mathbf{w}_k^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^{t+1}(\sum_{k=1}^{K}\mathbf{x}_k^{t+1}, \sum_{k=1}^{K}\mathbf{v}_k^{t+1}, \sum_{k=1}^{K}\mathbf{w}_k^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1})$$

$$TP^{t,t+1} = \frac{1}{2}[D^{t+1}(\sum_{k=1}^{K}\mathbf{x}_k^t, \sum_{k=1}^{K}\mathbf{v}_k^t, \sum_{k=1}^{K}\mathbf{w}_k^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^t(\sum_{k=1}^{K}\mathbf{x}_k^t, \sum_{k=1}^{K}\mathbf{v}_k^t, \sum_{k=1}^{K}\mathbf{w}^t; \mathbf{g}_v^t, \mathbf{g}_w^t) +$$
$$D^{t+1}(\sum_{k=1}^{K}\mathbf{x}_k^{t+1}, \sum_{k=1}^{K}\mathbf{v}_k^{t+1}, \sum_{k=1}^{K}\mathbf{w}_k^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1}) - D^t(\sum_{k=1}^{K}\mathbf{x}_k^{t+1}, \sum_{k=1}^{K}\mathbf{v}_k^{t+1}, \sum_{k=1}^{K}\mathbf{w}_k^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1})] \quad (9)$$

Furthermore, OE can be continually decomposed into a technical efficiency change (TE) and a structural efficiency change (SE). TE is the time-variation of the individual technical inefficiency scores, while SE captures the change of the structural component over time. This latter effect is operationally deduced through the difference of the two previous components:

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$$
\begin{aligned}
&OE^{t,t+1} = D^t(\sum_{k=1}^{K}\mathbf{x}_k^t, \sum_{k=1}^{K}\mathbf{v}_k^t, \sum_{k=1}^{K}\mathbf{w}_k^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^{t+1}(\sum_{k=1}^{K}\mathbf{x}_k^{t+1}, \sum_{k=1}^{K}\mathbf{v}_k^{t+1}, \sum_{k=1}^{K}\mathbf{w}_k^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1}) \\
&TE^{t,t+1} = \sum_{o=1}^{K}\Big[D^t(\mathbf{x}_k^t, \mathbf{v}_k^t, \mathbf{w}_k^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{v}_k^{t+1}, \mathbf{w}_k^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1})\Big] \qquad (10) \\
&SE^{t,t+1} = OE^{t,t+1} - TE^{t,t+1}
\end{aligned}
$$

Finally, one can estimate TFP growth for the whole group as the result of the three components' changes over time:

$$TFP^{t,t+1} = TE^{t,t+1} + SE^{t,t+1} + TP^{t,t+1} \qquad (11)$$

3.3. Estimations of the TFP components by linear programing for primal and dual DEA models

Each component of the $TFP^{t,t+1}$ index can be estimated by a linear program (LP). The primal directional distance function at the individual level is figured by the following linear program:

Primal directional distance function under an individual technology

$$
\begin{aligned}
&D^t(\mathbf{x}_{k'}^{t}, \mathbf{v}_{k'}^{t}, \mathbf{w}_{k'}^{t}; \mathbf{g}_{v}^{t}, \mathbf{g}_{w}^{t}) = \max_{\delta_{k'}^t, \boldsymbol{\lambda}} \ \delta_{k'}^t \\
&s.t. \ \sum_{k=1}^{K}\lambda_k v_{m,k}^t \geq v_{m,k'}^t + \delta_{k'}^t g_{v,m}^t \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k w_{j,k}^t = w_{j,k'}^t - \delta_{k'}^t g_{w,j}^t \quad \forall j = 1,\cdots,J \qquad \text{(LP0)} \\
&\sum_{k=1}^{K}\lambda_k x_{n,k}^t \leq x_{n,k'}^t \quad \forall n = 1,\cdots,N \\
&\lambda_k \geq 0 \quad \forall k = 1,\ldots,K
\end{aligned}
$$

LP0 is a traditional DEA model under a CRS technology that satisfies free disposability of the inputs and good outputs, as well as weak disposability for outputs. In this approach, the shadow price of bad output can be positive or negative. Since we consider that pollution is always a societal cost, we explicitly impose a negative shadow price on undesirable output by changing the equal sign in LP0 to inequality sign "$\leq$" in LP1.

Primal directional distance function under an individual technology

10

$$
\begin{aligned}
D^t(\mathbf{x}^{\mathbf{t}}_{\mathbf{k'}}, \mathbf{v}^{\mathbf{t}}_{\mathbf{k'}}, \mathbf{w}^{\mathbf{t}}_{\mathbf{k'}}; \mathbf{g}^{\mathbf{t}}_{\mathbf{v}}, \mathbf{g}^{\mathbf{t}}_{\mathbf{w}}) &= \max_{\delta^t_{k'}, \lambda} \ \delta^t_{k'} \\
s.t. \ \sum_{k=1}^{K} \lambda_k v^t_{m,k} &\geq v^t_{m,k'} + \delta^t_{k'} g^t_{v,m} \quad \forall m = 1, \cdots, M \\
\sum_{k=1}^{K} \lambda_k w^t_{j,k} &\leq w^t_{j,k'} - \delta^t_{k'} g^t_{w,j} \quad \forall j = 1, \cdots, J \\
\sum_{k=1}^{K} \lambda_k x^t_{n,k} &\leq x^t_{n,k'} \quad \forall n = 1, \cdots, N \\
\lambda_k &\geq 0 \quad \forall k = 1, \ldots, K
\end{aligned}
\tag{LP1}
$$

