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Essays on Green Productivity

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Essais pour une mesure de productivité durable

Résumé:

Pour faire face à une croissance continue de la population et maintenir un haut niveau de développement économique, les activités de production font porter un fardeau de plus en plus lourd à l'environnement naturel. Aujourd'hui, l'enjeu est clairement de se tourner vers un développement économique durable. Par conséquent, l'analyse de la relation entre les activités de production et leur impact environnemental attire beaucoup d'attention. Cette thèse a pour objectif de prendre en compte les externalités négatives liées aux outputs indésirables dans l'estimation d'une technologie de production et cherche à étudier leur impact sur la performance économique en général et sur la mesure des gains de productivité en particulier. L'intégration des externalités négatives comme les émissions de carbone dans la mesure de la productivité globale des facteurs fait référence à la notion de « productivité durable » ou de « green productivity ». Ce travail de thèse s'appuie sur une définition et une estimation non paramétrique des technologies de production pour lesquelles les fonctions distance directionnelles sont des outils appropriés pour définir et mesurer des indicateurs de productivité incluant une notion d'efficacité environnementale. Grâce à quelques développements méthodologiques originaux, nous parvenons à de nouveaux indicateurs de productivité totale des facteurs et à l'estimation de prix implicites des émissions de carbone pour les différents pays développés et en développement. Sur la base des résultats de nos analyses empiriques, nous tentons ainsi d'apporter des informations utiles aux décideurs et aux pouvoirs publics pour l'évaluation des réglementations environnementales entre pays et pour la définition de nouvelles politiques économiques respectueuses de l'environnement.

Mots-clés: Productivité Globale des Facteurs, Productivité Durable, Environnement, Outputs Indésirables, Data Envelopment Analysis, Prix Implicites, Emissions de Carbone.

Essays on Green Productivity

General Abstract:

As economic development and population growth, human's production activity lays a heavy burden on the natural environment. In order to maintain sustainable development, investigating the relationship between economic development and environmental impact has received much attention. This thesis takes into account undesirable factors in production technology and tries to integrate the negative externality of carbon emissions into the measurement of economic performance, referred to as green productivity. This thesis employs a nonparametric estimation approach with directional distance function to analyze environmental efficiency, total factor productivity, and carbon shadow prices among different developed and developing countries at the macro level. We propose new contributions to the measurement and decomposition of productivity indices which capture environmental efficiency. Based on empirical results, we discuss the current environmental regulations and economic policies among countries, to provide useful information for decision and policy makers from an economic point of view.

Keywords: Total Factor Productivity, Green Productivity, Environment, Undesirable Outputs, Data Envelopment Analysis, Shadow Prices, Carbon Emissions

Essais pour une mesure de productivité durable
Résumé substantiel

1. Objectif général de la thèse

Pour faire face à une croissance continue de la population et maintenir un haut niveau de développement économique, les activités de production font porter un fardeau de plus en plus lourd à l'environnement naturel. Aujourd'hui, l'enjeu est clairement de se tourner vers un développement économique durable. Par conséquent, l'analyse de la relation entre les activités de production et leur impact environnemental attire beaucoup d'attention. Cette thèse a pour objectif de prendre en compte les externalités négatives liées aux outputs indésirables dans l'estimation d'une technologie de production et cherche à étudier leur impact sur la performance économique en général et sur la mesure des gains de productivité en particulier. L'intégration des externalités négatives comme les émissions de carbone dans la mesure de la productivité globale des facteurs fait référence à la notion de « productivité durable » ou de « green productivity ». Ce travail de thèse s'appuie sur une définition et une estimation non paramétrique des technologies de production pour lesquelles les fonctions distance directionnelles sont des outils appropriés pour définir et mesurer des indicateurs de productivité incluant une notion d'efficacité environnementale. Grâce à quelques développements méthodologiques originaux, nous parvenons à de nouveaux indicateurs de productivité totale des facteurs et à l'estimation de prix implicites des émissions de carbone pour les différents pays développés et en développement. Sur la base des résultats de nos analyses empiriques, nous tentons ainsi d'apporter des informations utiles aux décideurs et aux pouvoirs publics pour l'évaluation des réglementations environnementales entre pays et pour la définition de nouvelles politiques économiques respectueuses de l'environnement.

2. Structuration de la thèse, objectifs méthodologiques et principaux résultats

Cette thèse est structurée autour de cinq chapitres. Le premier expose les aspects théoriques et méthodologiques des modèles d'analyse d'activité à la base des mesures de la productivité durable. L'un des défis majeurs pour ces modèles est d'intégrer explicitement les externalités négatives comme les émissions de carbone dans l'analyse des processus de production.

Dans un premier temps, la technologie de production est introduite grâce à la définition de l'ensemble des possibilités de production. Celle-ci repose sur une liste d'axiomes qui introduisent les conditions de régularité de l'ensemble des possibilités de production. Ces axiomes permettent de définir des fonctions distance en tant qu'instruments de mesure associés à la technologie de production. Les méthodes d'estimation de ces fonctions distance sont généralement réparties en deux grandes catégories : les approches paramétriques et non paramétriques. Dans cette thèse, nous avons privilégié une méthode non paramétrique d'estimation des fonctions distance par l'outil Data Envelopment Analysis (DEA) basé sur la programmation linéaire.

Dans un deuxième temps, nous nous intéressons aux technologies intégrant les outputs indésirables (émissions de carbone) et à leurs prix implicites que l'on peut calculer à partir des liens existant entre les programmes dual et primal. Enfin, nous donnons quelques extensions méthodologiques permettant d'élaborer des indicateurs de mesure de la productivité durable comme l'indice de productivité de Luenberger.

Le chapitre 2 développe une analyse de la prise en compte des aspects environnementaux sur le processus de croissance économique de la Chine qui depuis 2008 est devenu le pays émettant le plus de dioxyde de carbone au monde. Plus précisément, cette recherche estime les inefficacités productives de 30 provinces chinoises et leurs prix implicites respectifs pour les émissions de carbone sur une période allant de 1997 à 2010. Nous concluons qu'avec la prise en compte de la pollution dans les mesures de la performance productive, il existe un processus de convergence des prix implicites et de rattrapage technologique entre ces territoires économiques. Globalement au niveau de la Chine, le prix implicite des émissions de carbone s'est accru à un taux annuel moyen de 2,5% pour atteindre un niveau de 864 yuans par tonne en 2010.

Le chapitre 3 tente d'établir si la croissance économique des pays développés est associée ou non à des politiques environnementales efficientes. Sur base des informations macroéconomiques et d'émissions de carbones relatives à 30 pays de l'OCDE au cours de la période 1971-2011, nous décomposons les gains de productivité globale des facteurs en trois éléments : efficience technique, progrès technique et effet de réallocation des ressources factorielles pour discerner lequel de ces effets exerce un effet prépondérant sur les gains de productivité durable. Nos résultats indiquent que l'indice traditionnel de productivité globale des facteurs sous-estime les gains de productivité durable et que celle-ci est principalement tirée par le progrès technique.

Après les études des cas de la Chine et des pays développés, nous développons une analyse au niveau mondial dans le chapitre 4. Cette analyse s'attache à estimer les prix implicites des émissions de carbone pour 119 pays répartis en douze grandes zones géographiques au cours de la période 1990-2011. L'objectif de ces estimations est d'une part de mesurer les coûts d'opportunité entre croissance économique et diminution des émissions de carbone pour ces groupes de pays et d'autre part de voir si un processus de convergence de ces coûts d'opportunité existe ou non entre ces zones géographiques. Nos résultats empiriques indiquent qu'au niveau mondial le prix implicite des émissions de carbone augmente à un rythme tendanciel de 2,24% et atteint 2845 US$ par tonne en 2011. Un processus de sigma convergence des prix implicites du dioxyde de carbone est clairement identifié jusqu'en 2007 entre les groupes de pays tandis qu'à partir de 2008 (début de la crise financière mondiale) un mouvement de forte divergence apparait.

A titre exploratoire, le chapitre 5 propose deux extensions méthodologiques sur la prise en compte des externalités négatives dans les modèles d'analyse d'activités. La première, relative à la loi du prix implicite unique, impose un prix dual commun par output indésirable pour toutes les entités évaluées alors que l'approche traditionnelle tolère à chacune d'entre elles d'avoir un prix spécifique. La seconde s'intéresse aux processus de production associés stipulant qu'il existe à la fois une technologie de production d'outputs désirables et une technologie de production d'outputs indésirables. Par rapport à la formulation initiale de cette approche proposée par la littérature, nous proposons quelques améliorations techniques qui sont testées à partir de simulations préliminaires.

Mots-clés: Productivité Globale des Facteurs, Productivité Durable, Environnement, Outputs Indésirables, Data Envelopment Analysis, Prix Implicites, Emissions de Carbone.

List of Publications

This Ph.D. thesis is based on three essays from which the following papers have been written:

(1) Boussemart J.-P., Leleu H., Shen Z., (2015). Environmental Growth Convergence among Chinese Regions, *China Economic Review*, 34: 1-18.

-A first version is published at working paper series of IÉSEG School of Management, 2014-EQM-07. This paper was presented at BRICS workshop of IÉSEG School of Management in Paris, 2014, and at The 14th European Workshop on Efficiency and Productivity Analysis in Helsinki, 2015.

(2) Aggregate Green Productivity Growth in OECD'S Countries. This paper is submitted to *International Journal of Production Economics*.

-A first version is available from Discussion/Working papers of LEM-CNRS, DP2016-03. This paper was presented in an internal Economics seminar at University of Lille1, 2016.

(3) Worldwide Carbon Shadow Prices during 1990 – 2011. This paper is submitted to *Energy Policy*.

-A first version is available from Discussion/Working papers of LEM-CNRS, DP2016-04.

Table of contents

General Introduction

1. Background of the dissertation

In recent centuries, human activities have significantly affected the natural environment, due to economic productivity growth and population increase and the requisite need for fossil fuels. Nowadays, the green or low carbon growth is advocated by economists and policy makers, due to environmental deterioration which has a counteractive effect on the economic performance, caused by undesirable factors (or bad outputs or bad by-products) generating throughout production activity. A classical pollution indicator is carbon dioxide emissions which forms the main part of greenhouse gases. The global warming caused by greenhouse gases catches much attention throughout the world due to the threat of melting glaciers, extreme weather changes, flooding, and droughts. Not only have relevant strategies been developed by individual countries, numerous corresponding international organizations, negotiations and forums were also established for controlling this threat and risk based on the intergovernmental cooperation among regions and countries. Evaluation of the environmental productivity and costs of production activities can provide useful information for policy makers, who can then make justified and informed decisions for economic, social and environmental sustainability.

The relationship between environmental impact and economic growth has attracted much attention. The Environmental Kuznets Curve (EKC) is a well-known hypothesis which assumes an inverted U shaped evolution between environmental impact (pollutants) and economic growth (per capita income). In Figure 1, average pollutant increases initially with a rise in average income, then environmental quality improves when income peaks at a turning point.

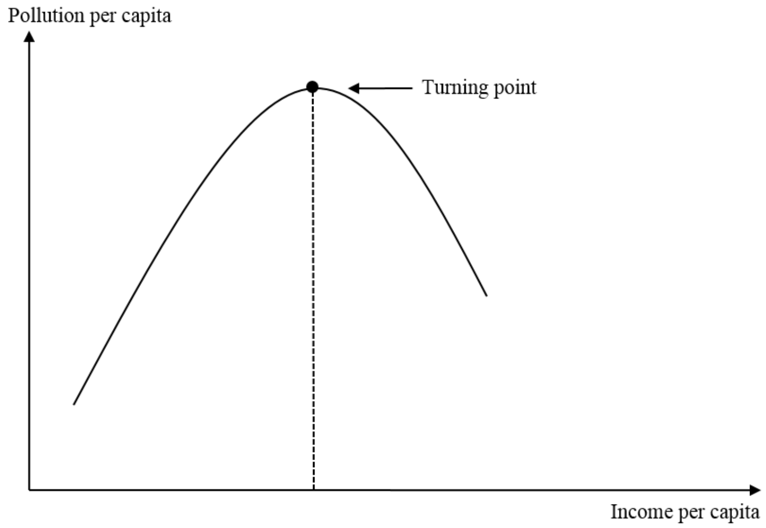


Figure 1 Environmental Kuznets Curve

This hypothesis postulates that environmental issues may be resolved automatically by the market mechanism without government interventions, and environmental tendency may be dependent on whether the country is on the left hand or right hand side of the turning point. Much literature proves the existence of the EKC using empirical estimations. We know that the emission right of carbon dioxide is similar to a public good because it is neither rivalrous nor excludable. One question may arise: is it possible that economic development can become sustainable without any government interventions for each country? If not, then we have to impose taxes on pollution and to introduce pollution permits. Then, the emission right of carbon dioxide may become a private good because it is both rivalrous and excludable. In fact, the agreement signings of the Kyoto Protocol in 1997, the Copenhagen Accord in 2009, and the Paris Climate Conference in 2015 confirm the necessity of government interventions and intergovernmental cooperation. Studying the impact of undesirable factors on economic performance can ensure environmental policies and regulations made by policy and decision makers are valid, effective and efficient.

Incorporating undesirable factors into economic performance evaluations has arisen in the recent analytic literature. Ecologists and economists both proposed various approaches and models to evaluate environmental efficiency, green productivity, and pollution abatement costs including Computational General Equilibrium model, Cost Benefit Analysis, Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). Debates have arisen in choosing a good approach for obtaining interpretable and rational results.

2. Research objectives and thesis outline

The methods for modeling undesirable outputs in the production process are at the heart of the thesis. In chapter 1, we review general economic concepts for modelling production technologies, defining productivity index and incorporating undesirable outputs into the definition of a green productivity index. We begin by introducing the production technology defined by production set which allows imposing some economic regularity conditions, referred to as axioms on production set. In order to assess the production set, we present distance functions as the measurement which is an equivalent representation of production technology. Estimations of distance functions are usually categorized into the parametric and nonparametric approaches, and DEA is a tool of linear programming for the nonparametric estimation employed by this thesis. We further discuss production technologies with undesirable outputs, and shadow prices of undesirable outputs based on primal and dual programs, and give extensions to green productivity measurement, such as the Luenberger productivity index.

In order to investigate the environmental impact on economic development and sustainability, in chapter 2 we begin by conducting research on the most polluted developing country, China, which has become the largest carbon dioxide emitter since 2008. The aim of the first paper is to estimate regional efficiency gaps and carbon shadow price levels for 30 Chinese provinces. We discover that there is an environmental growth convergence among regions. Then, we compare the results with and without incorporating carbon dioxide emissions into the production activity.

In chapter 3, we examine the case of developed countries, and we choose 30 industrialized countries from the Organization for Economic Co-operation and Development (OECD). These countries represent the most advanced productive forces in the world and environmental conditions are much better than developing nations. We attempt to discover whether economic growth in developed countries is driven by effective and efficient environmental policies, and which element contributes most to the aggregate green Total Factor Productivity (TFP) growth, from technology progress or technical efficiency or an effect of resource reallocation.

Besides environmental efficiency and productivity, the shadow prices of undesirable outputs can also provide useful information for environmental regulators and policy makers, such as carbon shadow prices implies the amount of revenue that producers have to give up for a certain amount of carbon emission abatement. After exploring the cases of China and OECD countries, we extend the horizon to the whole world: chapter 4 is to estimate carbon shadow prices for 119 countries from all continents in twelve large groups. The target is to determine the carbon shadow prices that are either convergent or dispersed among the twelve regions. We then discuss the effect of global environmental agreements (e.g. the Kyoto Protocol) on the evolution of carbon shadow prices.

In chapter 5, we further discuss two models: one is a law of one shadow price model which imposes a global constraint on shadow price estimation of bad outputs, and another is extension of by-production model, we point out some possible improvements on this model and a preliminary simulation result for comparing with weak disposability model is included.

3. Summary of research papers

3.1. Summary of Paper I

Since the end of the 20th century, numerous studies have analyzed Chinese economic development to gauge whether China's rapid growth is sustainable. Most of these studies focused on assessing TFP growth in Chinese mainland provinces but suffered from methodological weaknesses by assuming constant returns to scale (CRS) technology for the production frontier and/or incorrectly modeling variable returns to scale (VRS) technology taking into account bad output such as carbon dioxide emissions. This paper offers a defensible non-parametric programming framework based on weak disposability and VRS assumptions to estimate environmental growth convergence among Chinese regions characterized by size heterogeneity. We explicitly separate regional efficiency gaps into two components: The first studies the technical catching-up process on each one (technical effect), and the second reveals convergence or divergence in the combinations of input and output among regions (structural effect). Moreover, carbon shadow price levels for provinces can be derived through the dual version of our activity analysis framework. Our empirical work focuses on 30 Chinese regions from 1997 to 2010. The results emphasize that environmental growth convergence among regions has mainly relied on the structural effect. We find that the structural effect largely depends on the pollution cost convergence and not on the evolution of the relative prices of capital or labor. The carbon shadow price is increasing at an annual rate of 2.5% and was evaluated around 864 yuan per ton in 2010 in China while regional estimates show significant disparities at the beginning of the period.

3.2. Summary of Paper II

Most of previous research about TFP growth 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.

3.3. Summary of Paper III

Unlike most previous research efforts, which have focused on estimating carbon shadow prices at regional or sectoral levels, this paper attempts to estimate carbon shadow prices at a worldwide level. A non-parametric robust framework estimates carbon shadow prices for 119 countries from all continents in 12 large groups. Our empirical results reveal that the global carbon shadow price is increasing by around 2.24% per annum and reached $2,845 in US dollars per ton in 2011. Regional carbon shadow prices present significant disparities and evolve within different categories over the analyzed period. We find a substantial sigma convergence process of carbon shadow prices among countries during 1990–2007 while divergence appears after the global financial crisis. We then analyze the relationship between carbon shadow prices and the implementation of the Kyoto Protocol.

Chapter 1

Environmental Production Technologies and Green Productivity

Economy, society and environment are inextricably linked to global welfare. Productivity is an important indicator for assessing economic development and can be measured as the rate of output per unit of input. Usually, production technologies only include desirable outputs and inputs because people tend to emphasize economic growth while ignoring environmental costs. Then the reduction of social well-being usually forces us to reconsider about pollution problems when environmental costs are over economic values. In this context, this chapter tries to review production technologies and productivity efficiency measurements without/with undesirable outputs.

First, the definition and specification of classical production technologies and axioms of activity analysis models are reviewed. Next, we introduce distance functions as the measurement tool on production possibility sets, which can be estimated by parametric and nonparametric approaches. In Section 2 undesirable outputs into production sets are introduced and environmental technologies focusing on nonparametric estimations are discussed. In the third section dual formulations of analytic models, shadow prices, and productivity indicators are extended.