In LP1, we can obtain the technical inefficiency for country *k'*. In order to acquire the overall inefficiency at the aggregate level, the following LP2 is demonstrated:

Primal directional distance function under an aggregate technology

$$
\begin{aligned}
D^t(\sum_{k=1}^{K} \mathbf{x}^t_k, \sum_{k=1}^{K} \mathbf{v}^t_k, \sum_{k=1}^{K} \mathbf{w}^t_k; \mathbf{g}^{\mathbf{t}}_{\mathbf{v}}, \mathbf{g}^{\mathbf{t}}_{\mathbf{w}}) &= \max_{\delta^t_G, \lambda} \ \delta^t_G \\
s.t. \ K\sum_{k=1}^{K} \lambda_k v^t_{m,k} &\geq \sum_{k=1}^{K} v^t_{m,k} + \delta^t_G g^t_{v,m} \quad \forall m = 1, \cdots, M \\
K\sum_{k=1}^{K} \lambda_k w^t_{j,k} &= \sum_{k=1}^{K} w^t_{j,k} - \delta^t_G g^t_{w,j} \quad \forall j = 1, \cdots, J \\
K\sum_{k=1}^{K} \lambda_k x^t_{n,k} &\leq \sum_{k=1}^{K} x^t_{n,k} \quad \forall n = 1, \cdots, N \\
\lambda_k &\geq 0 \quad \forall k = 1, \ldots, K
\end{aligned}
\tag{LP2}
$$

Thus, the structural inefficiency at the aggregate level can be derived from the difference between overall inefficiency (LP2) and the summation of technical inefficiency (LP1) (Briec et al., 2003; Färe and Zelenyuk, 2003). This difference exists when we are dealing with quantity and technical inefficiency but disappears when price and profit function are used as proved by Koopmans (1957). Intuitively, the exact aggregation holds for a profit function which is linear in price and quantity terms while it is not the case for a convex technology.

Alternatively, the overall inefficiency can be computed from LP3 which is the dual of LP2.

Dual directional distance function under an aggregate technology

$$
\begin{aligned}
& D^t(\sum_{k=1}^{K}\mathbf{x}_k^t,\sum_{k=1}^{K}\mathbf{v}_k^t,\sum_{k=1}^{K}\mathbf{w}_k^t;\mathbf{g_v^t},\mathbf{g_w^t}) = \min_{\pi^v,\pi^w,\pi^x}(\sum_{m=1}^{M}\pi_m^v\sum_{k=1}^{K}v_{m,k}^t - \sum_{j=1}^{J}\pi_j^w\sum_{k=1}^{K}w_{j,k}^t - \sum_{n=1}^{N}\pi_n^v\sum_{k=1}^{K}x_{n,k}^t) \\
& s.t.\ K\sum_{m=1}^{M}\pi_m^v v_{m,k}^t - K\sum_{j=1}^{J}\pi_j^w w_{j,k}^t - K\sum_{n=1}^{N}\pi_n^v x_{n,k}^t \geq 0 \quad \forall k=1,\cdots,K \\
& \sum_{m=1}^{M}\pi_m^v g_{v,m}^t + \sum_{j=1}^{J}\pi_j^w g_{w,j}^t = 1 \\
& \pi_m^v \geq 0 \quad \forall m=1,\ldots,M \\
& \pi_j^w \geq 0 \quad \forall j=1,\ldots,J \\
& \pi_n^x \geq 0 \quad \forall n=1,\ldots,N
\end{aligned}
\tag{LP3}
$$

The main interest of LP3 is to get the contribution of each country to the overall inefficiency. Then, we can obtain the overall and structural inefficiencies for each individual country k as follows:

$$
\begin{aligned}
& OE_k^t = \sum_{m=1}^{M}\pi_m^v v_{m,k} - \sum_{j=1}^{J}\pi_j^w w_{j,k} - \sum_{n=1}^{N}\pi_n^v x_{n,k} \\
& SE_k^t = OE_k^t - TE_k^t \\
& \Rightarrow SE^{t,t+1} = \sum_{k=1}^{K}SE_k^t - \sum_{k=1}^{K}SE_k^{t+1}
\end{aligned}
\tag{12}
$$

We also provide models without incorporating undesirable output to compare green TFP indexes with traditional productivity indicators through disabling the corresponding constraints of undesirable outputs in relevant primal and dual models.

4. Data and results

4.1. Data

The database is from the Penn World Table and the International Energy Agency. This data covers 30 OECD countries including three groups from 1971−2011: OECD Americas (4 countries: Canada, Chile, Mexico, and the United States), OECD Asia-Oceania (5 countries: Australia, Israel, Japan, the Republic of Korea, and New Zealand), and OECD Europe (21 countries: Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Hungary, Ireland, Iceland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Sweden, and Turkey). The remaining 4 OECD countries (the Czech Republic, Estonia, the Slovak Republic, and Slovenia) are not included due to the lack of available data. We use two inputs, one desirable output, and one undesirable output: namely, capital stock, labor force, real GDP, and carbon dioxide emission, respectively. The

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capital stock uses the perpetual inventory method at current purchasing power parities in millions of 2005 US dollars. The labor force is the number of persons employed among 30 OECD countries in millions. The real GDP is output-side at current purchasing power parities in millions of 2005 US dollars. These three inputs and one good output are from the Penn World Table 8.1 (Feenstra et al., 2015) provided by the University of Groningen. The bad output (carbon emission) is based on a sectoral approach from fuel combustion in millions of tons (International Energy Agency, 2014).

Table 1 shows the average growth rates of inputs and outputs. From Table 1, we find that the GDP growth is driven by OECD Asia-Oceania which also maintains the highest increasing rates in capital stock (5.12%) and carbon emissions (2.10%). OECD Americas attracts a greater work force which maintains the highest growth rate at 1.72%. OECD Europe has the lowest trend in carbon emissions (only 0.07%). This low trend potentially proves that good policies of environmental protection or industrial technological adjustments to high energy consumption have been effectively executed in Europe. In Figure 2, the negative trend of carbon emissions per unit of GDP (-2.25%) suggests that low-carbon requirements of the production process improve environmental performance in the OECD.

Table 1 about here

Figure 2 about here

4.2. Results and discussion

Technical inefficiency measures gaps between the observed production plans and their best practices, while structural inefficiency components are estimated through differences between overall and technical inefficiency scores. Their evolution over time is displayed in Figures 3, 4, and 5, respectively. OECD Europe accounts for the main technical inefficiency before OECD Americas catches up to that level in 2004. OECD Americas dominates the primary parts of structural inefficiencies from 1997−2009 which leads to a falling trend in structural efficiency change for the all the OECD countries. For OECD Asia-Oceania, their evolutions of technical and structural inefficiencies are both relatively stable compared to the other two groups. We notice that structural inefficiency scores of OECD Europe show an increasing tendency after 2008 during the period of the European debt crisis. However, we note that OECD Asia-Oceania has no similar progress in structural inefficiency scores during the period of the Asian financial crisis. Woo et al. (2015) argue that environmental efficiency is affected by global financial crisis. In our results, we cannot confirm whether the structural inefficiency is directly related to the relevant financial crisis. From Figures 3, 4, and 5, we also detect a significant inefficiency fluctuation for OECD Americas which is mainly caused by the United States during the period of 1998−2009 which is no longer a benchmark. Because the weight of the United States in the total sample is huge compared to the other individual countries, its directional inefficiency scores are therefore high and impact significantly on the score evolutions of OECD America.

Figure 3 about here

Figure 4 about here

Figure 5 about here

In Figure 6, our empirical results show that the technical efficiency component of the TFP indexes keeps a growth rate at around 0.1% from 1975−2000, and then it shows a declining trend and reaches the bottom in 2005. In Figure 7, the structural efficiencies in 30 OECD countries show an increasing trend from 1973−1993 and a declining movement from 1993−2008.

Figure 6 about here

Figure 7 about here

Although these significant declines arise in the technical efficiency and structural efficiency in the late stage of the period, the green TFP maintains an increasing trend at all times, which is attributed to a weighty rise in technology progress as shown in Figure 8 and Figure 9. This is consistent with the empirical results of Mahlberg and Sahoo (2011) who argue that productivity growth in most of OECD countries during the period of 1995−2004 is dependent on their technology progress only. Our results also reveal the lowest fluctuations for the TFP index and its three components (technical efficiency, structural efficiency, and technology progress) when undesirable outputs are explicitly included in the referent technology. In Figure 9, the trend of TFP index with undesirable output is 0.82%, which indicates that the productive performance of the OECD group is underestimated by the traditional approach if carbon emissions are ignored (0.49%). Similarly, Yörük and Zaim (2005) argue that the Malmquist indexes undervalue the Luenberger indicators for the OECD countries from 1983−1998. The green productivity growth can be attributed to improved environmental and technological situations in the OECD, which is consistent with Mahlberg

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et al.'s conclusions (2011). One can note a substantial decrease after 2007 in the traditional productivity index, while the green TFP maintains a more or less flat trend. This TFP gap may be due to the correlation between carbon emissions and GDP downturns, which, in the end, do not significantly impact the green TFP level but do negatively affect traditional TFP through a decline of the good output.

Figure 8 about here

Figure 9 about here

5. Conclusions and further work

We attempt to employ a Luenberger productivity index incorporating carbon emission into TFP measures for a group of 30 OECD countries. According to our empirical results, several conclusions can be drawn.

(1) The traditional TFP index without considering carbon emissions underestimates that of green growth as a result of effective and efficient environmental protection policies in OECD countries during the sample period. Meanwhile, the green TFP level is maintained after the financial crisis in 2008, while the traditional measure shows a significant drop. This green productive performance is motivated by upgraded environmental situations in the OECD and could be evidence for rational thinking about the trade-off between economic growth and environmental cost.

(2) Improvements of technical and structural efficiencies mainly contributed to the green TFP growth from 1971−2000, while technological progress contributes the remainder during the sample period. This result indicates that technological progress becomes a dominant force in productivity growth in the 21st century.