1. Modeling production technologies by production sets

1.1. Definition and specification of the production sets

Parametric or nonparametric approaches, whatever is applied, understanding theoretical production principles behind productive reality are critical to model production functions. The seminal works of Koopmans (1951), Debreu (1951) Shephard (1953), and Farrell (1957) have developed the basis of the Neo-Walrasian production theory based on production possibility sets. We start a basic production technology without considering undesirable outputs. Assume that decision making units (DMUs) have N number of inputs (x) can be used to produce M number of outputs (y). The classical production possibility set (or technology) can be defined as follows:

$$T = \left\{ (\mathbf{x}, \mathbf{y}) \in R_{+}^{N+M} : \mathbf{x} \text{ can produce } \mathbf{y} \right\} \qquad (1)$$

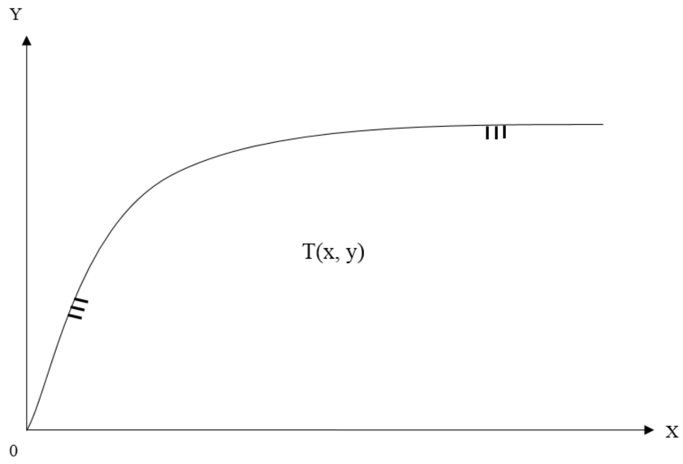


Figure 1 Production possibility set

As shown in Figure 1, the production technology is convex and can also be represented by an output set: all possible output combinations that can be produced by a given level of inputs. The output correspondence is defined as:

$$P(\mathbf{x}) = \left\{ \mathbf{y} \in R_{+}^{M} : (\mathbf{x}, \mathbf{y}) \in T \right\} \qquad (2)$$

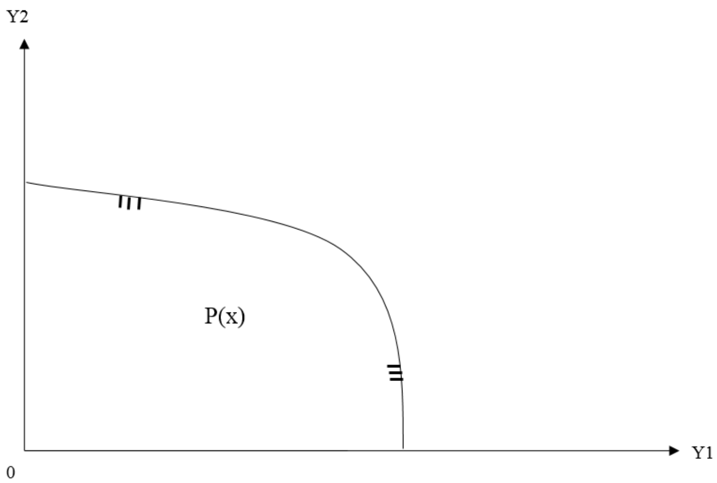


Figure 2 Output correspondence

In Figure 2, this output correspondence is closed, and feasible output combinations are between two axis and frontier. Similarly, the production technology can be characterized by an input set, namely all possible input combinations that can produce a given level of outputs in Figure 3. The input correspondence is defined as:

$$L(\mathbf{y}) = \left\{ \mathbf{x} \in R_{+}^{N} : (\mathbf{x}, \mathbf{y}) \in T \right\} \qquad (3)$$

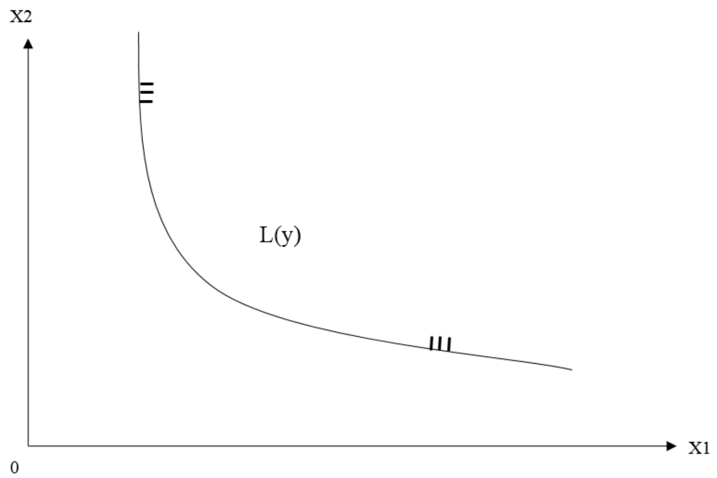


Figure 3 Input correspondence

Both output correspondence (*P(x)*) and input correspondence (*L(y)*) are equivalent representation to production possibility set (*T*).

1.2. Axioms on production sets

In order to make sure the technology is able to satisfy reasonable economic assumptions, general axioms can be defined for production sets. Initially, three basic axioms are usually imposed on the production possibility set (Shephard, 1953).

$$\begin{aligned} &A1: (0,0) \in T \text{ and if } (y,0) \in T \ then\ y = 0. \\ &A2: T\ is \text{ closed.} \\ &A3: For\ each\ input\ x \in R_{+}^{N},\ T\ is\ bounded. \end{aligned} \qquad (4)$$

A1 assumption emphasizes it is always feasible to produce nothing and moreover that there is no free lunch, namely outputs cannot be generated if inputs are null. A2 and A3 guarantee that unlimited outputs cannot be produced by given inputs and efficient production plan onto the frontier belong to the technology. Beside the latter basic axioms, three other assumptions (disposability of inputs and outputs, convexity and returns to scale) are often introduced into production sets.

A Free Disposal Hull (FDH) frontier is proposed by Deprins et al. (1984), it is non-convex and can be figured in Figure 4.

$$A4: if\ (x,y)\in T\ then\ (\tilde{x},\tilde{y})\in \mathrm{T}\ for\ all\ (-\tilde{x},\tilde{y})\leq(-x,y). \quad (5)$$

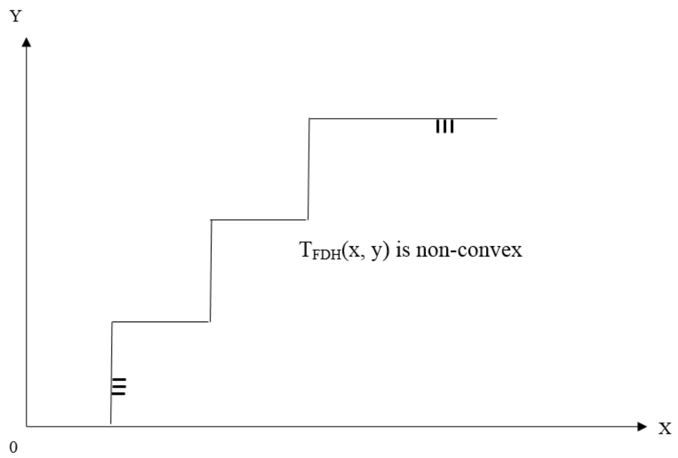


Figure 4 Free Disposal Hull

A4 axiom implies free (strong) disposability of inputs and outputs: given outputs can be produced by more inputs than is absolutely necessary, or given inputs can produce less outputs. A free disposability of outputs can be interpreted in Figure 5. Alternatively, a weak disposability assumption indicates that outputs and inputs cannot be disposed freely but proportional decrease is allowed. A weak disposability of outputs is shown in Figure 6 and its axioms is discussed in Section 2.1.2.

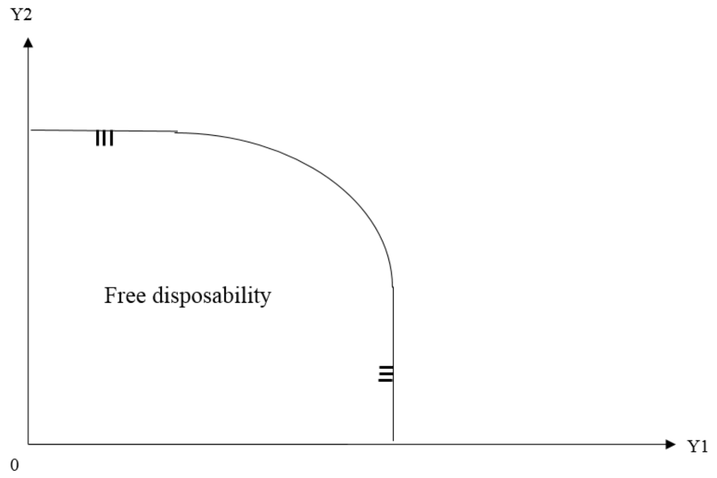


Figure 5 Free disposability of outputs

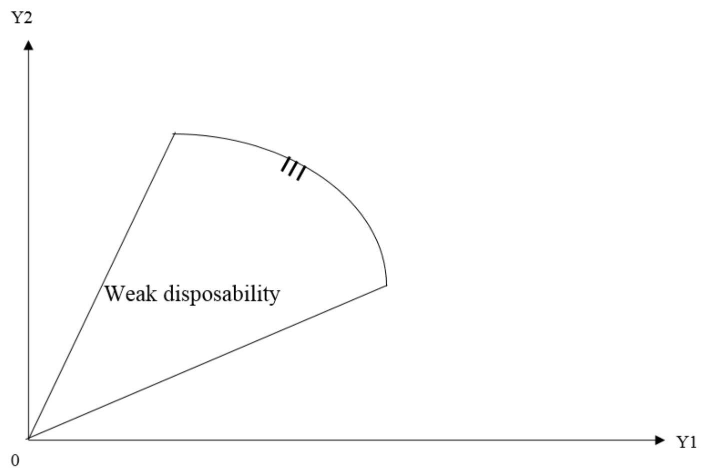


Figure 6 Weak disposability of outputs

$$A5: T \ is \ \text{convex.} \quad (6)$$

A5 assumption adds convexity axiom to the production possibility set, for example if $(\mathbf{x}_1,\mathbf{y}_1)\in T$ and $(\mathbf{x}_2,\mathbf{y}_2)\in T$ then $(\alpha\mathbf{x}_1,\alpha\mathbf{y}_1)+((1-\alpha)\mathbf{x}_2 \ , \ (1-\alpha)\mathbf{y}_2)\in T$, $0\leq\alpha\leq 1$. A convex production frontier is displayed in Figure 7.

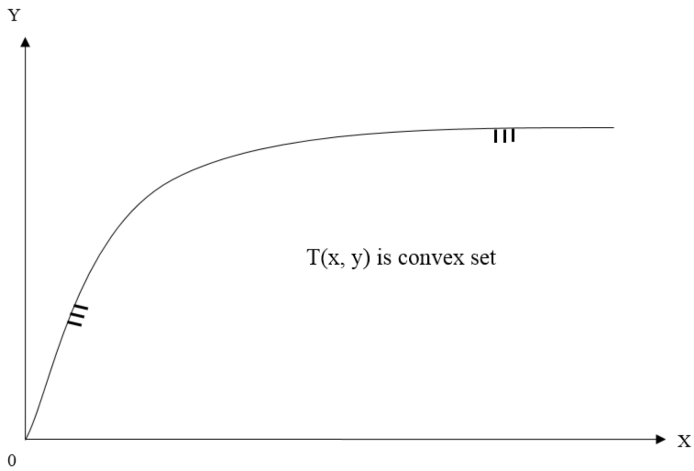
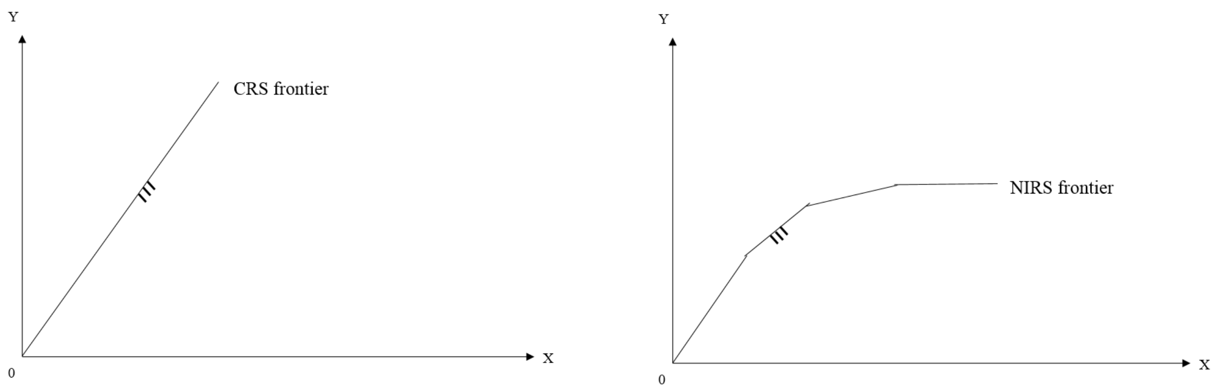


Figure 7 Convexity

$$\begin{aligned}&A6: if\ \lambda T = T, \lambda \in R_+, and\ (x,y)T\ and\ if\ \lambda \geq 0,\ then\ CRS;\\&if\ \ 0 \leq \lambda \leq 1, then\ NIRS;\\&if\ \ \lambda \geq 1, then\ NDRS;\\&if\ \ none\ of\ \ the\ above\ situation\ holds\ then\ VRS.\end{aligned} \tag{7}$$

Moreover, the axiom of returns to scale (A6) implies the rate of change in outputs to inputs. A constant returns to scale (CRS) assumes that all outputs are expended or reduced by a proportional increase or decrease in all inputs. A non-increasing returns to scale (NIRS) shows outputs are scaled less than or equal to inputs. A non-decreasing returns to scale (NDRS) indicates outputs are scaled more than or equal to inputs. If none of these cases, the technology is characterized by variable returns to scale (VRS). The demonstrations of CRS, NIRS, NDRS, and VRS are presented in Figure 8 respectively.



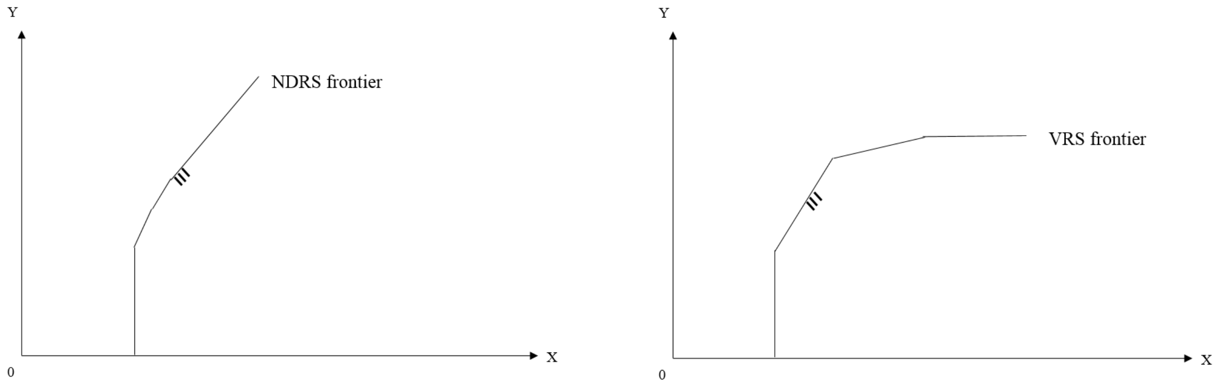


Figure 8 Returns to scale

1.3. Representation of production sets by distance functions

Distance function is an equivalent representation of production technology and it is usually a measurement of production sets. To improve efficiency performance of production activity, there are two alternative ways: to maximize outputs at given inputs or to minimize the inputs at given outputs (Koopmans, 1951). Following Shephard (1953, 1970), the Shephard output distance function is formulated as:

$$D_{output}(\mathbf{x},\mathbf{y}) = \min\left\{ \theta \in \Re_{+} : (\mathbf{y}/\theta) \in P(\mathbf{x}) \right\} \quad (8)$$

where θ is the adjustment factor measuring technical efficiency, namely the maximum value that outputs can be proportionally achieved at given inputs level. In Figure 9, the production possibility set is the area where the production possibility curve is connected with axis of two outputs Y_1 and Y_2. Points A and B are both on the production frontier which imply efficient DMUs, while C is located inside production possibility curve and represents an inefficient unit. The technical efficiency θ is equal to 0C/0B and less than 1.

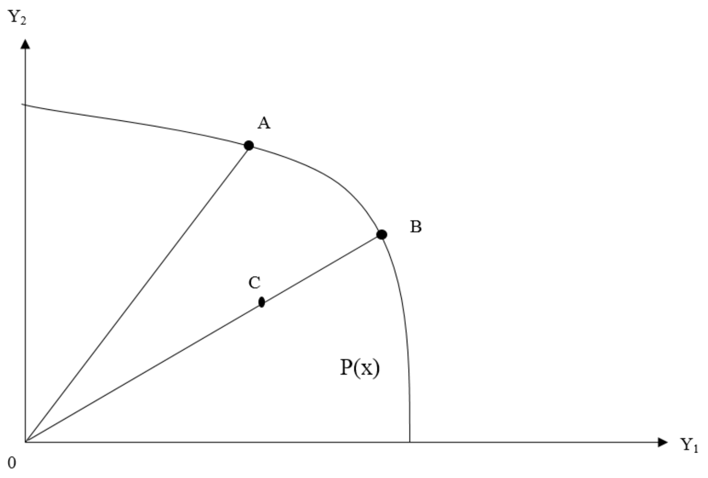


Figure 9 Shephard output distance function

Similarly, as suggested by Shephard (1970), the Shephard input distance function is defined as:

$$D_{input}(\mathbf{y},\mathbf{x}) = \max\left\{ \varphi \in \Re_{+} : (\mathbf{x}/\varphi) \in L(\mathbf{y}) \right\} \quad (9)$$

where φ implies the possible decrease in inputs at given outputs level. The Shephard input distance function seeks the radial maximum reduction in inputs. As shown in Figure 10, points A, B and C have the same level of outputs, and C is not on the frontier thus expending more inputs than A and B. The ratio φ measures technical efficiency which is equal to 0C/0A and greater than 1.

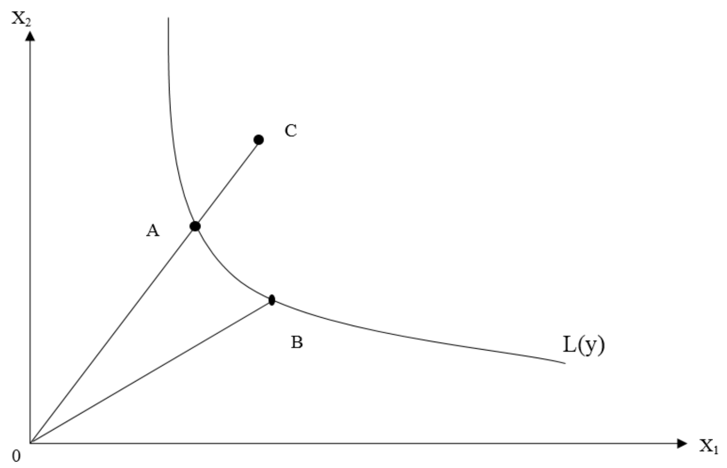


Figure 10 Shephard input distance function

Chambers et al. (1996) introduce the directional distance function which can increase outputs and reduce inputs simultaneously that is defined as:

$$D_{DDF}(\mathbf{x},\mathbf{y};\mathbf{g}_{\mathrm{x}},\mathbf{g}_{\mathrm{y}}) = \max\left\{ \delta \in \Re_{+} : (\mathbf{x}-\boldsymbol{\delta}\times\mathbf{g}_{\mathbf{x}},\mathbf{y}+\boldsymbol{\delta}\times\mathbf{g}_{\mathbf{y}}) \in T \right\} \qquad (10)$$

where $(\mathbf{g}_{\mathrm{x}},\mathbf{g}_{\mathrm{y}}) \geq 0$ and $(\mathbf{g}_{\mathrm{x}},\mathbf{g}_{\mathrm{y}}) \neq 0$ are directional vectors of inputs and outputs, δ measures the maximum possibility of simultaneously increasing outputs and decreasing inputs. Compared to Shephard distance functions, directional distance functions are more flexible in choosing objective directions as illustrated in Figure 11.