(3) Our results reveal the presence of substantial structural effects on TFP evolution for the OECD that have not previously been quantified. This structural component captures potential improvement space of productivity growth if OECD countries can converge to more homogeneous input or output mixes. We also notice that decreases in structural efficiency from 1997−2009 are mostly dependent on a decline of that component for OECD Americas. The structural proxy can be accompanied by dynamic evolution of resource reallocation in the economic organization.

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In this paper, most of sample countries are developed countries, and we cannot identify whether the productivity evolution of other developing countries is also motivated by their environmental conditions. To further determine the value of sustainable development and ecological innovations, possible future work could calculate green productivity growth and carbon abatement costs for additional groups of developed and developing countries. Intergovernmental cooperation plays an increasingly important role in global environmental governance, such as the Kyoto Protocol proposed by the United Nations Framework Convention on Climate Change in 1997. A positive correlation between environmental performance and carbon emission protocol has been detected by Yörük and Zaim (2005), and it seems essential in analyzing the potential influence of new international treaties and intergovernmental negotiations. In that way, future researches could also be further extended at a worldwide level for countries engaged in treaties, such as the Copenhagen Accord or the Kyoto Protocol.

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Table 1: Average growth rates of inputs and outputs (1971−2011)

Regions	Capital Stock	Labor Force	Real GDP	CO_2
OECD Americas	3.19%	1.72%	2.93%	0.84%
OECD Asia-Oceania	5.12%	0.95%	3.61%	2.10%
OECD Europe	3.29%	0.55%	2.87%	0.07%
Total OECD	3.57%	1.04%	3.02%	0.76%

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Figure 1: Illustration of structural efficiency

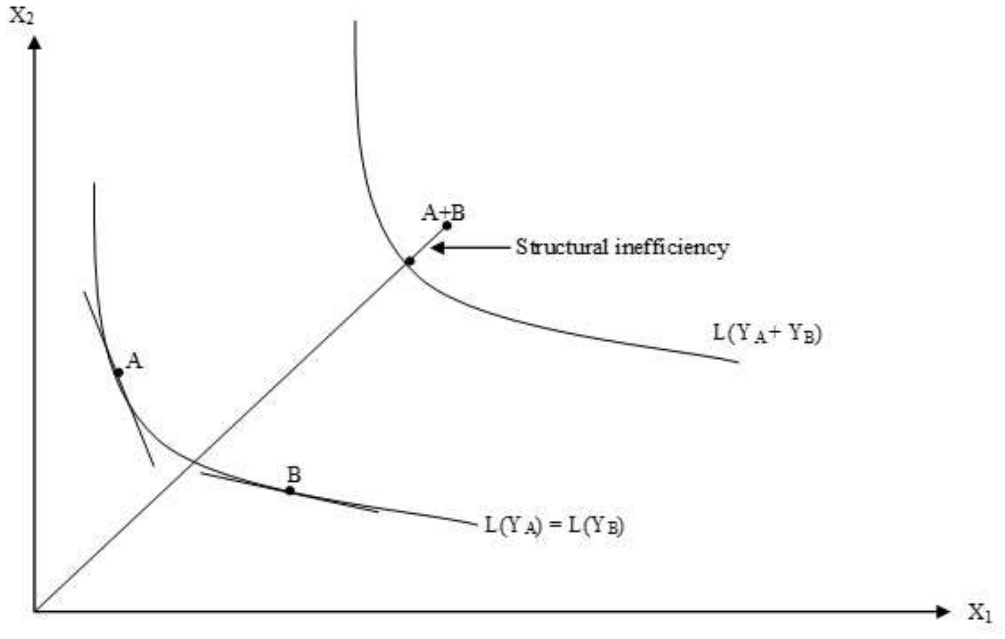

Figure 2: Evolutions of input and output indexes for the OECD (in logarithm terms)