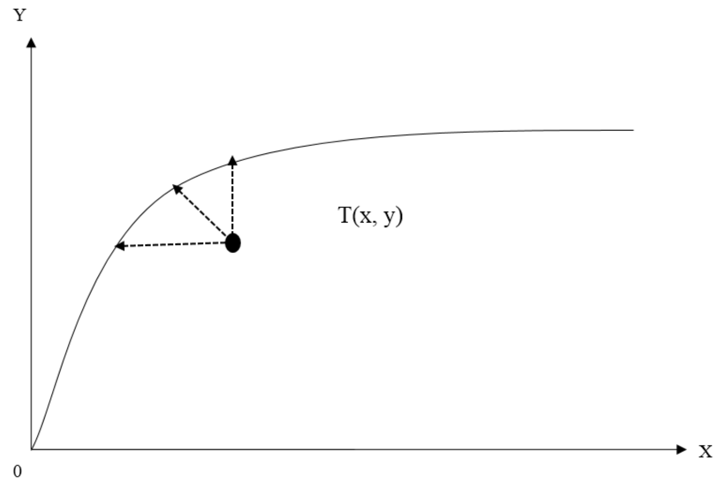


Figure 11 Directional distance function

1.4. Estimation of distance function

1.4.1. Parametric estimation

Both parametric and nonparametric estimations are popular in the literature. The main difference between parametric and nonparametric approaches is whether functional forms of production technologies can be predefined or not. For the former two forms usually used in literature are translog and quadratic functional forms (Färe et al., 1993; Färe et al., 2005). The translog functional forms are often linked with Shephard distance function, while quadratic functional forms are usually related to directional distance function. After the functional forms are determined, stochastic frontier analysis (SFA) can be employed to estimate parameters of distance functions (Zhou et al., 2014). Since this thesis we mainly use nonparametric estimations, we do not discuss parametric models in depth.

Introduced by Aigner et al. (1977), and Meeusen and Broeck (1977), SFA requires a specific function form that parameters can be estimated by econometrics models, such as ordinary least squares (OLS), maximum likelihood or Bayesian estimations. Assume that $f(\mathbf{x};\boldsymbol{\beta})$ is a production function as follows:

$$\begin{aligned} y &= f(\mathbf{x};\boldsymbol{\beta}) + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} &= \mathbf{u} - \mathbf{v} \end{aligned} \tag{11}$$

where $\boldsymbol{\beta}$ *and* $\boldsymbol{\varepsilon}$ are vector of parameters and error term. One advantage is to allow incorporating a statistical noise in results. Then $\boldsymbol{\varepsilon}$ can be decomposed into inefficiency scores **v** and statistical noise **u**.

1.4.2. DEA as a nonparametric approach

Besides parametric models, nonparametric DEA approaches are also usually employed to estimate the production frontier. Compared to SFA, DEA does not require a predefined functional form and a piecewise linear production frontier is created on combinations of the best observed practices, due to an optimization of a linear program. For example, a basic production set under CRS technology is defined as:

$$\begin{aligned} T_{CRS} = \Big\{ &(\mathbf{x},\mathbf{y}) : \mathbf{x} \in R_+^N,\ \mathbf{y} \in R_+^M,\ \sum_{k=1}^{K} \mu_k y_k^m \geq y^m,\ m = 1,\cdots,M,\ \sum_{k=1}^{K} \mu_k x_k^n \leq x^n,\ n = 1,\cdots,N, \\ &\mu_k \geq 0 \ \ k = 1,\ldots,K, \Big\} \end{aligned} \tag{12}$$

where μ_k is the intensity variable. To measure distance functions via linear programming, the objective is to maximize outputs or (and) minimize inputs by assessing the distance between observed DMUs and production frontier. Taking the directional distance function as an example, we can define the linear program as:

$$\begin{aligned} & D(\mathbf{x}_{\mathbf{k'}},\mathbf{y}_{\mathbf{k'}};\mathbf{g}_{\mathbf{x}},\mathbf{g}_{\mathbf{y}}) = \max_{\delta,\mu} \ \delta \\ & s.t. \sum_{k=1}^{K} \mu_k y_k^m \geq y_{k'}^m + \delta g_y, \ m = 1,\cdots,M \\ & \sum_{k=1}^{K} \mu_k x_k^n \leq x_{k'}^n - \delta g_x, \ n = 1,\cdots,N \\ & \mu_k \geq 0 \ \ k = 1,...,K \end{aligned} \tag{13}$$

where $\boldsymbol{\delta}$ measures radial maximums reduction in inputs and expansion in outputs. Each of linear programs (primal) have equivalent dual formulations. The corresponding dual program of Equation 13 is defined as follows:

$$\begin{aligned} & D(\mathbf{x}_{\mathbf{k'}},\mathbf{y}_{\mathbf{k'}};\mathbf{g}_{\mathbf{x}},\mathbf{g}_{\mathbf{y}}) = \min_{\pi_y,\pi_x} \ (\sum_{n=1}^{N} \pi_x^n x_{k'}^n - \sum_{m=1}^{M} \pi_y^m y_{k'}^m) \\ & s.t. \ \sum_{m=1}^{M} \pi_y^m y_k^m - \sum_{n=1}^{N} \pi_x^n x_k^n \geq 0 \ \ \forall k = 1,\cdots,K \\ & \sum_{m=1}^{M} \pi_y^m g_y^m + \sum_{n=1}^{N} \pi_x^n g_x^n = 1 \\ & \pi_y^m \geq 0 \ \ \forall m = 1,...,M \\ & \pi_x^n \geq 0 \ \ \forall n = 1,...,N \end{aligned} \tag{14}$$

where π_x and π_y represent shadow prices of inputs and outputs. We further discuss about dual formulations and shadow prices in section 3.

2. Environmental production technologies with bad outputs

2.1. Introduction of undesirable outputs into production sets

2.1.1. Modeling bad outputs as inputs

There are two main paths to model production technologies with undesirable factors (e.g. Zhou et al., 2008, Leleu, 2013). The first group of modeling pollution is to treat bad outputs (denoted by "z") as inputs (or costs) based on data transformation with classical free disposability assumptions, for instance, some change values of bad outputs to their reciprocals (e.g. Lovell et al., 1995, Athanassopoulos and Thanassoulis, 1995), or add big enough positive numbers to inverse values of bad outputs (e.g. Seiford and Zhu, 2002, Wu et al., 2013). However, considering bad outputs as inputs may not reflect the real mechanism inside the production activity and as such data transformation cannot be reasonable interpreted (Färe and Grosskopf, 2004, Dakpo et al., 2015).

2.1.2. Weak disposability axioms

Another approach is to introduce additional axioms on production sets, such as weak disposability, which is introduced by Shephard (1970) and Shephard and Färe (1974), and null-jointness condition linked to desirable and undesirable outputs (e.g. Färe and Grosskopf, 2004). The production possibility set, weak disposability (A7), and null-jointness assumption (A8) are defined as:

$$T_{WD} = \left\{ (\mathbf{x},\mathbf{y},\mathbf{z}) \in R_{+}^{N+M+J} : \mathbf{x} \text{ can produce } (\mathbf{y},\mathbf{z}) \right\} \quad (15)$$

$$\begin{aligned} &A7: If\ \ (\mathbf{y},\mathbf{z}) \in T_{WD}\ \ and\ \ 0 \le \theta \le 1\ then\ (\theta\mathbf{y},\theta\mathbf{z}) \in T_{WD}. \\ &A8: If\ \ (\mathbf{y},\mathbf{z}) \in T_{WD}\ \ and\ \ \mathbf{y} = \mathbf{0}\ then\ \mathbf{z} = \mathbf{0}. \end{aligned} \quad (16)$$

A7 reflects that a unique constraint θ is imposed on desirable and undesirable outputs allowing proportional decreases in outputs, and output set as shown in Figure 12. A8 requires that undesirable outputs can be eliminated if and only if desirable outputs are at null level. In other words, A8 assumption suggests that pollution is difficult to abandon and emphasizes the symbiosis between good and bad outputs. Indeed, the WDA is not applicable when emissions are easily controlled, such as SO_2, which can be soluble in water and it is possible to be fully disposed in the production activity.

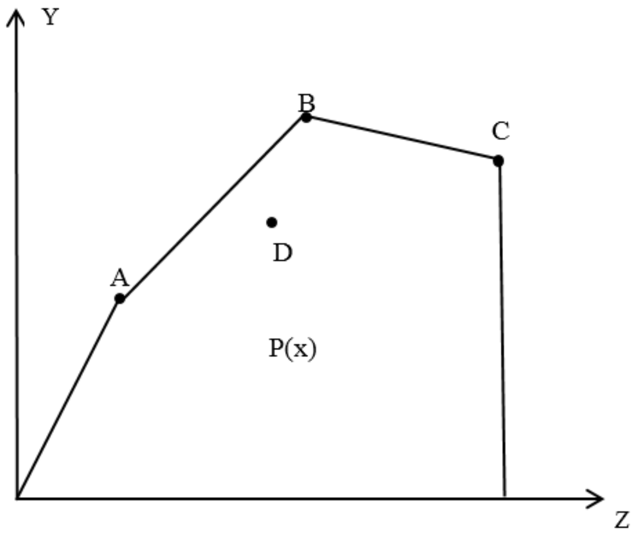


Figure 12 Output correspondence of WDA

This approach has been widely applied in nonparametric estimation. Kuosmanen (2005), and Kuosmanen and Podinovski (2009) argue that the Shephard's model violates convexity axiom of the production set T(x,y,z), and they make an improvement in this model which can provide new economic insights to WDA. Leleu (2013) suggests a hybrid WDA model and brings a new economic interpretation for Shephard's technology.

2.1.3. By-production technology

Murty and Russell (2002) and Murty et al. (2012) argue that the WDA may lead to unacceptable economic implications and they propose a by-production model including two sub technologies: one is to model a traditional production process for desirable outputs produced by all inputs (T1); another is to focus on a pollution generating process for undesirable outputs created by pollution generating inputs (T2). The by-production technology is defined as:

$$
\begin{aligned}
T_{BP} &= T_1 \cap T_2 \\
&= \left\{ (\mathbf{x_1}, \mathbf{x_2}, \mathbf{y}, \mathbf{z}) \in R_+^{N_1+N_2+M+J} : (\mathbf{x_1}, \mathbf{x_2}) \text{ can produce } \mathbf{y};\ \mathbf{x}_2 \text{ can generate } \mathbf{z} \right\} \\
T_1 &= \left\{ (\mathbf{x_1}, \mathbf{x_2}, \mathbf{y}, \mathbf{z}) \in R_+^{N_1+N_2+M+J} \mid f(\mathbf{x_1}, \mathbf{x_2}, \mathbf{y}) \le 0 \right\} \\
T_2 &= \left\{ (\mathbf{x_1}, \mathbf{x_2}, \mathbf{y}, \mathbf{z}) \in R_+^{N_1+N_2+M+J} \mid g(\mathbf{x_2}) \le \mathbf{z} \right\}
\end{aligned}
\tag{17}
$$

where f and g are continuously differentiable functions. The free disposability is imposed on T_1 for all inputs and desirable outputs (A9) while the cost disposability is added to T2 for pollution generating inputs and undesirable outputs (A10).

$$
\begin{aligned}
&A9: (\mathbf{x_1}, \mathbf{x_2}, \mathbf{y}, \mathbf{z}) \in T_1 \textit{ then } (\tilde{\mathbf{x}}_1, \tilde{\mathbf{x}}_2, \tilde{\mathbf{y}}, \tilde{\mathbf{z}}) \in T_1 \textit{ for all } (-\tilde{\mathbf{x}}_1, -\tilde{\mathbf{x}}_2, \tilde{\mathbf{y}}) \le (-\mathbf{x_1}, -\mathbf{x_2}, \mathbf{y}). \\
&A10: (\mathbf{x_1}, \mathbf{x_2}, \mathbf{y}, \mathbf{z}) \in T_2 \textit{ then } (\tilde{\mathbf{x}}_1, \tilde{\mathbf{x}}_2, \tilde{\mathbf{y}}, \tilde{\mathbf{z}}) \in T_2 \textit{ for all } (\tilde{\mathbf{x}}_2, -\tilde{\mathbf{z}}) \le (\mathbf{x_2}, \tilde{\mathbf{z}}).
\end{aligned}
\tag{18}
$$

2.2. Estimating environmental production technologies by distance functions

2.2.1. Distance functions with bad outputs

From an economic point of view, good outputs bring benefit for social welfare thus to be increased while bad ones generate negative externalities should be reduced. The main shortcoming of flexibility is that the Shephard output/input distance functions can only simultaneously increase outputs or decrease inputs at the same proportion. According to Chung et al. (1997) and Färe et al. (2005), the directional distance function which can increase desirable outputs and reduce undesirable ones simultaneously is defined as:

$$
D_{DDF}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_y,\mathbf{g}_z) = \max\left\{ \delta \in \Re_+ : (\mathbf{x}, \mathbf{y} + \delta\mathbf{g}_\mathbf{y}, \mathbf{z} - \delta\mathbf{g}_\mathbf{z}) \in T \right\} \tag{19}
$$

where $(\mathbf{0},\mathbf{g}_y,\mathbf{g}_z) \ge 0$ and $(\mathbf{0},\mathbf{g}_y,\mathbf{g}_z) \ne 0$ are directional vectors of desirable and undesirable outputs, $\boldsymbol{\delta}$ measures the maximum possibility of increasing desirable outputs and decreasing undesirable ones. In Figure 13, point D is inefficient and projects on the segment between A and B on the piecewise production frontier.

The technical inefficiency δ gauges the possible improvement space for increasing good outputs and abating bad ones. The detail specific properties and projection mapping of distance functions is available from Zhou et al. (2014).

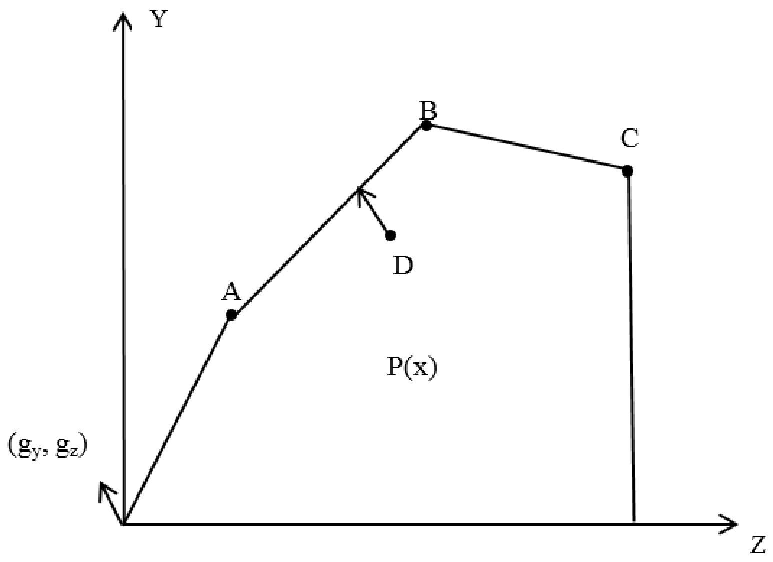


Figure13 Directional distance function with undesirable outputs

2.2.2. Non-radial efficiency measurements

The efficiency measurements are directly linked with distance functions, and we can find that the adjustment ratio represents a radial value that the distance as a ray from the original point (C) to intersect (B) on the frontier (e.g. Figure 9), and the ratio is same for each input or output. This means inputs/outputs are reduced/increased in the same proportion. In DEA methods, if one allows adjustments in the same proportions, efficiency scores may be overestimated if slacks exist. An alternative path is usually advocated to mitigate the impact of slacks on efficiency scores, namely using a non-radial measurement which allow adjustments in different proportions. The efficiency scores generated by non-radial measurements vary to each output or input and an efficiency index is often used to generalize final scores.

For instance, Cooper et al. (2000) propose a non-radial range-adjusted measurement (RAM), and Sueyoshi et al. (2010, 2011, and 2012) introduce natural and managerial disposability models which efficiency scores are computed based on RAM. Their RAM efficiency index is defined as:

$$E_{RAM} = \max \frac{1}{N+M+J}\left[\sum_m \frac{S_m^y}{RAN_m^y} + \sum_n \frac{S_n^x}{RAN_n^x} + \sum_j \frac{S_j^z}{RAN_j^z}\right] \qquad (20)$$

where S_m^y, S_n^x *and* S_j^z are slacks of desirable outputs, inputs and undesirable outputs; RAN_m^y, RAN_n^x *and* RAN_j^z are ranges (differences) of maximum and minimum for desirable outputs, inputs and undesirable outputs. Murty et al. (2012) propose an improved output-oriented Färe-Grosskopf-Lovell index which can be defined as:

$$E_{FGL}(\mathbf{x,y,z}) = \frac{1}{2}\min\left\{ \frac{\sum_m \theta_m}{M} + \frac{\sum_j \gamma_j}{J} \mid (\mathbf{y} \otimes^{-1} \boldsymbol{\theta}, \boldsymbol{\gamma} \otimes \mathbf{z}) \in P(\mathbf{x}) \right\} \qquad (21)$$

where $\mathbf{y} \otimes^{-1} \boldsymbol{\theta} = (y_1/\theta_1, ..., y_m/\theta_m)$ *and* $\boldsymbol{\gamma} \otimes \mathbf{z} = (\gamma_1 z_1, ..., \gamma_j z_j)$ and this index is used to maximize the good outputs and minimize the bad ones. Similarly, Zhou et al. (2012) introduce a non-radial measure to include pollutions with directional distance function and weighted efficiency as follows:

$$D_{output}(\mathbf{x,y,z;g_x,g_y,g_z}) = \max\left\{ \mathbf{W}^{\mathrm{T}}\boldsymbol{\delta} \in \Re_+ : (\mathbf{x} - \boldsymbol{\delta}_\mathbf{x}\mathbf{g_x}, \mathbf{y} + \boldsymbol{\delta}_\mathbf{y}\mathbf{g_y}, \mathbf{z} - \boldsymbol{\delta}_\mathbf{z}\mathbf{g_z}) \in T \right\}$$

(22)

where **W** is a normalized weighted vector and efficiency scores put directions on all inputs and outputs. The Shephard output distance function can also be formulated to expand good outputs and decrease bad ones. A hyperbolic measurement introduced by Färe et al. (1989) can be defined as follows:

$$D_{output}(\mathbf{x,y,z}) = \min\left\{ \theta \in \Re_+ : (\mathbf{y}/\theta, \theta\mathbf{z}) \in P(\mathbf{x}) \right\} \qquad (23)$$

however the main problem it is nonlinear, Färe et al. (2016) propose a linear programming algorithm for the hyperbolic measurement.

2.3. Parametric estimations

The translog model meets the requirements of the linear homogeneity of Shephard distance function based on the WDA and can be defined as follows (Färe et al., 1993):

$$\begin{aligned}
&\ln D_{Shephard}(\mathbf{x},\mathbf{y},\mathbf{z}) \;=\; \alpha_0 + \sum_n \beta_n \ln x_n + \sum_m \beta_m \ln y_m + \sum_j \beta_j \ln z_j \\
&+\frac{1}{2}\sum_n\sum_{n'}\gamma_{nn'} \ln x_n \ln x_{n'} + \frac{1}{2}\sum_m\sum_{m'}\gamma_{mm'} \ln y_m \ln y_{m'} + \frac{1}{2}\sum_j\sum_{j'}\gamma_{jj'} \ln z_j \ln z_{j'} \\
&+\sum_n\sum_m \rho_{nm} \ln x_n \ln y_m + \sum_n\sum_j \rho_{nj} \ln x_n \ln z_j + \sum_m\sum_j \rho_{mj} \ln y_m \ln z_j \\
&\text{where } \gamma_{nn'} = \gamma_{n'n}, n \neq n'; \gamma_{mm'} = \gamma_{m'm}, m \neq m'; \gamma_{jj'} = \gamma_{j'j}, j \neq j'.
\end{aligned} \tag{24}$$

The quadratic functional form with bad outputs can be defined as follows (Färe et al., 2005):

$$\begin{aligned}
&\ln D_{DDF}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z}) \;=\; \alpha_0 + \sum_n \beta_n x_n + \sum_m \beta_m y_m + \sum_j \beta_j z_j \\
&+\frac{1}{2}\sum_n\sum_{n'}\gamma_{nn'} x_n x_{n'} + \frac{1}{2}\sum_m\sum_{m'}\gamma_{mm'} y_m y_{m'} + \frac{1}{2}\sum_j\sum_{j'}\gamma_{jj'} z_j z_{j'} \\
&+\sum_n\sum_m \rho_{nm} x_n y_m + \sum_n\sum_j \rho_{nj} x_n z_j + \sum_m\sum_j \rho_{mj} y_m z_j \\
&\gamma_{nn'} = \gamma_{n'n}, n \neq n'; \gamma_{mm'} = \gamma_{m'm}, m \neq m'; \gamma_{jj'} = \gamma_{j'j}, j \neq j'.
\end{aligned} \tag{25}$$

By defining: $\mathbf{b} = (\mathbf{x},\mathbf{y},\mathbf{z})$, the translation property related to directional distance function which can be explained as follows (e.g. Färe et al., 2005; Färe and Lundberg, 2006):

$$\begin{aligned}
&D_{DDF}(\mathbf{b}+\alpha\mathbf{g};\mathbf{g}) = \max\left\{ \delta \in \Re_+ : (\mathbf{b}+\alpha\mathbf{g}+\delta\mathbf{g}) \in T \right\} \\
&= \max\left\{ \delta \in \Re_+ : (\mathbf{b}+(\alpha+\delta)\mathbf{g}) \in T \right\} \\
&= -\alpha + \max\left\{ \alpha+\delta \in \Re_+ : (\mathbf{b}+(\alpha+\delta)\mathbf{g}) \in T \right\} \\
&= D_{DDF}(\mathbf{b};\mathbf{g}) - \alpha
\end{aligned} \tag{26}$$

One can use SFA or linear programming to compute parameters of above distance functions when functional forms are determined (Zhou et al., 2014).