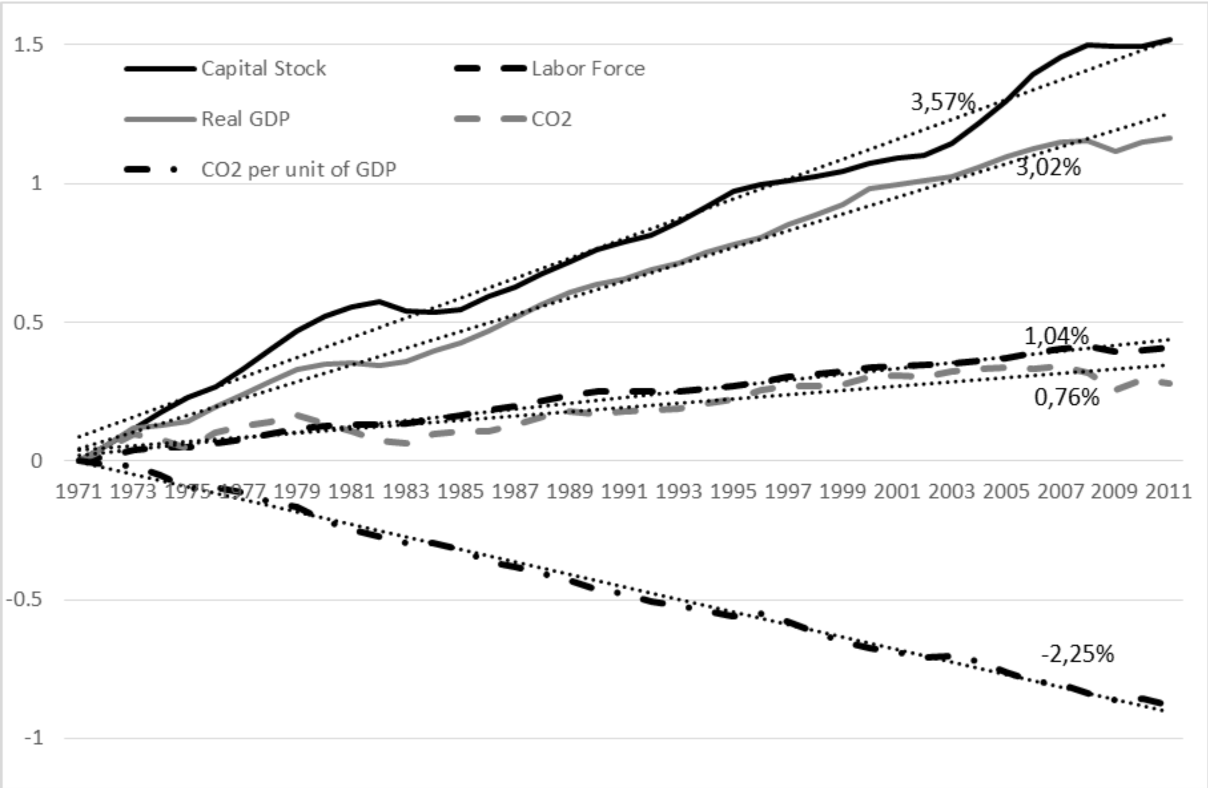

Figure 3: Technical inefficiency scores for groups

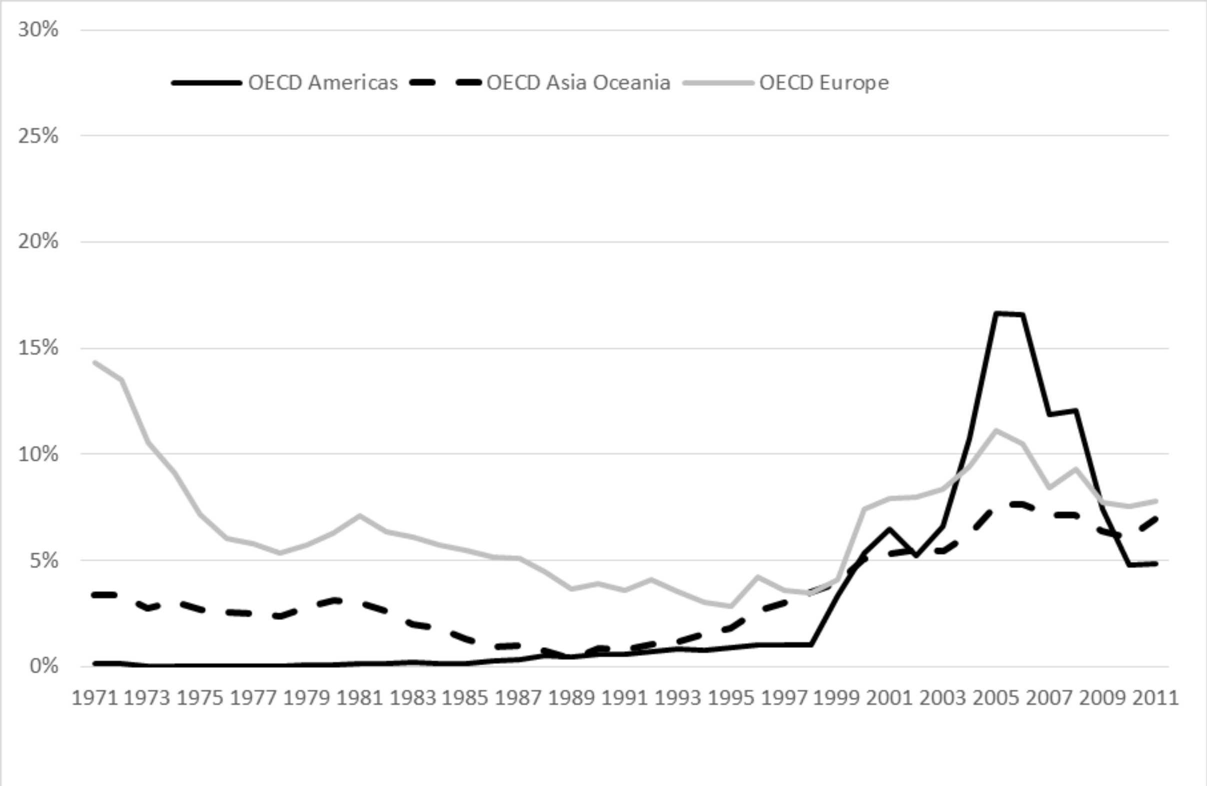

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Figure 4: Structural inefficiency scores for groups

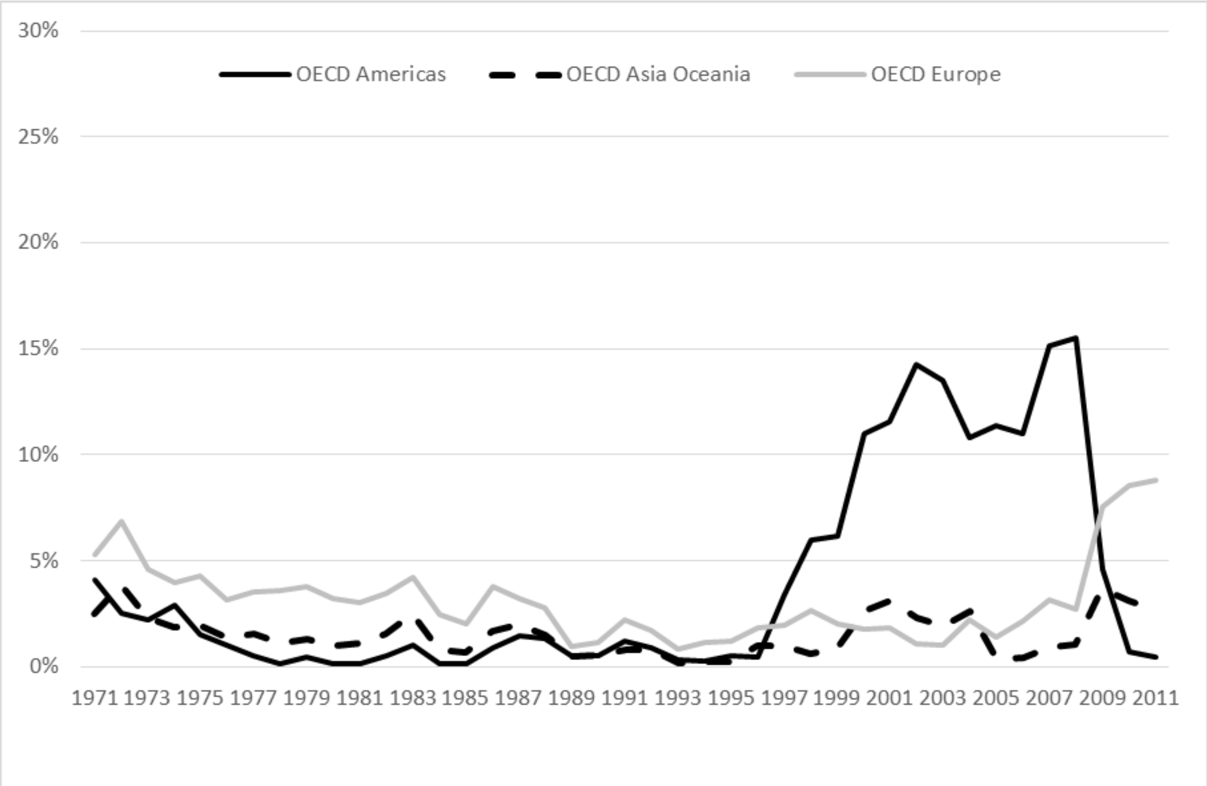

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Figure 5: Overall inefficiency scores for groups