2.4. Nonparametric estimations

2.4.1. Färe-Grosskopf's approach

As we have discussed in Section2, the classical DEA of modeling undesirable outputs is based on the WDA and null-jointness conditions. The production possibility set under a CRS technology can be defined as:

$$T_{CRS}^{WD} = \left\{ (\mathbf{x}, \mathbf{y}, \mathbf{z}) : \mathbf{x} \in R_{+}^{N}, \mathbf{y} \in R_{+}^{M}, \mathbf{z} \in R_{+}^{J}, \sum_{k=1}^{K} \mu_k y_k^m \geq y^m,\ m = 1, \cdots, M,\ \sum_{k=1}^{K} \mu_k z_k^j = z^j,\ j = 1, \cdots, J, \right.$$
$$\left. \sum_{k=1}^{K} \mu_k x_k^n \leq x^n,\ n = 1, \cdots, N,\ \mu_k \geq 0\ \ k = 1, ..., K, \right\}$$

(27)

In order to compute a distance function of this technology, Färe et al. (1989) proposed the hyperbolic distance function initially. However, the hyperbolic measurement is nonlinear and the linear model with directional distance function suggested by Chung et al. (1997) is widely used in the literature (Leleu, 2013). In chapter 3, we further use this CRS technology to compute the Luenberger productivity indicator at aggregate level with directional distance functions.

The misspecification issue occurs in the VRS technology because the VRS assumption that directly imposes constraints on intensity variable does not comprise the WDA. Thus the VRS model based on the WDA needs to be explicitly specified. The non-linear VRS technology is defined as:

$$T_{VRS}^{Nonlinear} = \left\{ (\mathbf{x}, \mathbf{y}, \mathbf{z}) : \mathbf{x} \in R_{+}^{N}, \mathbf{y} \in R_{+}^{M}, \mathbf{z} \in R_{+}^{J}, \theta \sum_{k=1}^{K} \mu_k y_k^m \geq y^m,\ m = 1, \cdots, M,\ \theta \sum_{k=1}^{K} \mu_k z_k^j = z^j,\ j = 1, \cdots, J, \right.$$
$$\left. \sum_{k=1}^{K} \mu_k x_k^n \leq x^n,\ n = 1, \cdots, N,\ \sum_{k=1}^{K} \mu_k = 1,\ 0 \leq \theta \leq 1, \mu_k \geq 0\ \ k = 1, ..., K, \right\}$$

(28)

where θ is an uniform abatement factor linked good and bad outputs. While this technology is nonlinear, some authors use the following "wrong" technology:

$$T_{VRS}^{Wrong} = \left\{ (\mathbf{x}, \mathbf{y}, \mathbf{z}) : \mathbf{x} \in R_+^N, \mathbf{y} \in R_+^M, \mathbf{z} \in R_+^J, \sum_{k=1}^{K} \lambda_k y_k^m \geq y^m, \ m = 1, \cdots, M, \ \sum_{k=1}^{K} \lambda_k z_k^j = z^j, \ j = 1, \cdots, J, \right.$$
$$\left. \sum_{k=1}^{K} \lambda_k x_k^n \leq x^n, \ n = 1, \cdots, N, \ \sum_{k=1}^{K} \lambda_k = 1, \ \lambda_k \geq 0 \ \ k = 1, ..., K, \right\}$$

(29)

Leleu (2013) systematically summarizes incorrect linearizations applied in literature, for instance, Jeon and Sickles (2004), Hua and Bian (2007), Piot-Lepetit and Le Moing (2007), and Kjærsgaard et al. (2009). In addition to the above misspecified model, Färe et al. (1994) make a typing error in VRS technology of the WDA since only applies the uniform abatement factor to bad outputs, and Ferrier et al. (2006) and Clement et al. (2008) repeat this approach (Kuntz and Sülz, 2011). The correct linearization is proposed by Zhou et al. (2008), or Sahoo et al. (2011). By introducing a variation $\lambda_k = \theta \mu_k$, the correct VRS technology can be defined as:

$$T_{VRS}^{FG} = \left\{ (\mathbf{x}, \mathbf{y}, \mathbf{z}) : \mathbf{x} \in R_+^N, \mathbf{y} \in R_+^M, \mathbf{z} \in R_+^J, \sum_{k=1}^{K} \lambda_k y_k^m \geq y^m, \ m = 1, \cdots, M, \ \sum_{k=1}^{K} \lambda_k z_k^j = z^j, \ j = 1, \cdots, J, \right.$$
$$\left. \sum_{k=1}^{K} \lambda_k x_k^n \leq \theta x^n, \ n = 1, \cdots, N, \ \sum_{k=1}^{K} \lambda_k = \theta, \ 0 \leq \theta \leq 1, \ \lambda_k \geq 0 \ \ k = 1, ..., K, \right\}$$

(30)

2.4.2. Kuosmanen's approach

Kuosmanen (2005), and Kuosmanen and Podinovski (2009) argue that the Shephard's model violates convexity axiom which may not provide obvious economic interpretation. They replace the unique abatement factor θ by non-uniform one θ_k and claim this model can provide new economic insights to the

WDA (Kuosmanen and Matin, 2011). This VRS technology based on the WDA is defined as:

$$T_{VRS}^{Kuosmanen} = \left\{ (\mathbf{x},\mathbf{y},\mathbf{z}) : \mathbf{x} \in R_+^N,\ \mathbf{y} \in R_+^M,\ \mathbf{z} \in R_+^J,\ \sum_{k=1}^{K} \lambda_k y_k^m \geq y^m,\ m=1,\cdots,M,\ \sum_{k=1}^{K} \lambda_k z_k^j = z^j,\ j=1,\cdots,J, \right.$$
$$\left. \sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^n \leq x^n,\ n=1,\cdots,N,\ \sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1,\ \lambda_k \geq 0\ \ k=1,...,K,\ \sigma_k \geq 0\ \ k=1,...,K \right\}$$

(31)

The empirical applications are available from Mekaroonreung and Johnson (2009), Berre et al. (2013), Berre et al. (2014), and Lee and Zhou (2015). In chapter 4, we use Kuosmanen's model to analyze the global carbon shadow prices.

2.4.3. Leleu's approach

Leleu (2013) introduces a hybrid approach which is slightly different from Shephard's VRS model and the shadow prices of bad outputs are constrained, which implies bad outputs can only generate negative revenue (costs). Leleu (2013) argues that the revenue from good outputs must at least compensate the cost of bad outputs, and this hybrid model can bring clear economic explanations to the WDA approach. We further study this hybrid approach and analyze environmental growth convergence for Chinese regions in chapter 2. Following Leleu (2013), we can also propose a slightly different but equivalent approach as Kuosmanen's model. Using directional distance function, one can note that constraint $\sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1$ is equivalent to $\sum_{k=1}^{K} \lambda_k + \sum_{k=1}^{K} \sigma_k = 1$ and with some simple algebraic transformations following primal and dual programs are obtained:

$$
\begin{aligned}
& D(\mathbf{x_{k'}}, \mathbf{y_{k'}}, \mathbf{z_{k'}}; \mathbf{0}, \mathbf{g_y}, \mathbf{g_z}) = \max_{\delta,\lambda,\sigma} \ \delta \\
& s.t. \ -\sum_{k=1}^{K} \lambda_k (y_k^m - y_{k'}^m) + \sum_{k=1}^{K} \sigma_k y_{k'}^m + \delta g_y^m \leq 0 \ \ \forall m = 1, \cdots, M \\
& \sum_{k=1}^{K} \lambda_k (z_k^j - z_{k'}^j) - \sum_{k=1}^{K} \sigma_k z_{k'}^j + \delta g_z^j \leq 0 \ \ \forall j = 1, \cdots, J \\
& \sum_{k=1}^{K} \lambda_k (x_k^n - x_{k'}^n) + \sum_{k=1}^{K} \sigma_k (x_k^n - x_{k'}^n) \leq 0 \ \ \forall n = 1, \cdots, N \\
& \sum_{k=1}^{K} \lambda_k + \sum_{k=1}^{K} \sigma_k = 1 \\
& \lambda_k \geq 0 \ \ \forall k = 1, ..., K \\
& \sigma_k \geq 0 \ \ \forall k = 1, ..., K
\end{aligned}
\tag{32}
$$

$$
\begin{aligned}
& D(\mathbf{x_{k'}}, \mathbf{y_{k'}}, \mathbf{z_{k'}}; \mathbf{0}, \mathbf{g_y}, \mathbf{g_z}) = \min_{\eta,\pi_x,\pi_y,\pi_z} \ \eta \\
& s.t. \ (\sum_{m=1}^{M} \pi_y^m y_k^m - \sum_{j=1}^{J} \pi_z^j z_k^j - \sum_{n=1}^{N} \pi_x^n x_k^n) - \ (\sum_{m=1}^{M} \pi_y^m y_{k'}^m - \sum_{j=1}^{J} \pi_z^j z_{k'}^j - \sum_{n=1}^{N} \pi_x^n x_{k'}^n) \leq \eta \ \ \forall k = 1, \cdots, K \\
& \sum_{m=1}^{M} \pi_y^m y_{k'}^m - \sum_{j=1}^{J} \pi_z^j z_{k'}^j + \eta \geq \sum_{n=1}^{N} \pi_x^n x_{k'}^n - \sum_{n=1}^{N} \pi_x^n x_k^n \ \ \forall k = 1, \cdots, K \\
& \sum_{m=1}^{M} \pi_y^m g_y^m + \sum_{j=1}^{J} \pi_z^j g_z^j = 1 \\
& \pi_y^m \geq 0 \ \ \forall m = 1, ..., M \\
& \pi_z^j \geq 0 \ \ \forall j = 1, ..., J \\
& \pi_x^n \geq 0 \ \ \forall n = 1, ..., N
\end{aligned}
\tag{33}
$$

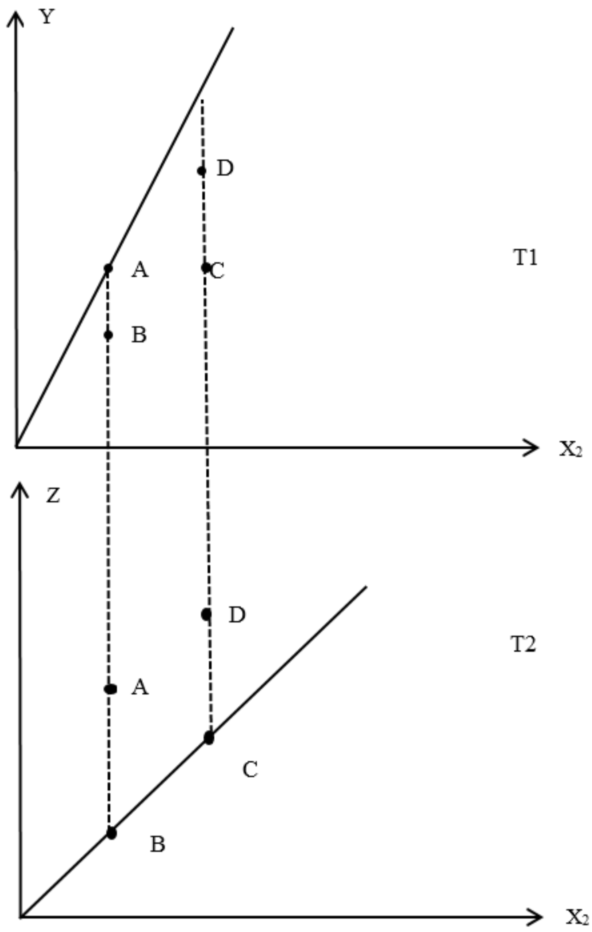
where π_x , π_y and π_z denote shadow prices of inputs, good and bad outputs associated to each constraint in linear programs. With such transformed programs the objective η is now to seek minimum profit inefficiency that must be greater than or equal to the difference between optimal profit for all DMUs and evaluated profit of DMU k'. The left hand side of second constraint $\sum_{m=1}^{M} \pi_y^m y_{k'}^m - \sum_{j=1}^{J} \pi_z^j z_{k'}^j + \eta$ can be interpreted as efficient net revenue indicating what it is possible to earn from production activities. The right hand side reveals cost inefficiency comparing evaluated cost to optimal cost. Therefore the economic content of this constraint is that efficient net revenue at least shall compensate cost inefficiency in production process.

In summary, the main feature of these models is that: WDA emphasizes the symbiosis between good and bad outputs, in other words, null level of bad outputs requires null level of good outputs; and this symbiosis requires an identical estimating technology by arranging the same intensity variable for good and bad outputs. Thus, WDA is more suitable to the case when pollution is difficult to abandon, for example CO_2. However, some pollutants are easily disposed of by the introduction of additional equipment, such as SO_2, negating the need for WDA methods. For additional discussions and comparisons on the WDA see (e.g. Sahoo et al., 2011; Dakpo et al., 2015).

2.4.4. Murty et al.'s approach

The by-production approach is a method of modeling undesirable outputs proposed by Murty and Russell (2002) and Murty et al. (2012). They claim that unacceptable economic implications may appear in classical ways of modeling undesirable outputs in one technology, such as WDA. Dakpo et al. (2015) argue that multiple frontiers methods have broader prospects in future research. By using two sub-technologies, one technology is for good outputs and another one is for modeling bad outputs, and with different intensity variables in such sub-technology, the by-production technology can be defined as follows:

$$\begin{aligned} T_{CRS}^{BP} = \Big\{ & (\mathbf{x_1}, \mathbf{x_2}, \mathbf{y}, \mathbf{z}) : \mathbf{x_1} \in R_+^O, \mathbf{x_2} \in R_+^P, \mathbf{y} \in R_+^M, \mathbf{z} \in R_+^J, \sum_{k=1}^K \lambda_k y_k^m \geq y^m, \ m = 1, \cdots, M, \\ & \sum_{k=1}^K \lambda_k x_k^o \leq x_1^o, \ o = 1, \cdots, O, \sum_{k=1}^K \lambda_k x_k^p \leq x_2^p, \ p = 1, \cdots, P; \\ & \sum_{k=1}^K \sigma_k x_k^p \geq x_2^p, \ p = 1, \cdots, P, \ \sum_{k=1}^K \sigma_k z_k^j \leq z^j, \ j = 1, \cdots, J, \\ & \lambda_k, \ \sigma_k \geq 0, \ k = 1, \ldots, K \Big\} \end{aligned} \tag{34}$$

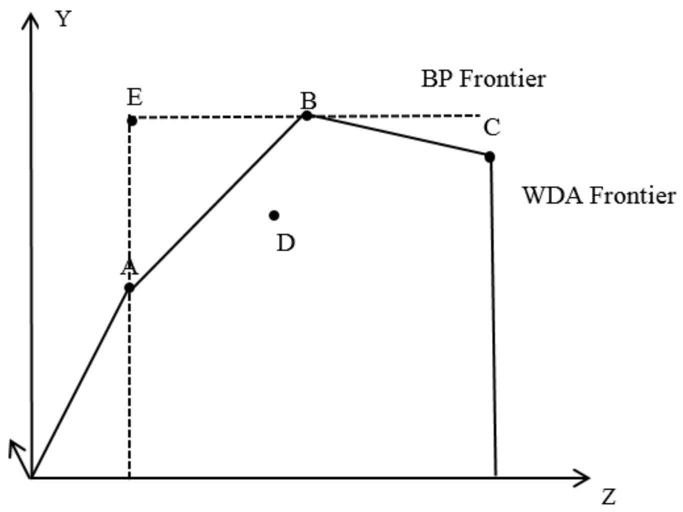


Source: Murty et al. (2012).

Figure 14 Multiple frontiers in by-production CRS technology

where λ_k *and* σ_k are intensity variables for two sub-technologies in Figure 14 which imply two technology frontiers are allowed with different benchmarks, and x_1 and x_2 denote good inputs and pollution generating inputs. In the first sub-technology T1, all inputs are modeled in production activity to yield good outputs, while only pollution-generating inputs (e.g. energy consumptions) are used to produce bad outputs in the second sub-technology T2. The two sub-technology can be displayed in Figure14, T1 is to maximize good outputs and to minimize all inputs while T2 is to minimize bad outputs and to maximize pollution-generating inputs which can produce more good outputs.

Compared with WDA technology, by-production approach may have less efficient DMUs, for example in Figure 15, A, B, and C are efficient DMUs on WDA frontier, while only E is efficient on BP frontier and it is an artificial DMU.



Source: Murty et al. (2012).

Figure 15 Frontier comparison

If we evaluate different countries, the USA generates the highest GDP on T1 frontier, while Luxembourg produces the lowest pollution on T2 frontier. One question may arise, can we conclude the efficient benchmark with USA's GDP and Luxembourg's pollution is a rational yardstick? Thus we argue that the operational meaning of by-production is not explicit and we further study this model in Chapter 5.

2.4.5. Stochastic semi-nonparametric estimations

Parametric and nonparametric approaches both have several shortcomings: the functional forms have to be predefined parametric approaches while it is difficult to incorporate a statistical noise into a nonparametric assessment. In order to deal with this problem, some approaches can be applied by mimicking the data generating process on resampling and creating confident intervals, such as the bootstrap DEA models (Simar and Wilson, 1998, 2000), and sub-sampling frontiers estimations, such as the robust frontiers DEA models (Cazals et al.,2002 and Kneip et al.,2008). The stochastic semi-nonparametric estimations (StoNED), proposed by Kuosmanen (2008), Kuosmanen and Johnson (2009), and Kuosmanen and Kortelainen (2012), is to integrate stochastic SFA and axiomatic DEA together and it does not require any functional forms assumptions but it is based on the general axioms of production technologies. Kuosmanen et al. (2013) argue that the StoNED method can provide the most precise results comparing with SFA and DEA approaches by the Monte Carlo simulations.

In the first stage, the StoNED production function is estimated by Convex Nonparametric Least Squares (CNLS). Assume that all deviations attribute to technical efficiency without statistical noise, the deterministic production frontier estimation of the CNLS under the WDA assumptions can be formulated as (e.g. Mekaroonreung and Johnson 2012):

$$
\begin{aligned}
&\min_{\alpha,\beta,\lambda,\varepsilon} (-\sum_{k=1}^{K} \varepsilon_k) \\
&\varepsilon_k = \ln(y_k) - \ln(\alpha_k + \beta_k x_k + \gamma_k z_k) \quad k = 1,...,K \\
&\alpha_k + \beta_k x_k + \gamma_k z_k \le \alpha_l + \beta_l x_k + \gamma_l z_k \quad k,l = 1,...,K \\
&\alpha_l + \beta_l x_k \ge 0 \quad k,l = 1,...,K \\
&\beta_k, \gamma_k \ge 0, \ \varepsilon_k \le 0 \quad k = 1,...,K
\end{aligned}
\tag{35}
$$

where $\alpha_k, \beta_k, and\ \gamma_k$ are constant, parameters of input and undesirable output respectively. Based on the CNLS residuals, the expected efficiency with assumed distributions can be computed by adding additional distributional assumptions on efficiency and noise (Kuosmanen and Kortelainen, 2012). Alternative estimation strategies are available in the second stage, such as the method of moments, quasi-likelihood estimation, and nonparametric kernel deconvolution (e.g. Kuosmanen et al., 2015).

Complimenting the above approaches, some recent methods dealing with undesirable outputs are also available in literature, for instance, slacks based model (e.g. Tone, 2001), material balance approach (e.g. Coelli et al., 2005; Hampf and Rødseth, 2015), natural and managerial disposability approach is proposed by (e.g. Sueyoshi et al., 2010). Most these models use non-radial efficiency measurements with inputs and outputs slacks which cannot provide a clear interpretation from an economic point of view, and are not discussed here in depth.

3. Extensions: duality and productivity

3.1. Duality and shadow prices

Pittman (1983) analyzes multilateral productivity comparisons based on price information of bad outputs using a translog function. When the issue of pollution is not serious, policy and decision makers may not impose emission taxes on bad outputs. In this case, undesirable outputs do not have real prices in the market and price information is not available. Using the DEA approach, shadow prices of outputs and inputs can be deduced from marginal values related to the constraints in primal model based on quantity information without the information of market prices.

According to Shephard (1970) Färe et al. (1993, 2005), and Hailu and Veeman (2000), Zhou et al. (2014) defined the revenue function as:

$$R(\mathbf{x},\mathbf{p_y},\mathbf{p_z}) = \max\left\{(\mathbf{p}_y y - \mathbf{p}_z z) : D_{output}(\mathbf{x},\mathbf{y},\mathbf{z}) \leq 1\right\} \quad (36)$$

where $(\mathbf{p_y},\mathbf{p_z}),(\mathbf{p_y},\mathbf{p_z}) \geq 0,(\mathbf{p_y},\mathbf{p_z}) \neq 0$ are real prices of outputs. The dual formulation on input-oriented distance function is cost function, which is defined to minimize cost as:

$$C(\mathbf{y},\mathbf{z},\mathbf{p_x}) = \min\left\{\mathbf{p}_x\mathbf{x} : D_{input}(\mathbf{y},\mathbf{z},\mathbf{x}) \geq 1\right\} \quad (37)$$

where $\mathbf{p_x},\mathbf{p_x} \geq 0,\mathbf{p_x} \neq 0$ are the real prices of inputs.

The ratio of prices of bad to good outputs can be computed by the Lagrangian method. Based on distance functions, the ratio of prices of bad to good outputs are equal to:

$$\frac{p_z}{p_y} = \frac{\partial D_{output}(\mathbf{x},\mathbf{y},\mathbf{z}) / \partial z}{\partial D_{output}(\mathbf{x},\mathbf{y},\mathbf{z}) / \partial y} \qquad (38)$$

Equation (38) is the basis to compute the ratio of shadow prices for outputs whenever prices are unknown. Indeed we can obtain these values by the dual linear programs when we estimate the output distance function by DEA. Assume that the primal program is based on WDA with CRS technology and directional distance function, the corresponding dual program is defined as:

$$\begin{aligned}
& D_{DDF}(\mathbf{x_{k'}},\mathbf{y_{k'}},\mathbf{z_{k'}};\mathbf{0},\mathbf{g_y},\mathbf{g_z}) = \max_{\pi_y,\pi_z,\pi_x,\pi_{xp}} \left(\sum_{m=1}^{M}\pi_y^m y_{k'}^m - \sum_{j=1}^{J}\pi_z^j z_{k'}^j - \sum_{n=1}^{N}\pi_x^n x_{k'}^n\right) \\
& s.t.\ \sum_{m=1}^{M}\pi_y^m y_k^m - \sum_{j=1}^{J}\pi_z^j z_k^j - \sum_{n=1}^{N}\pi_x^n x_k^n \le 0 \quad \forall k = 1,\cdots,K \\
& \sum_{m=1}^{M}\pi_y^m g_y^m + \sum_{j=1}^{J}\pi_z^j g_z^j = 1 \qquad\qquad (39) \\
& \pi_y^m \ge 0 \quad \forall m = 1,\ldots,M \\
& \pi_x^n \ge 0 \quad \forall n = 1,\ldots,N
\end{aligned}$$

Therefore we have:

$$\frac{p_z}{p_y} = -\frac{\partial D_{DDF}(\mathbf{x},\mathbf{y},\mathbf{z}) / \partial z}{\partial D_{DDF}(\mathbf{x},\mathbf{y},\mathbf{z}) / \partial y} = \frac{\pi_z}{\pi_y} \qquad (40)$$

Equation (40) allows us to compute relative shadow prices between bad and good output based on the estimation of the directional distance function.

3.2. Productivity indicators

Compared to environmental efficiency scores, productivity indices can provide evaluation information for policy makers over time. The traditional productivity indicators do not include the attributes for undesirable outputs because of using of the Shephard distance function, such as Malmquist index. Two popular environmental productivity indicators are usually employed in literature: the Malmquist- Luenberger productivity and Luenberger productivity indices.

3.2.1. Malmquist productivity index

Malmquist productivity index is a ratio-based indicator with Shephard distance functions. Malmquist output/input-oriented TFP indicator over the time period t and t+1 can be defined as follows:

$$TFP_M^{t,t+1} = \left[\frac{D_{output}^{t}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})}{D_{output}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})} \frac{D_{output}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})]}{D_{output}^{t+1}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})} \right]^{\frac{1}{2}} \quad (41)$$

$$TFP_M^{t,t+1} = \left[\frac{D_{input}^{t}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})}{D_{input}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})} \frac{D_{input}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})]}{D_{input}^{t+1}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})} \right]^{\frac{1}{2}} \quad (42)$$

This output/input-oriented indicator can be further traditionally decomposed to efficiency change (EC) and technology progress (TP) as follows:

$$TFP_M^{t,t+1} = EC^{t,t+1} TP^{t,t+1} \quad (43)$$

$$EC^{t,t+1} = \frac{D_{output}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})}{D_{output}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})} \; or \; \frac{D_{input}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})}{D_{input}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})} \quad (44)$$

$$TP^{t,t+1} = \left[\frac{D_{output}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})}{D_{output}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})} \frac{D_{output}^{t+1}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})]}{D_{output}^{t}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})} \right]^{\frac{1}{2}} or \left[\frac{D_{input}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})}{D_{input}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})} \frac{D_{input}^{t+1}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{z}^{t})]}{D_{input}^{t}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{z}^{t+1})} \right]^{\frac{1}{2}} (45)$$

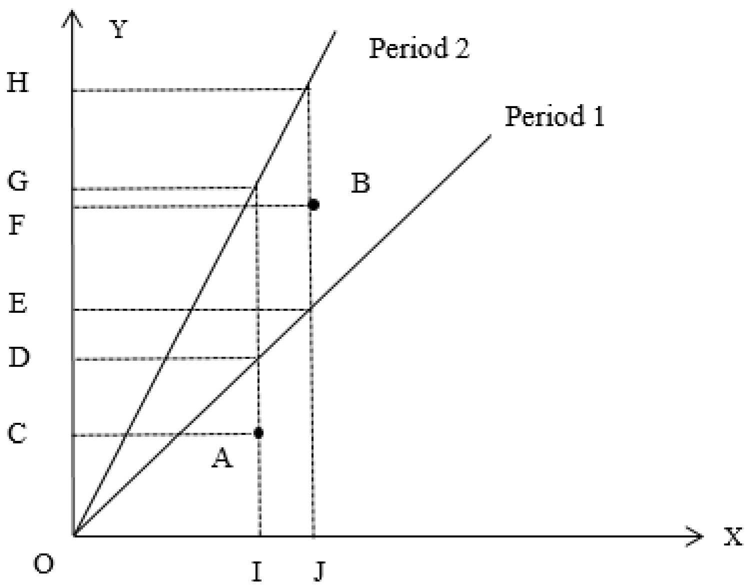


Figure16 Malmquist productivity

As shown in Figure16, point A and B are two evaluated DMUs in period 1 and 2. EC is measured by $\frac{OF/OH}{OC/OD}$ and it implies an improvement in relative efficiency between two periods if EC is higher than 1. TP indicates the frontier shift over periods, and it is computed by $\frac{OG}{OD}$ in terms of A, and $\frac{OH}{OE}$ in terms of B. There is a progress in TP over periods if $\sqrt{\frac{OG}{OD}\frac{OH}{OE}}$ is higher than 1.

According to our discussion in section 1, the traditional Malmquist productivity indicator is using the Shephard distance function which can only simultaneously increase or decrease desirable and undesirable outputs proportionately. This property does not suit social or economic expectations for policy makers and producers who wish to increase desirable outputs and to reduce undesirable ones.

3.2.2. Luenberger productivity index

Chambers (2002) introduces the Luenberger productivity indicator based on the directional distance functions proposed by Luenberger (1992). Compared to

Shephard distance functions, one advantage of the directional distance function is to increase desirable outputs and reduce undesirable ones simultaneously. The Luenberger TFP indicator over the time period t and t+1 for a DMU can be defined as follows:

$$TFP_L^{t,t+1} = \frac{1}{2}[D^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t; \mathbf{g}_y^t, \mathbf{g}_z^t) - D^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{z}^{t+1}; \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}) + D^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t; \mathbf{g}_y^t, \mathbf{g}_z^t) - D^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{z}^{t+1}; \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})] \quad (46)$$

Similarly, this difference-based indicator can be decomposed to EC and TP as follows:

$$TFP_L^{t,t+1} = EC^{t,t+1} + TP^{t,t+1} \quad (47)$$

$$EC^{t,t+1} = D^t(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_v^t, \mathbf{g}_w^t) - D^{t+1}(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1}) \quad (48)$$

$$TP^{t,t+1} = \frac{1}{2}[D^{t+1}(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_\mathbf{v}^t, \mathbf{g}_\mathbf{w}^t) - D^t(\mathbf{x}^t, \mathbf{v}^t, \mathbf{w}^t; \mathbf{g}_\mathbf{v}^t, \mathbf{g}_\mathbf{w}^t) + D^{t+1}(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_\mathbf{v}^{t+1}, \mathbf{g}_\mathbf{w}^{t+1}) - D^t(\mathbf{x}^{t+1}, \mathbf{v}^{t+1}, \mathbf{w}^{t+1}; \mathbf{g}_v^{t+1}, \mathbf{g}_w^{t+1})] \quad (49)$$

In the same manner, Chung et al. (1997) propose the Malmquist-Luenberger index using the directional distance function which is consistent with the property increasing desirable outputs and decreasing undesirable ones simultaneously, and it is also a ratio-based indicator in terms of Malmquist index:

$$TFP_{ML}^{t,t+1} = \left[\frac{1 + D^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t; \mathbf{g}_y^t, \mathbf{g}_z^t)}{1 + D^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{z}^{t+1}; \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})} \frac{1 + D^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t; \mathbf{g}_y^t, \mathbf{g}_z^t)]}{1 + D^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{z}^{t+1}; \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})}\right]^{\frac{1}{2}} \quad (50)$$

Malmquist-Luenberger has been widely applied to measure environmental performance in the literature. In addition, some other environmental productivity indices are also available. For example, Abad (2015) proposes an innovative ratio-based Hicks-Moorsteen productivity index and a new difference-based Luenberger-Hicks-Moorsteen productivity indicator. Feng and Serletis (2014) extend a Divisia-Luenberger productivity index by taking into account undesirable outputs and they parameterize the directional output distance function by decomposing index into technological change term and efficiency change term consistently.

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Chapter 2

Environmental Growth Convergence among Chinese Regions

In this chapter, we analyze the evolution of environmental efficiencies and carbon shadow prices among 30 Chinese regions. Following Leleu's (2013a) hybrid WDA approach, we model carbon emissions as undesirable outputs with constrained shadow prices under a VRS technology, and we propose a novel decomposition for regional environmental efficiencies which are separated into a technical efficiency change, and a structural efficiency change which captures the heterogeneity across Chinese regions relative to their input or output accumulations. We also examine the environmental growth convergence process among Chinese regions.

1. Introduction

Recently, the rapid Chinese economic growth has attracted much attention, and many researchers have tried to discover whether this type of growth is sustainable due to the increasingly serious environmental problems. Related to the convergence debate, two processes lead to income convergence between regions: (1) capital deepening linked to the property of diminishing returns and (2) technological transfer/diffusion related to total factor productivity (TFP) differences. Assuming perfect capital mobility and identical technology, the neoclassical standard theory has devoted attention mostly to the first process. In addition, standard growth theory presumes that the technological progress is exogenous and is available to all at no cost, and thus says little about technology adoption. This was a restrictive assumption needed at that initial step of the advancement of growth theory (Solow, 1994). Several researchers such as Jorgenson (1995) and Durlauf and Johnson (1995) concluded that the identical production technologies assumption may not hold. Abramovitz (1986) adopted a less radical approach by considering a common available technology, but regions may differ in their ability to recognize, incorporate, and use it. He introduced "social capabilities" to explain productivity gaps among regions. Therefore, interest in cross-regional TFP differences has become a key element for investigating economic growth (Islam, 2003).

Since the end of the 1980s, many empirical studies focused on regional comparisons of TFP have revealed that differences in technology may contribute to gaps in TFP levels.[1] Since TFP is an empirical measure of technology, TFP convergence investigates whether regions can catch up in terms of the highest observed TFP levels and how income convergence depends on TFP growth rates and initial TFP levels. For example, among others, Özyurt and Guironnet (2011) investigated the causes of the rapid Chinese economic growth and its sustainability by the parametric approach creating a stochastic production frontier for 30 regions between 1994 and 2006. These scholars decomposed productive efficiency to the technological progress and scale effect such that the latter's negative values are compensated by the former. They concluded that foreign direct investment and foreign trade are the two main driving forces of economic growth. The results show an apparent trend of economic convergence among Chinese regions and growth sustainability for the near future.

Christopoulos (2007) considered a data envelopment analysis (DEA) approach for measuring efficiency and examined the impact of human capital and openness on productive performance in a sample of 83 developed and less developed countries. His results supported the view that movements toward openness increase a country's efficiency performance significantly, whereas human capital does not contribute to efficiency. However, his analysis relied on an assumption of restrictive constant returns to scale technology. Chen et al. (2008) measured China's TFP growth in agricultural sector using DEA and the Malmquist index between 1990 and 2003. Their results show that the main source of productivity growth is from technical progress which is determined by

[1] See Islam (2001) for a review of different approaches to international comparisons of TFP and the issue of convergence.

agricultural tax reduction, investment in research and development, infrastructure and mechanization. They argued that the deterioration in scale efficiency should be improved by structural adjustment facilitations.

Most of these studies suffered from three weaknesses. First, they ignored environmental damage in economic outputs that might cause biased results. Other scholars who considered pollution mostly focused on the company level while a few studied the entire economy level (Zhou et al., 2014). Second, the technology level was evaluated with a TFP index measured as a Solow-residual indicator with a particular functional form with parametric approaches (Cobb–Douglas, CES, Translog, etc.). Third, TFP gaps may in part be due to the constant returns to scale assumption, which does not consider size heterogeneity across regions. Some papers incorrectly modeled technologies with bad outputs although the researchers used the VRS technology, while another modeled correctly but provided positive and negative shadow prices for undesirable outputs whose economic content is not meaningful. These methodological choices may modify or bias an evaluation of the technical catching-up process.

China experienced different stages of development under the influence of various leaders. The first period was led by Zedong Mao from 1949 to the 1970s. The national economy mainly relied on outdated agriculture practices and light industry with a slow development rate, because he considered the class struggle the primary task rather than development of the economy. After his death, Xiaoping Deng and his reformist allies overthrew the Maoist faction, and China entered the second period in 1978. The reformists also proposed the primary stage of socialism that meant conditionally accepting capitalism during the early development period. True economic progress began in 1992 after political reforms were enacted when the leadership recognized the necessity of reform after the Soviet Union collapsed. This is the period on which this paper focuses. Disregarding pollution and taking economic construction as the central target inevitably led to environmental problems. The Chinese Communist Party recently realized the unsustainability due to the economic slowdown no matter what incentives had been carried out. The growth rates of the real gross domestic product (GDP), energy consumption, and carbon dioxide emissions between 1997 and 2010 were 11.32%, 7.79%, and 8.93%, respectively, and energy consumption is the important driving force of GDP growth (China Statistical Abstract, 2013). Especially, haze has emerged in most big cities, which shows the increased consumption of many types of energy. However, the benefit of implementing environmental control is debatable, since economic cooling and slowdown may cause massive unemployment and will bring social instability if effective and immediate environmental regulations are carried out. Thoughtful strategies for sustainable development have attracted increasing attention. More and more papers take into account undesirable outputs in productivity and/or efficiency evaluation, which can provide a comprehensive benchmark for decision making to identify the distance between each region's performance and the best one.

Empirical DEA research on dealing with undesirable outputs has 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. Tone (2001) first proposed a slacks-based measure (SBM) based on the proportional decrease, but this approach cannot give a clear interpretation from an economic point of view. Chen (2014) used an SBM based theoretical model to measure the Chinese ecological TFP by simultaneously incorporating energy consumption and pollutions. His results reveal a deterioration of ecological development performance during the period from 2003 to 2007 and he argued that China's economic development started a transition from resources-driven extensive model to an environment-friendly one after international economic crises. Sahoo et al. (2011) investigated 11 alternative DEA models based on weak disposability and strong disposability assumptions by testing a data set of ten firms and 22 OECD countries. They argued that special treatment of undesirable outputs would not affect the productivity ranking in the final result. The researchers also concluded that there is no consensus in choosing a preferred model. Zhou et al. (2014) summarized the literature about estimating the shadow prices of undesirable outputs on parametric and non-parametric methods. They argued that developing countries attract increasing attention and research pollutants shift from early sulfur or nitrogen oxide to carbon oxide emissions because of global warming.

The Malmquist-Luenberger index is a popular productivity index based on the directional distance function that allows incorporating undesirable outputs as introduced by Chung et al. (1997). Zhang et al. (2011) evaluated the environmental TFP using the Malmquist-Luenberger index among 30 regions in China during the period 1989–2008. They used an integrated environmental factor as the undesirable output which obtained by utilizing dimension decrease on various pollution indicators. The TFP index is decomposed into technical and efficiency changes by creating a DEA model under a weak disposability assumption and constant returns to scale (CRS) technology. Their results showed environmental productivity was lower than the traditional level and proved TFP growth is overestimated if undesirable outputs are ignored.

Similarly, Chen and Golley (2014) estimated China's green productivity in 38 industrial sectors over the period 1980–2010. The researchers used carbon dioxide emissions as the undesirable output in the directional distance function under the CRS technology. Their results showed green TFP growth was less than the traditional TFP counterpart, which considered only desirable output during all periods. The researchers also found an unsustainable feature in the sector-level green TFP growth.

Färe et al. (2012) used Luenberger TFP indicators in the Swedish manufacturing industry between 1990 and 2008 to test whether bad outputs should be incorporated when productivity is measured. Their results showed TFP growth was underestimated if bad outputs are excluded and decreases in bad outputs should also be credited. Leleu (2013a) developed a hybrid approach of modeling undesirable outputs with non-positive shadow prices and argued that productive reasonability from the revenue of desirable outputs should exceed the cost of undesirable outputs, which provides an unambiguous economic interpretation of the weak disposability assumption. Feng and Serletis (2014) extended the Divisia-Luenberger productivity index by considering undesirable outputs and parameterized the directional output distance function by decomposing the index consistently into the technological change term and the efficiency change term. The researchers used data from 15 OECD countries during 1981-2000 and showed biased results that included misleading ranking and incorrect conclusions if bad outputs were not considered.