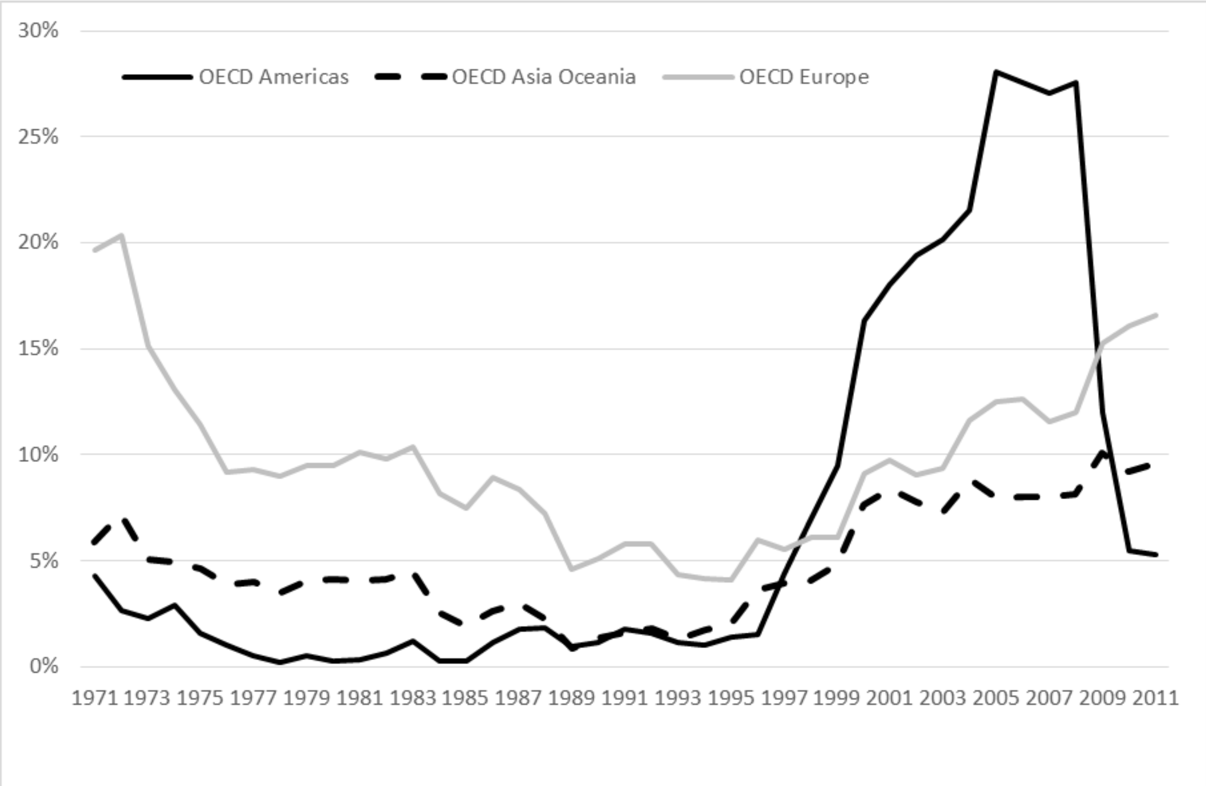

Figure 6: Technical efficiency index for the OECD (in logarithm terms)

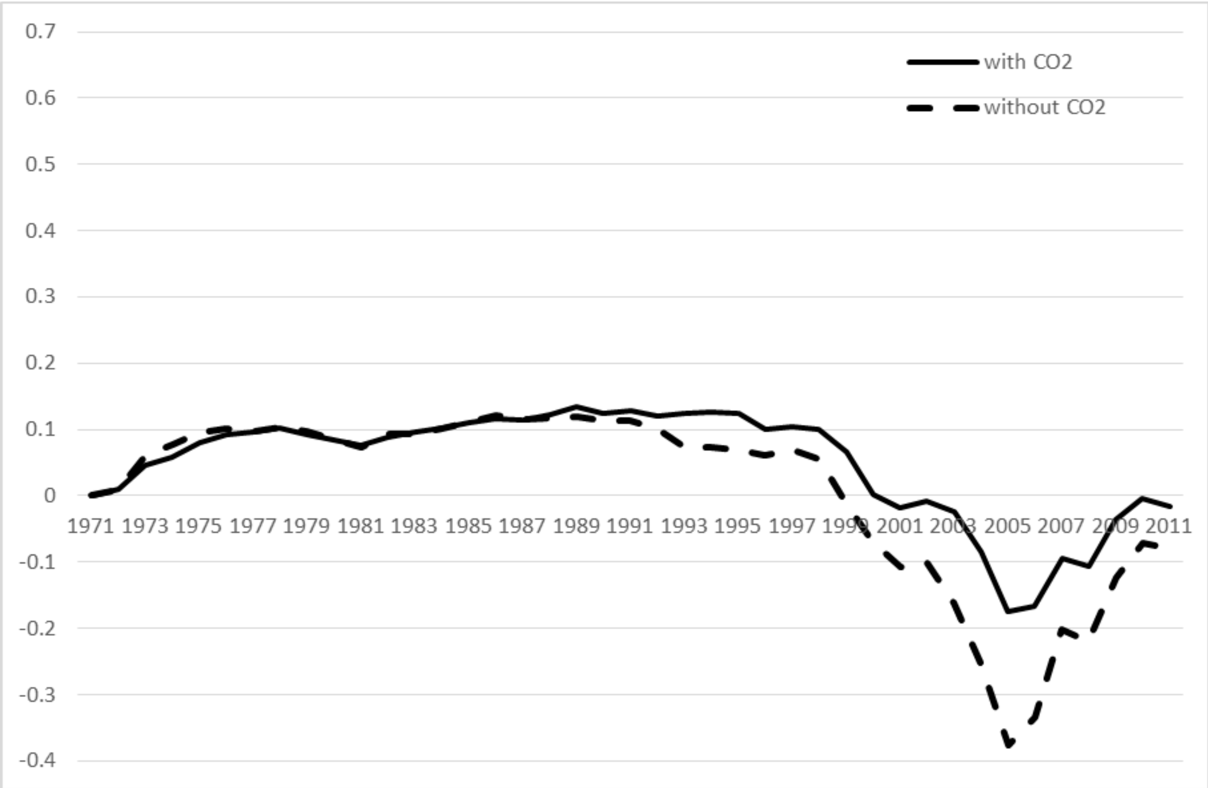

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Figure 7: Structural efficiency index for the OECD (in logarithm terms)