We used the above non-parametric programming method to focus on the convergence process among 30 Chinese provinces from 1997 to 2010. From a methodological point of view, the first contribution of this paper is to expose how a growth convergence process within a group, regions, and/or countries characterized by heterogeneous sizes is better achieved through technical efficiency changes based on a VRS technology than is traditionally done by productivity-level estimates assuming a CRS technology. Compared to previous studies on growth convergence, the second originality of our research is to separate regional efficiency changes into two components: a technical catching-up effect (movement toward the production frontier) and a structural effect (homogenization of input/output combinations). The two effects can be derived from efficiency scores evaluated at the aggregated level and the sum of individual production plans. In accordance with the VRS assumption, the third contribution is to propose a right non-parametric framework that models individual and aggregate technologies. These technologies are necessarily based on weak disposability in order to estimate technical catching-up effects including environmental damage implying non-negative shadow prices for carbon dioxide emissions.

From an empirical point of view, the first outcome is to study the growth convergence process among Chinese regions taking into account environmental damage such as carbon dioxide emissions and to reveal which effect between technical catching-up and homogenization of input/output combined components prevails. The second achievement is to assess the level of pollution cost due to Chinese economic development through the shadow price estimates of carbon emissions.

This paper is structured as follows. Using weak disposability and VRS assumptions to conceptualize the production frontier, in the next section, we discuss the measures of the two effects that may influence the convergence process in China (technical and structural effects). In Section 3, we analyze growth convergence with its driving forces and link them to the evolution of labor, capital, and carbon shadow prices. Conclusions appear in the final section.

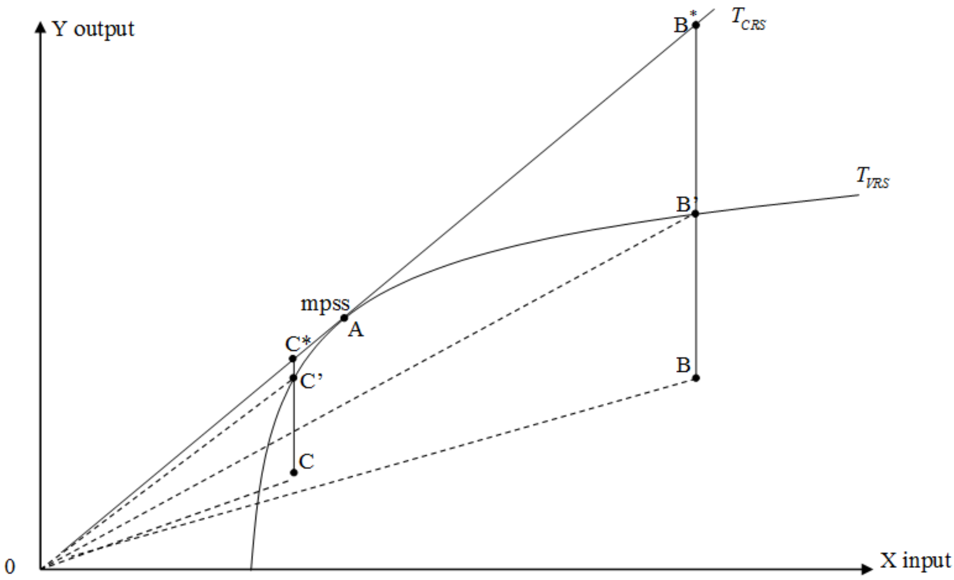
2. Analyzing the convergence process with directional distance functions including undesirable outputs

The objective of the model is to gauge a growth convergence process among economic regions through a technical effect and a structural effect. While the former depends on social capabilities to adopt available technology, the latter encompasses the heterogeneity across regions relative to their input or output accumulations. This can be viewed as a structural component due to changes in input and output mixes that signal the role of an input or output deepening or expanding effects on productivity growth.

2.1. Definitions and concepts

2.1.1. Technical catching-up process and growth convergence

Traditionally, the applied literature about technological adoption compares TFP levels across regions and tests an inverse relationship between growth TFP rates and their initial levels. Convergence in productivity levels turns out if regions with the lowest initial TFP have the highest growth rates: The followers catch up with the leaders. This approach relies on an implicit assumption of CRS since the optimal TFP, used as a benchmark for all regions, is the maximum observed productivity. However, if the CRS assumption does not hold and the production technology shows increasing and/or decreasing returns to scale (VRS), the maximal feasible level of TFP for a specific region does not necessarily coincide with the maximal observed TFP among all regions but must be precisely gauged at its own economic size (input levels for instance). By assuming a CRS technology while a VRS technology prevails, some bias may be introduced in the analysis of technological diffusion. Indeed, a divergence in TFP levels can be observed while provinces, reaching their production frontier, play a part in the technical catch-up process as illustrated in Figure 1.

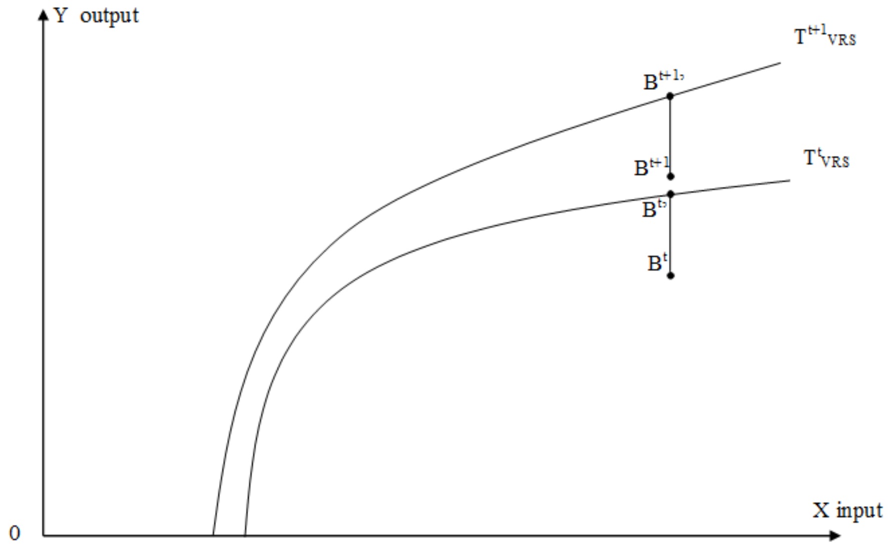


Note: Y is the output produced from the input X. T_{CRS} and T_{VRS} are the production frontiers under constant and variable returns to scale respectively. A, B and C are observed production plans and mpss is the production plan with the most productive scale size. B', B*, C' and C* are efficient production plans onto the frontiers.

Figure 1. TFP measure and its decomposition into technical and scale effects

In Figure 1, three provinces (A, B, and C) produce one output (Y) from one input (X) under a variable returns to scale technology T_{VRS}. The observed levels of TFP for B are easily computed as $\frac{0y_B}{0x_B}$ while the maximal productivity is observed for A, which characterizes the most productive scale size (mpss). If we consider this mpss as the benchmark for all other regions, we implicitly assume a CRS technology. In that case, if B and C come up to B* and C*, convergence TFP will arise since all provinces achieve the same maximal TFP level. However, under the true VRS technology, regions will be able at best to reach B' and C' as their respective sizes (measured in the input levels, for instance) cannot be easily modified. Thus, while B and C will never be observed at B* and C*, one will conclude that divergence of TFP levels between these two regions occurs. The TFP change is higher for region C than for region B even though the former was initially more productive than the latter, a contradiction of the TFP convergence hypothesis. By considering the true VRS technology of the example regions, we assume that the maximal feasible productivity levels evaluated at B' and C' on the production frontier are their own respective optimal benchmarks rather than the mpss TFP level. Thus, a decrease with time in the distances between countries and their respective benchmarks on the production frontier denotes such a catching-up process to the maximal feasible productivity levels evaluated at the current size of the region. Traditional sigma or beta convergence tests on TFP levels are unable to point out this technological adoption effect. We will introduce the directional distance function later to formally measure the distance of a production plan to the production frontier.

In our approach, the technical catching-up process is independent from the usual technical change definition since we compare the observed levels of TFP to their current technological benchmark. Comparisons are therefore performed within the same period and not across time. Although shifts in the production frontier modify productivity levels, they do not interfere with our technical catching-up measure since technical progress affects provinces and their benchmarks on the frontier uniformly. This is illustrated in Figure 2. While there is technical progress over the two periods, the distances to the frontiers have not changed, implying there was no technical catching-up.

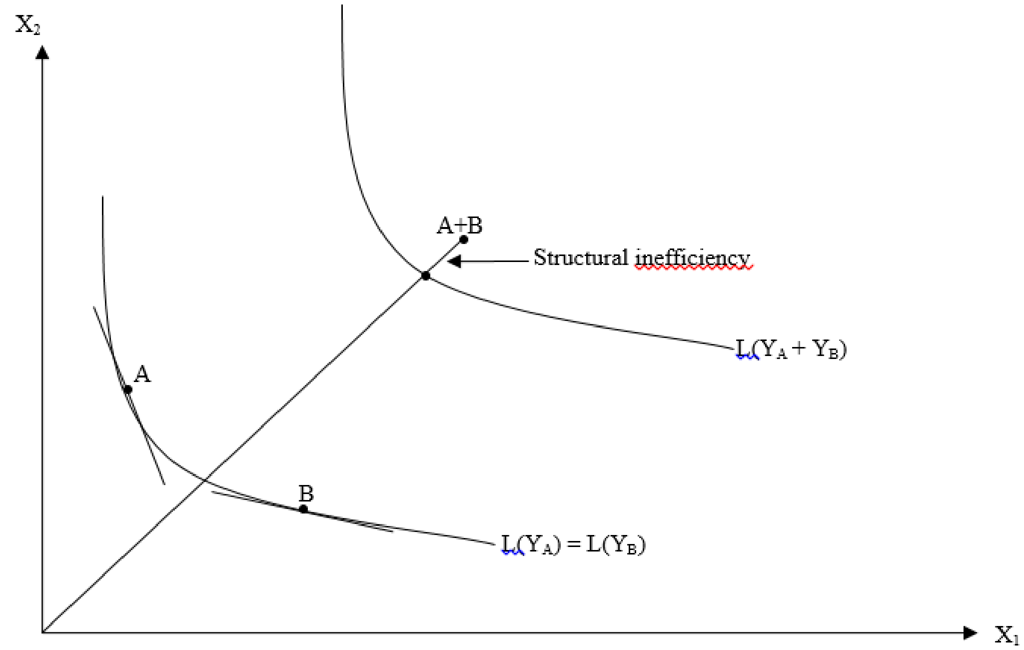


Note: Y is the output produced from the input X. T^{t}_{VRS} and T^{t+1}_{VRS} are the production frontiers at time t and t+1 respectively. B^t and B^{t+1} are observed production plans in t and t+1. $B^{t'}$ and $B^{t+1'}$ are efficient production plans onto the frontiers.

Figure 2. Technical progress and technical catching-up

2.1.2. Structural inefficiency and convergence of output/input mixes

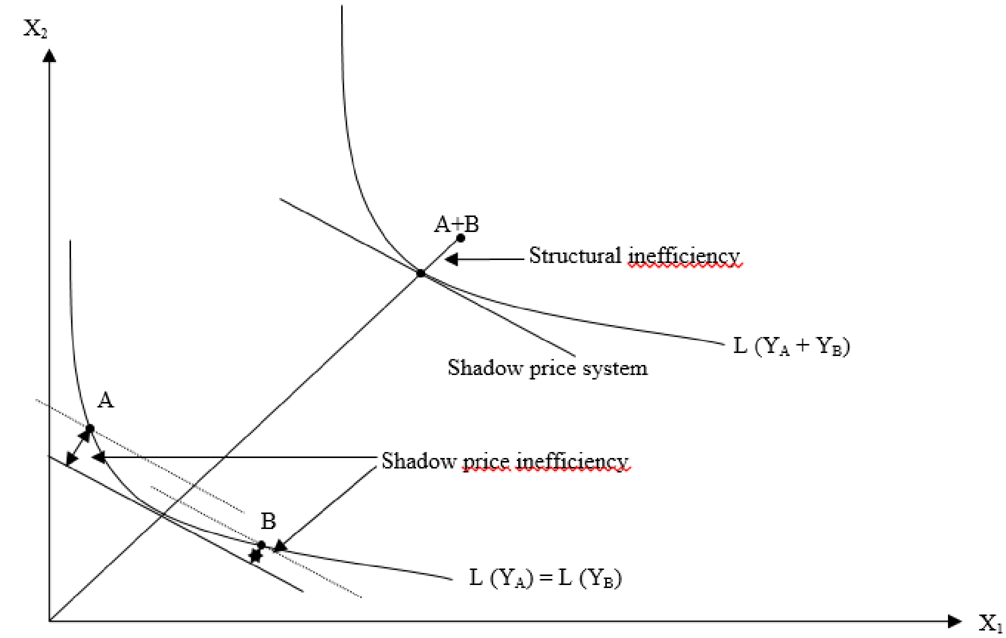
We further illustrate the structural inefficiency effect in a multiple output-input case as a subtle source of inefficiency due to heterogeneity in output and factor accumulation among regions. Assume that two regions are technically efficient and price efficient in the sense of Farrell (1957). Therefore, no inefficiencies arise at the individual level. However, if the regions face different price systems, a type of inefficiency clearly prevails in the group of provinces in line with the second welfare theorem. This market inefficiency is captured by a structural inefficiency component as shown in Figure 3a. Let us consider two production plans (region A and region B) that are represented in the input space producing the same level of outputs. Although A and B are both technically and price efficient, there is still inefficiency at the aggregate level. This structural inefficiency comes from differences in relative input allocations among the two regions. In a perfect competition market, only one input price vector has to coordinate the two regions, and this structural effect computes the inefficient market allocation in the spirit of the Debreu (1951) coefficient of resource use.



Note: X_1 and X_2 are two inputs. $L(Y_A)$, $L(Y_B)$ and $L(Y_A+Y_B)$ are input sets. A and B are observed production plans.

Figure 3a. Illustration of structural efficiency

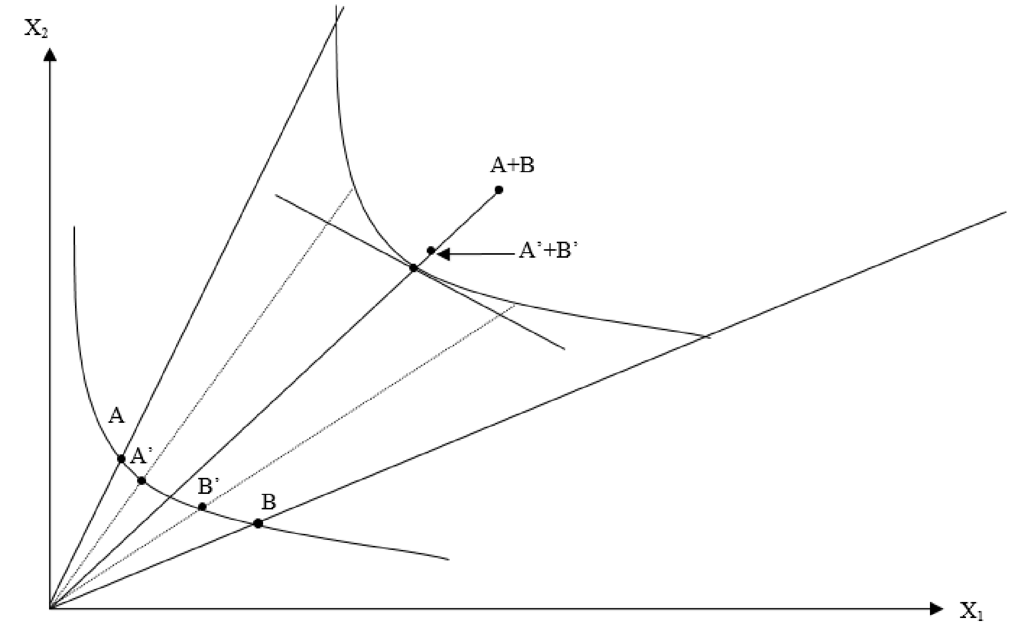
Measuring the respective contributions of A and B to this global structural inefficiency and thus to split it between them would be interesting. This can be done thanks to the shadow price system defined at the aggregate technology and then applied at each provincial production plan. As shown in Figure 3b, structural inefficiency evaluated at the aggregated level can be decomposed as the sum of individual shadow price inefficiencies.



Note: X_1 and X_2 are two inputs. $L(Y_A)$, $L(Y_B)$ and $L(Y_A+Y_B)$ are input sets. A and B are observed production plans.

Figure 3b. The measurement of structural efficiency

Before turning to a formal presentation of the model we use to gauge the technical and structural effects, we briefly discuss the implications of these concepts for the convergence process among regions. First, a decrease in technical inefficiency with time appears as a technical catching-up effect. Note that we control for a potential region's size bias by rejecting the CRS assumption and estimating the technical effects under a VRS technology. Second, the lower the structural inefficiency, the less heterogeneity we have in the output and input mixes between provinces. Therefore, a decrease in structural inefficiency over time (from A+B to A'+B') reveals a convergence toward a common expansion path linked to an input-mix convergence effect as shown in Figure 3c.



Note: X_1 and X_2 are two inputs. A, A', B and B' are observed production plans.

Figure 3c. The measurement of structural efficiency

2.1.3. Definition of a weakly disposable technology

Using Shephard's definition of weakly disposable technology (Färe and Grosskopf, 2003), let $\mathbf{x} \in R_+^N$ denote the vector of the inputs, $\mathbf{y^G} \in R_+^M$ and $\mathbf{y^B} \in R_+^P$ the vectors of the desirable (good) and undesirable (bad) outputs for a region, respectively. Chinese regions are assumed to face the same technology represented by the production set T and the corresponding output set P:

$$T = \left\{ (\mathbf{x}, \mathbf{y^G}, \mathbf{y^B}) : \mathbf{x} \text{ can produce } (\mathbf{y^G}, \mathbf{y^B}) \right\} \tag{1}$$

$$P(\mathbf{x}) = \left\{ (\mathbf{y^G}, \mathbf{y^B}) : (\mathbf{x}, \mathbf{y^G}, \mathbf{y^B}) \in T \right\} \tag{2}$$

The whole country (W) is composed of K regions ($k=1,\dots K$). The aggregate technology at the nation level inherits properties from the regional technology. Formally, we define the nation technology T^W as the sum of the provincial technologies:

$$T^W = \sum_{k=1}^{K} T \tag{3}$$

It is possible to prove that the aggregate CRS technology is equal to the individual CRS technology (Li, 1995):

$$T_{CRS}^{W} = \sum_{k=1}^{K} T_{CRS} = T_{CRS} \tag{4}$$

Li (1995) also showed that if convexity holds, then the VRS aggregate technology is equal to *K* times the individual technology:

$$T_{VRS}^{W} = \sum_{k=1}^{K} T_{VRS} = K \times T_{VRS} \tag{5}$$

We now turn to the weak disposability axiom introduced by Shephard (1970) and Shephard and Färe (1974). The assumption of weak disposability means that inputs are freely disposable while proportional decreases in outputs are feasible:

$$\text{If } (\mathbf{y^G}, \mathbf{y^B}) \in P(\mathbf{x}) \text{ and } 0 \le \theta \le 1 \text{ then } (\theta\mathbf{y^G}, \theta\mathbf{y^B}) \in P(\mathbf{x}) \tag{6}$$

Meanwhile, undesirable and desirable outputs are null-joint, which means the former cannot be produced without generating the latter:

$$\text{If } (\mathbf{y^G}, \mathbf{y^B}) \in P(\mathbf{x}) \text{ and } \mathbf{y^B} = 0 \text{ then } \mathbf{y^G} = 0 \tag{7}$$

2.2. Measuring overall technical and structural inefficiencies

We now turn to the definition of the directional distance function, which measures the distances between the observed production plans and the boundary of the technology. These distances are interpreted as gaps between the observed TFP levels and their maximal feasible or desired levels of TFP. The function defined by:

$$\vec{D}_T(\mathbf{x},\mathbf{y}^{\mathbf{G}},\mathbf{y}^{\mathbf{B}};\mathbf{g}_{\mathbf{x}},\mathbf{g}_{\mathbf{y}^{\mathrm{G}}},\mathbf{g}_{\mathbf{y}^{\mathrm{B}}}) = \sup_{\lambda}\left\{ \lambda \in \Re_{+} : (\mathbf{x}-\lambda\cdot\mathbf{g}_{\mathbf{x}},\mathbf{y}+\lambda\cdot\mathbf{g}_{\mathbf{y}^{\mathrm{G}}},\mathbf{y}-\lambda\cdot\mathbf{g}_{\mathbf{y}^{\mathrm{B}}}) \in T \right\}, \qquad (8)$$

is called the directional distance function where $(\mathbf{g}_{\mathbf{x}},\mathbf{g}_{\mathbf{y}^{\mathrm{G}}},\mathbf{g}_{\mathbf{y}^{\mathrm{B}}})$ is a nonzero vector that determines the direction in which $\vec{D}_T(\cdot)$ is defined. An analysis of the properties of directional distance functions can be found in Chambers et al. (1996). Note that $(\mathbf{x},\mathbf{y}^{\mathbf{G}},\mathbf{y}^{\mathbf{B}}) \in T \Longleftrightarrow \vec{D}_T(\mathbf{x},\mathbf{y}^{\mathbf{G}},\mathbf{y}^{\mathbf{B}};\mathbf{g}_{\mathbf{x}},\mathbf{g}_{\mathbf{y}^{\mathrm{G}}},\mathbf{g}_{\mathbf{y}^{\mathrm{B}}}) \geq 0$. Thus, it is possible to characterize the production set from the directional distance function.

For estimation purposes, we follow the literature on non-parametric frontier estimation by specifying an operational definition of *T* based on a set of observed regions and a set of axioms that add some structure to the definition of *T* in (1). A convex production set that satisfies free disposability of the inputs and weak disposability for outputs following Leleu's approach (2013a, 2013b). In this approach, good outputs and inputs are freely disposable, meaning that good outputs can be reduced while maintaining inputs. Similarly, inputs can be increased while maintaining the level of both good and bad outputs. On the contrary, bad outputs are not freely disposable as they cannot be decreased without affecting good outputs (see equation 6 which formalizes this jointness assumption). That is why bad outputs are characterized as weakly disposable.

Under variable returns to scale, T_{VRS} is defined as:

$$\begin{aligned} T_{VRS} = \Bigg\{ & (\mathbf{x},\mathbf{y}^{\mathbf{G}},\mathbf{y}^{\mathbf{B}}) : \mathbf{x} \in R_{+}^{N}, \mathbf{y}^{\mathbf{G}} \in R_{+}^{M}, \mathbf{y}^{\mathbf{B}} \in R_{+}^{P}, \sum_{k=1}^{K} y_{m,k}^{G} z_k \geq y_{m}^{G}, m = 1,\ldots,M, \\ & \sum_{k=1}^{K} y_{p,k}^{B} z_k \leq y_{p}^{B}, p = 1,\ldots,P, \\ & \sum_{k=1}^{K} x_n^k z_k \leq \theta x^n, n = 1,\ldots,N, \sum_{k=1}^{K} z_k = \theta, z_k \geq 0, k = 1,\ldots,K, \theta \leq 1 \Bigg\} \end{aligned} \qquad (9)$$

Concerning the directional distance function, we use the aggregate output vector to construct the direction of the translation; i.e., $(\mathbf{g_x},\mathbf{g_{y^G}},\mathbf{g_{y^B}})=\left(0,\sum_{k\in W}\mathrm{y}_\mathrm{k}^\mathrm{G},\sum_{k\in W}\mathrm{y}_\mathrm{k}^\mathrm{B}\right)$. Therefore, technical inefficiencies are computed as percentages of the aggregated GDP and of the total carbon dioxide emissions of the entire country.

For a specific region $(\mathbf{x}_o,\mathbf{y}_o^\mathbf{G},\mathbf{y}_o^\mathbf{B})$, the productivity gap is defined in relation to a VRS technology by $\vec{D}_{T_{VRS}}(\mathbf{x}_o,\mathbf{y}_o^\mathbf{G},\mathbf{y}_o^\mathbf{B};0,\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{G},\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{B})$. This distance function is computed by the following linear programs (LPs)[2]:

$$\begin{aligned}
&\vec{D}_{T_{VRS}}(\mathbf{x}_o,\mathbf{y}_o^\mathbf{G},\mathbf{y}_o^\mathbf{B};0,\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{G},\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{B})=\max_{z,\theta,\lambda}\ \lambda\\
s.t.\ &\sum_{k\in W} z_k y_{k,m}^G \geq y_{o,m}^G+\lambda\sum_{k\in W} y_{k,m}^G \quad \forall m=1,\cdots,M\\
&\sum_{k\in W} z_k y_{k,\mathrm{p}}^B \leq y_{o,p}^B-\lambda\sum_{k\in W} y_{k,p}^B \quad \forall p=1,\cdots,P \qquad \text{(LP1)}\\
&\sum_{k\in W} z_k x_{k,n} \leq \theta x_{o,n} \quad \forall n=1,\cdots,N\\
&\sum_{k\in W} z_k=\theta\\
&z_k\geq 0 \quad \forall k=1,\dots,K\\
&\theta\leq 1
\end{aligned}$$

As a result, the technical inefficiency at the country level can be measured by the summation of regional technical inefficiencies:

$$\sum_{o\in W}\vec{D}_{T_{VRS}}(\mathbf{x}_o,\mathbf{y}_o^\mathbf{G},\mathbf{y}_o^\mathbf{B};0,\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{G},\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{B}) \qquad (10)$$

While the overall inefficiency evaluated at the aggregated level is defined by:

$$\vec{D}_{T_{VRS}^W}(\sum_{k\in W}\mathbf{x}_k,\sum_{k\in W}\mathbf{y}_k^\mathbf{G},\sum_{k\in W}\mathbf{y}_k^\mathbf{B};0,\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{G},\sum_{k\in W}\mathbf{y}_\mathbf{k}^\mathbf{B}) \qquad (11)$$

[2] These linear programs are the correct linearizations of the VRS technology with a weak disposable assumption on bad outputs as developed in Leleu (2013a).

and computed by the following LP.:

$$
\begin{aligned}
&\vec{D}_{T_{VRS}^{W}}(\sum_{k\in W}\mathbf{x}_k,\sum_{k\in W}\mathbf{y}_k^{\mathbf{G}},\sum_{k\in W}\mathbf{y}_k^{\mathbf{B}};0,\sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{G}},\sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{B}})=\max_{z,\theta,\lambda}\lambda\\
s.t.\ &K\sum_{k\in W}z_k y_{k,m}^G \geq \sum_{o\in W} y_{o,m}^G+\lambda\sum_{k\in W}y_{k,m}^G \quad \forall m=1,\cdots,M\\
&K\sum_{k\in W}z_k y_{k,p}^B \leq \sum_{o\in W} y_{o,p}^B-\lambda\sum_{k\in W}y_{k,p}^B \quad \forall p=1,\cdots,P\\
&K\sum_{k\in W}z_k x_{k,n} \leq \theta\sum_{o\in W} x_{o,n} \quad \forall n=1,\cdots,N\\
&\sum_{k\in W}z_k=\theta\\
&z_k\geq 0 \quad \forall k=1,...,K\\
&\theta\leq 1
\end{aligned}
\qquad \text{(LP2)}
$$

Finally, the structural inefficiency part of the productivity gap is based on the difference between the overall and technical inefficiencies:

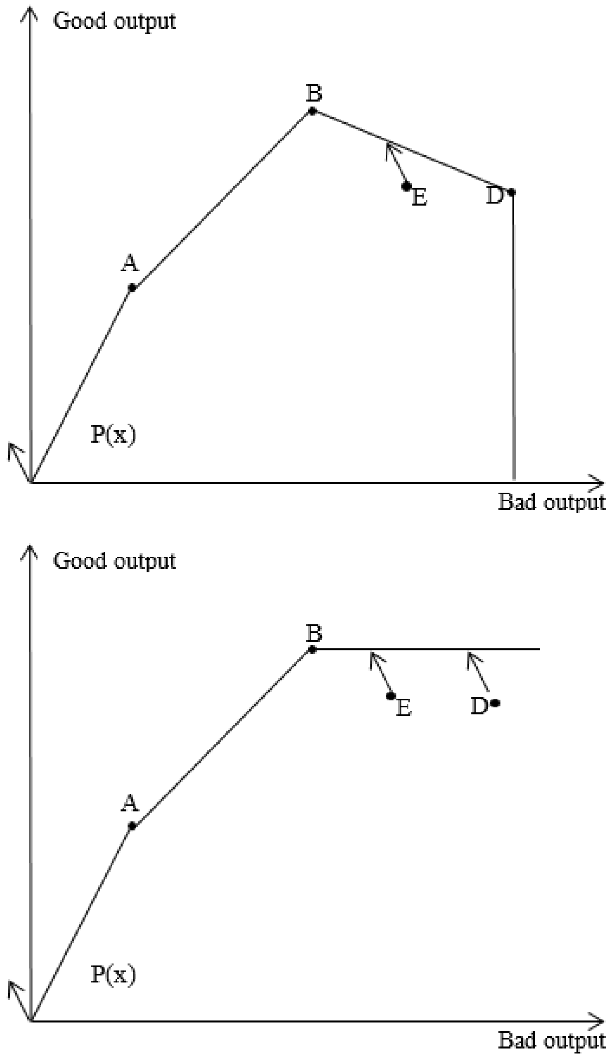
$$
\vec{D}_{T_{VRS}^{W}}(\sum_{k\in W}\mathbf{x}_k,\sum_{k\in W}\mathbf{y}_k^{\mathbf{G}},\sum_{k\in W}\mathbf{y}_k^{\mathbf{B}};0,\sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{G}},\sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{B}})-\sum_{o\in W}\vec{D}_{T_{VRS}}(\mathbf{x}_o,\mathbf{y}_o^{\mathbf{G}},\mathbf{y}_o^{\mathbf{B}};0,\sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{G}},\sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{B}}) \qquad (12)
$$

The overall and structural inefficiencies are computed for the entire country while the technical inefficiency is province-specific.

2.3. Measuring non-positive shadow prices for bad outputs

Unlike other weakly disposable technology that uses an unconstrained shadow price for an undesirable output that may obtain positive and negative values, we adopt Leleu's approach (2013a, 2013b) that changes the equality sign to inequality on the constraints for undesirable outputs in order to get a positive shadow price. This means that the undesirable output cannot generate positive revenue and is considered a cost in the production process. As shown in Figure 4a, point D is on the efficient frontier if the shadow price of the undesirable output is unconstrained, and point E is projected on the segment between B and D, which appears as an unexpected negative value. In Figure 4b, point D becomes inefficient if the shadow price of the undesirable output is constrained as an expected positive value. The benefit of this approach is to obtain an explicit economic interpretation for the weak disposability assumption. Correspondingly, the shadow price comes from the dual program of LP1, which is determined as follows:

$$
\begin{aligned}
&\min_{\phi,\pi_m^G,\pi_p^B,\pi_n} \phi \\
&s.t.\ \Big(\sum_{m\in M}\pi_m^G y_{k,m}^G - \sum_{p\in P}\pi_p^B y_{k,p}^B - \sum_{n\in N}\pi_n x_{k,n}\Big) \\
&\quad -\Big(\sum_{m\in M}\pi_m^G y_{o,m}^G - \sum_{p\in P}\pi_p^B y_{o,p}^B - \sum_{n\in N}\pi_n x_{o,n}\Big) \le \phi \quad \forall k=1,\cdots,K \\
&\sum_{m\in M}\pi_m^G \sum_{k\in W} y_{k,m}^G + \sum_{p\in P}\pi_p^B \sum_{k\in W} y_{k,p}^B = 1 \\
&\sum_{m\in M}\pi_m^G y_{o,m}^G - \sum_{p\in P}\pi_p^B y_{o,p}^B + \phi \ge 0 \\
&\pi_m^G \ge 0 \quad \forall m=1,\dots,M \\
&\pi_p^B \ge 0 \quad \forall p=1,\cdots,P \\
&\pi_n \ge 0 \quad \forall n=1,\cdots,N
\end{aligned}
\qquad \text{(LP3)}
$$



Note: A, B, E and D are observed production plans. P(X) is the output set.

Figure 4. Unconstrained and non-positive shadow price for bad outputs

Next, we determine the dual directional distance function under the VRS aggregate technology. Similarly to the correspondence between LP1 and LP3, the shadow price comes from the dual program of LP2, which is determined as follows:

$$\begin{aligned}
&\min_{\phi,\pi_m^G,\pi_p^B,\pi_n} \quad \phi \\
&s.t.\ (K\sum_{m\in M}\pi_m^G y_{k,m}^G - K\sum_{p\in P}\pi_p^B y_{k,p}^B - K\sum_{n\in N}\pi_n x_{k,n}) \\
&\quad -(\sum_{m\in M}\pi_m^G(\sum_{o\in W} y_{o,m}^G) - \sum_{p\in P}\pi_p^B(\sum_{o\in W} y_{o,m}^B) - \sum_{n\in N}\pi_n(\sum_{o\in W} x_{o,n})) \le \phi \quad \forall k=1,\cdots,K \\
&\sum_{m\in M}\pi_m^G \sum_{k\in W} y_{k,m}^G + \sum_{p\in P}\pi_p^B \sum_{k\in W} y_{k,p}^B = 1 \\
&\sum_{m\in M}\pi_m^G y_{o,m}^G - \sum_{p\in P}\pi_p^B y_{o,p}^B + \phi \ge 0 \\
&\pi_m^G \ge 0 \quad \forall m=1,\ldots,M \\
&\pi_p^B \ge 0 \quad \forall p=1,\cdots,P \\
&\pi_n \ge 0 \quad \forall n=1,\cdots,N
\end{aligned} \tag{LP4}$$

We can allocate the overall and structural inefficiencies across regions by using the shadow prices derived in LP4. Indeed, it can be shown that overall inefficiency can be decomposed in individual effects as the countries' price inefficiency (allocative + technical components) computed with the shadow prices derived from the aggregate technology (Briec et al., 2003). As a result, the individual structural inefficiency is computed by the difference between the price and technical inefficiencies for each region. Although the shadow prices could be generated from marginal values with the primal models, the dual models clearly reveal positive and non-positive shadow prices on good and bad outputs, respectively, to offer a meaningful economic interpretation.

3. Efficiency convergence among Chinese regions

3.1. Data

The data come from the China Statistical Yearbook (National Bureau of Statistics of China, from 1997 to 2011) and the China Compendium of Statistics (National Bureau of Statistics of China, 2010). A total of 30 mainland regions include three economic zones: the eastern region (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan), inland region (Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan), and western region (Sichuan, Chongqing, Guizhou, Yunnan, Shannxi, Gansu, Qinhai, Ningxia, and Xinjiang), respectively. The eastern region is relatively rich compared to the western region while the inland region is average. Chongqing and Sichuan were not united as a province until 1997, but we combined these two regions as one in the calculations.

These data are not perfect because the local governments deliberately submitted overstated performance of political achievements to the central government. Özyurt and Guironnet (2011) argued that although there are some inconsistencies or accuracy issues in official Chinese statistics, they remain reliable reference data.

The technology is defined with two inputs, one desirable output and one undesirable output, namely, capital stock, labor force, and real GDP and carbon dioxide emissions of region, respectively. We calculate the capital stock following Shan (2008) using the perpetual inventory system proposed by Goldsmith in 1951. In China, there is an important controversy that cannot be avoided: The labor force can be regarded as an input and an output from the government's perspective. In certain regions, labor employment and GDP are the two main performance indicators simultaneously. In Xinjiang province, high unemployment among Uighurs caused frequent violent incidents. Ferrier et al. (2014) proposed a data-driven parametric approach to identify inputs and outputs based on directional distance function. However, in our application we introduce labor as an input according to the traditional method of modeling a production frontier. Real GDP is obtained by treating regional GDP values with deflators at base year 1996. For undesirable outputs, we follow the Intergovernmental Panel on Climate Change's (IPCC) approach to transfer them to carbon dioxide emissions. In Equation 9, the total carbon quantity is equal to the sum of per energy quantity (E) multiplied by the net calorific value (NCV) multiplied by the carbon emission factor (CEF) multiplied by the carbon oxidation factor (COF), and the carbon quantity accounts for 12/44 in carbon dioxide emissions. We collected the energy consumption rates for the eight main regions and calculated the emission coefficients with Equation 13: coal (1.978 kg, CO_2/kg), coke (3.043 kg, CO_2/kg), crude oil (3.065 kg CO_2/kg), gasoline (2.985 kg, CO_2/kg), kerosene (3.097 kg, CO_2/kg), diesel fuel (3.161 kg, CO_2/kg), fuel oil (2.990 kg, CO_2/kg), and natural gas (2.184 kg, CO_2/m^3).

$$CO_2 = \sum_{n=1}^{8} CO_2^n = \sum_{n=1}^{8} E_n * NCV_n * CEF_n * COF_n * 44/12 \qquad (13)$$

Table 1 displays the annual growth rates of the output and input variables for the mainland regions and all of China. The real GDP trends surpass 10% while the growth rates for CO_2 emissions are nearly 9%. Consequently, slow decreases in CO_2 emissions by GDP unit can be observed for all mainland regions. Compared to the GDP trends, the labor force is characterized by slow growth rates. As a result, labor productivity improved significantly for the 14-year period. At the same time, capital stocks increased with rates around or greater than 13%, which may be caused by national and foreign investors attracted by the financial opportunities and preferential policies favoring industrial development in China.

Regions	**Labor Force**	**Capital Stock**	**Real GDP**	**CO_2**
China	1.34%	13.49%	11.32%	8.93%
Eastern region	1.91%	12.81%	11.62%	9.25%
Inland region	0.77%	15.30%	11.04%	8.48%
Western region	1.09%	13.39%	10.51%	8.96%

Notes: the Eastern Region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan. The Inland Region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western Region includes Sichuan, Chongqing, Guizhou, Yunnan, Shannxi, Gansu, Qinhai, Ningxia, and Xinjiang. The total sample includes all above 30 regions except Tibet, Hong Kong, Macao and Taiwan in China.

Source: regional dataset described in text and authors' calculation.

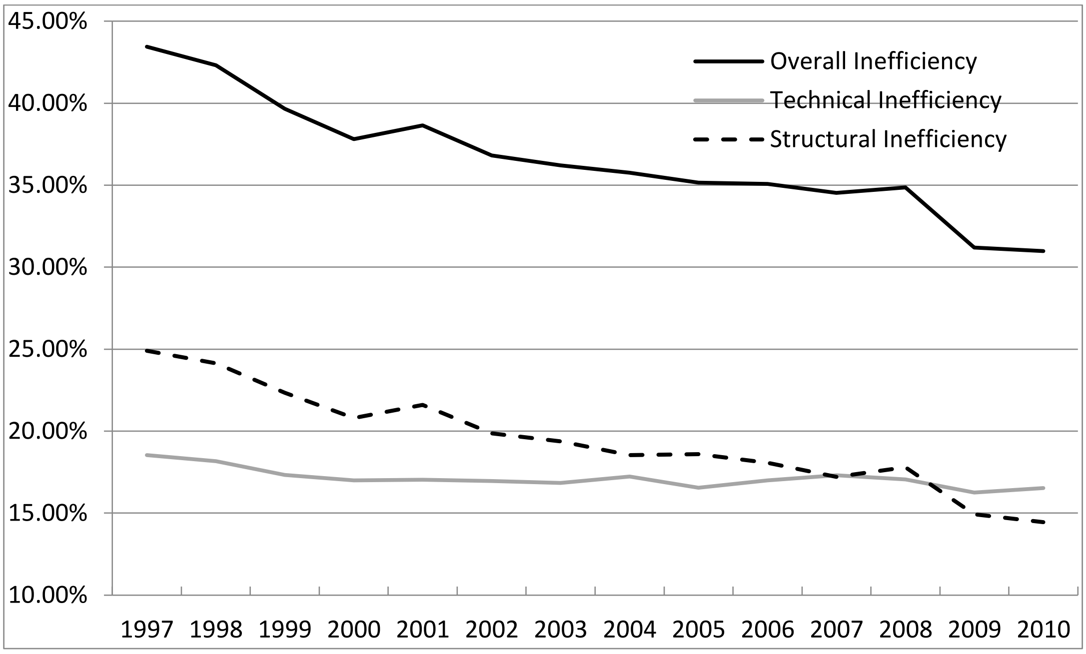
Table 1 Average growth rates of inputs and outputs
(Estimated trends over the period 1997–2010)

3.2. Results and discussion

Annual production frontiers are calculated with the linear programs LP1, LP2, LP3, and LP4 associated with their respective directional distance functions to evaluate the overall, technical, and structural efficiency scores for each individual region or group of regions. For each year of the period, the Tianjin, Liaoning, Shanghai, and Fujian regions are located on the production frontier. This result shows that although there may be statistical evidence that the eastern region is a technolog ical leader at the aggregate level the provinces in the coastal economic zone also have high productive performances and constitute referents for the inland benchmark. Not only the eastern region but also several underdeveloped regions (friendly environment), namely, Qinhai, Ningxia, and Yunnan, are on the frontier. This explains that seeking a balance between economic development and environmental abatement is a feasible challenge.