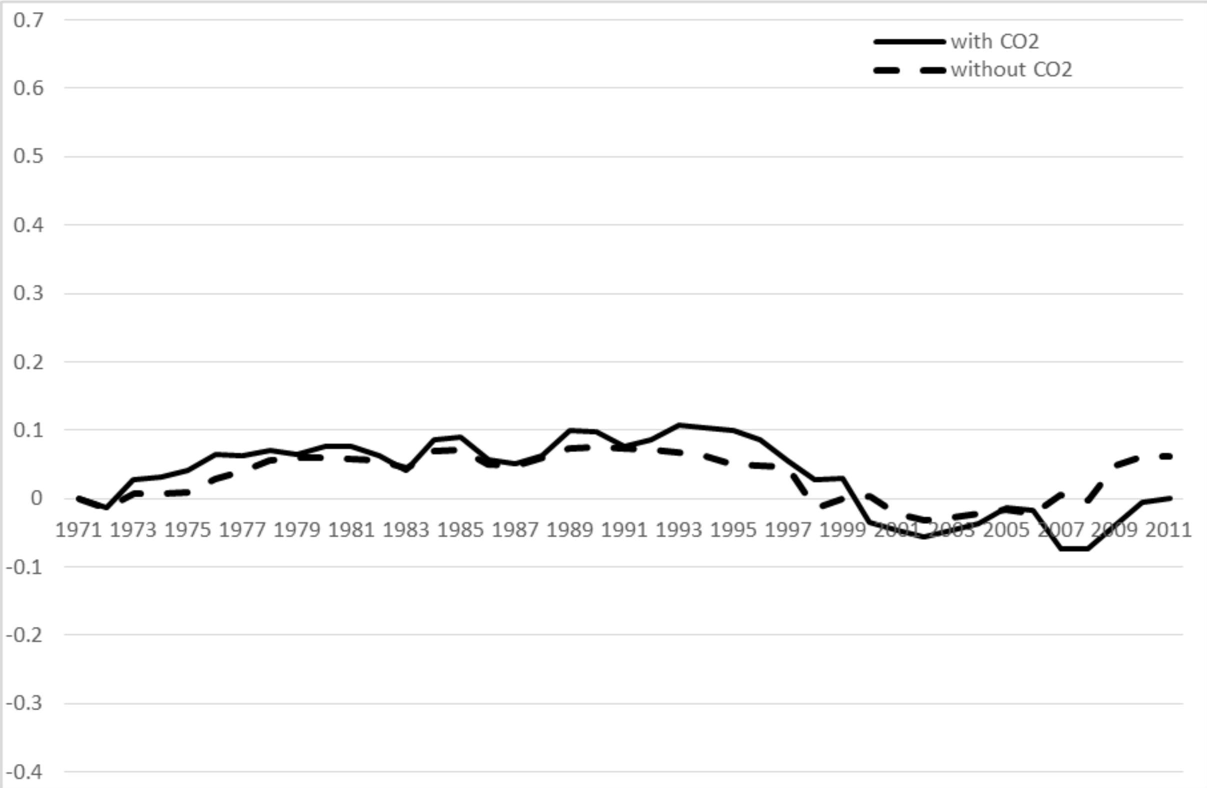

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Figure 8: Technical progress index for the OECD (in logarithm terms)

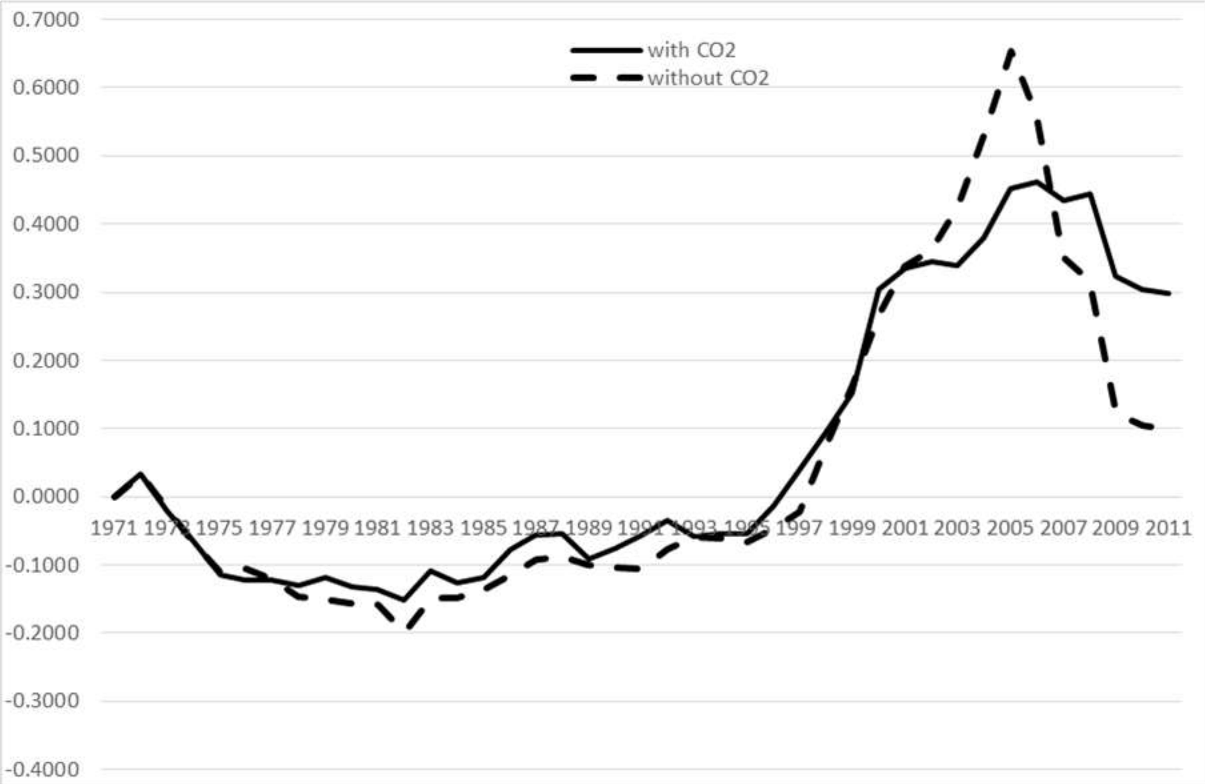

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Figure 9: TFP index for the OECD (in logarithm terms)