Before we interpret the results, we recall that the directional distance function is based on the summation of the total output vectors. Therefore, technical inefficiencies are computed as percentages of the aggregated GDP of the total group of regions (China). Thus, an inefficiency score of 1% means that the region could improve its output by 1% of the output sum of all regions. In fact, this improvement could represent, for example, 10% to 20% of its own output. We chose this directional distance function instead of the usual radial one to aggregate province scores and perform a meaningful catching-up analysis of the growth convergence for aggregated production plans for all of China or the eastern, inland, and western regions.

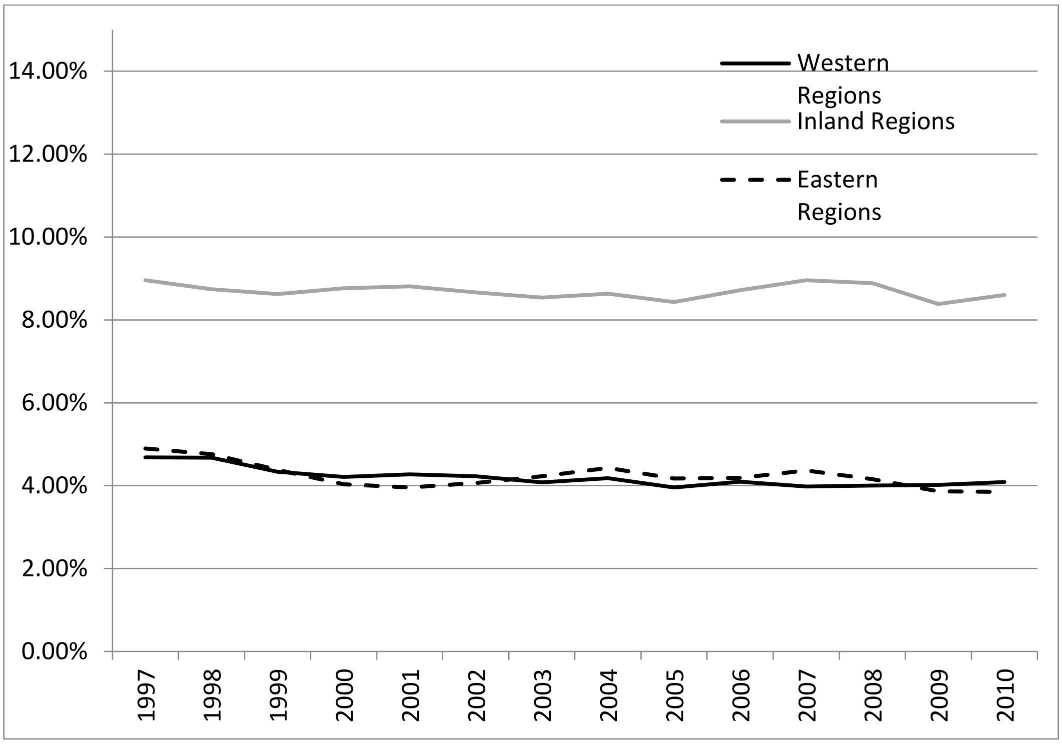
The overall inefficiency scores are plotted in Figure 5, and the aggregated inefficiency scores show a convergence process mainly due to the structural component that predominates the technical effect.



Source: authors' calculation.

Figure 5. Total inefficiency scores for China

On average, the technical inefficiency score is almost stable about 17% for China (total aggregation of regions over the period) meaning that if all provinces adopted the best productive practices and aligned on the VRS benchmark, the TFP for China could improve nearly 17%. As shown in Figure 6, most of this technical inefficiency comes from the inland region (8.7%). According to the Chinese Getting Rich First (Deng's dictum) unbalanced development strategy, the eastern provinces inevitably shift their polluted industries to the inland region, which has recently become an important industrialized zone. Given our, this zone has the most potential of technical catching-up as compared to the eastern provinces since the inland region's technical inefficiency is significantly higher thereby permitting more room for improvement. Finally, Figure 6 shows that no significant productivity catching-up effect operates within the three mainland economic zones.

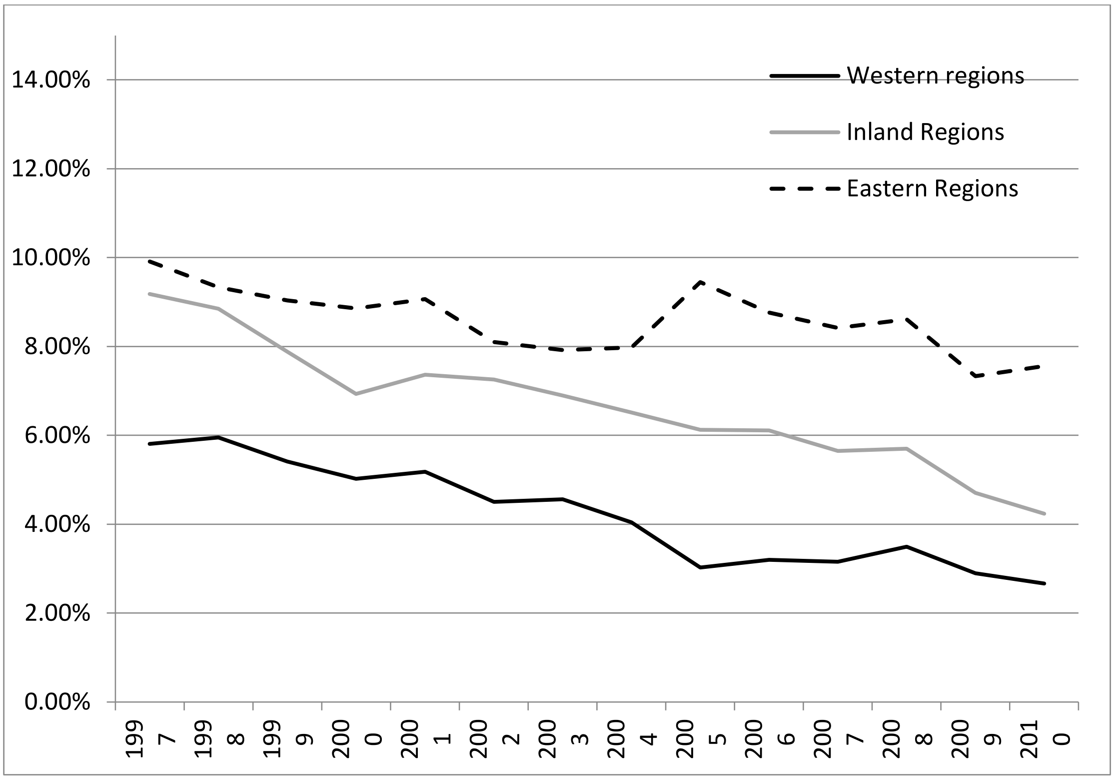


Notes: the Eastern Region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan. The Inland Region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western Region includes Sichuan, Chongqing, Guizhou, Yunnan, Shannxi, Gansu, Qinhai, Ningxia, and Xinjiang.

Source: authors' calculation.

Figure 6. Technical inefficiency scores for regions

Structural inefficiency is steadily decreasing from 25% in 1997 to 14% in 2010 (cf. Figure 5), meaning that if all regions adopted common input or output mixes, the TFP level of China would improve by the correspondent amounts. This decrease of structural inefficiency shows that the input/output deepening effect plays a major role in the growth convergence process as measured by the significant decrease of the overall inefficiency (cf. Figure 5 and Table 2). In Figure 7, the structural inefficiency component is distributed among eastern, inland, and western regions. Our results reveal that the convergence process established at the macroeconomic level can be found through the decrease in structural inefficiency for each region as it is revealed by their respective statistically significant negative trends displayed in Table 2. The main reason for the decrease of structural inefficiency over time is directly linked to the convergence of the shadow price of carbon dioxide emissions among the 30 individual regions. This is clarified and commented below through Figures 9 and 10.



Notes: the Eastern Region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan. The Inland Region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western Region includes Sichuan, Chongqing, Guizhou, Yunnan, Shannxi, Gansu, Qinhai, Ningxia, and Xinjiang.

Source: authors' calculation.

Figure 7. Structural inefficiency scores for regions

Regions	**Overall** coefficient	t-value	**Technical** coefficient	t-value	**Structural** coefficient	t-value
China	–2.24	–11.75	–0.61	–3.79	–3.71	–13.82
Eastern region	–1.34	–3.80	–1.08	–2.86	–1.46	–3.36
Inland region	–2.22	–11.02	–0.15	–1.11	–5.03	–12.39
Western region	–3.66	–11.87	–1.08	–5.42	–6.37	–11.41

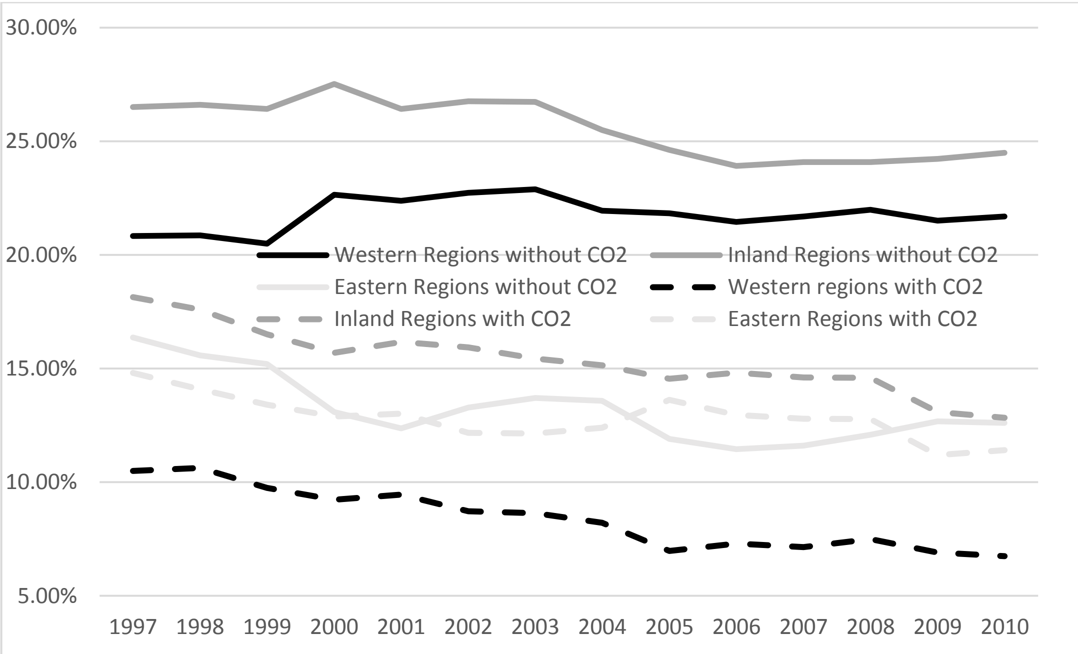
Notes: the Eastern Region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan. The Inland Region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western Region includes Sichuan, Chongqing, Guizhou, Yunnan, Shannxi, Gansu, Qinhai, Ningxia, and Xinjiang. The total sample includes all above 30 regions except Tibet, Hong Kong, Macao and Taiwan in China.

Source: regional dataset described in text and authors' calculation.

Table 2 Average growth rates in % of inefficiency scores

(Estimated trends over the period 1997–2010)

The inefficiency scores computed with a technology excluding carbon dioxide emissions are overestimated compared to the scores obtained with LPs 1, 2, and 3. This comparison provides powerful proof of the necessity of including undesirable output to analyze convergence processes. In Figure 8, the comparison between overall inefficiencies with and without bad outputs for the eastern, inland, and western regions indicates there is a potential bias that proves the necessity of considering bad output in the calculations. Taking into account friendly environmental constraints, underdeveloped provinces such as Qinhai, Ningxia, and Yunnan improve their productive efficiency as they become new potential benchmarks for other Chinese regions even if their economic performances in terms of GDP per head of population are below that of the eastern region. As a result, without incorporating CO_2, the eastern region's inefficiencies are underestimated while the western and inland regions' scores are overestimated.

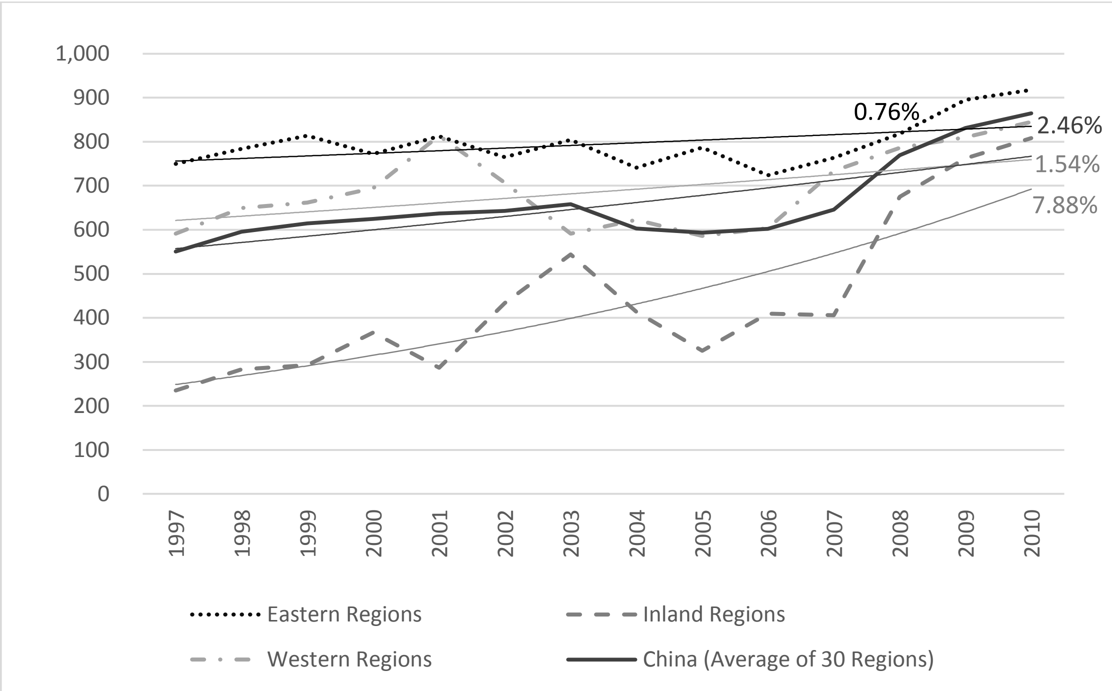


Notes: the Eastern Region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan. The Inland Region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western Region includes Sichuan, Chongqing, Guizhou, Yunnan, Shannxi, Gansu, Qinhai, Ningxia, and Xinjiang.

Source: authors' calculation.

Figure 8. Comparison of inefficiencies with and without CO_2

As shown in Figure 9, the shadow price index of carbon dioxide emissions compared to the GDP price illustrates that the real cost of pollution of average Chinese regions is increasing at an annual trend of 2.5% annually. Although the eastern region has the highest carbon shadow prices during all sample years, the environmental growing cost prevails in the inland region by contrast significant lower trends in the eastern and western regions, 7.9%, 0.8%, and 1.5%, respectively.



Notes: the Eastern Region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan. The Inland Region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western Region includes Sichuan, Chongqing, Guizhou, Yunnan, Shannxi, Gansu, Qinhai, Ningxia, and Xinjiang. The total sample includes all above 30 regions, except Tibet, Hong Kong, Macao and Taiwan in China.

Source: authors' calculation.

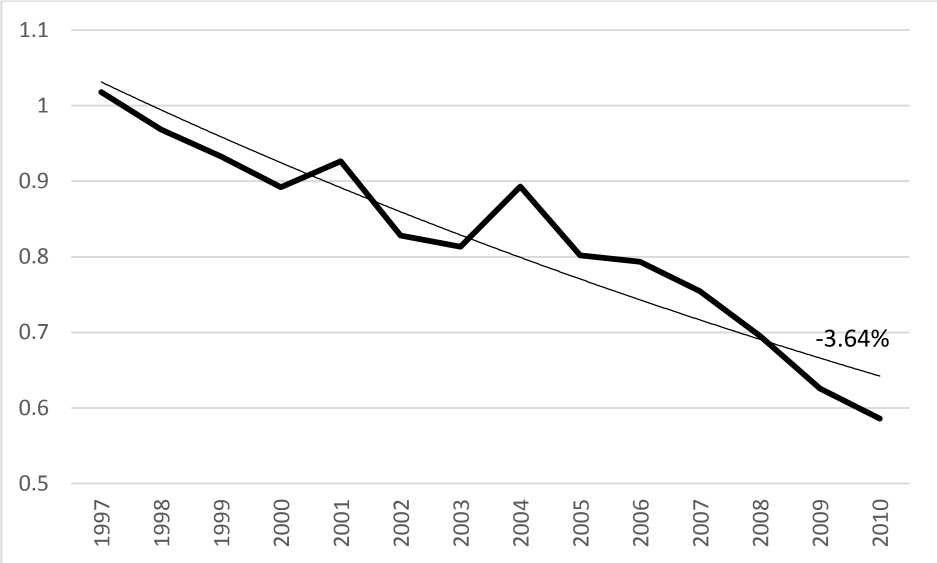
Figure 9. Shadow prices of carbon dioxide (yuan/ton)

The average Chinese carbon shadow price is about 864 yuan/ton in 2010, 645 yuan/ton in 2007 and 603 yuan/ton in 2004 while the regional estimates show a significant difference at the beginning of the sample years. As compared to other similar research, our estimated value is in the same order such as the carbon shadow prices estimated by Wang et al. (2011) and Wang and Wei (2014) are about 475 yuan/ton (for China in 2007) and 480 yuan/ton (for Chinese industrial sectors in 2010) respectively. In Wei et al. (2013) the carbon shadow price for Chinese thermal power enterprises is 613 yuan/ton in 2004.

The carbon shadow prices in the eastern region are higher than those in the inland region while the latter rose dramatically from 235 in 1997 to 808 in 2010 (yuan per ton). This result is implied by the fact that polluting industries in the eastern region are moving to the inland region because of the national strategic shift. Higher environmental abatement costs in the eastern region lead to this shift, which is shown by the higher growth rate of capital stock in the inland region (Table 1). This significant difference presented during the beginning of the sample years, was also found by Zhang et al. (2014) and Wang and Wei (2014). Some researchers argue that a carbon trading scheme should be established if unbalanced shadow prices of carbon emissions exist among Chinese regions or sectors (Peng et al., 2012; Wang and Wei, 2014). The significant growth of carbon shadow prices suggests that recent Chinese growth is not sustainable if the costs of pollution exceed the economic benefits. Therefore, the central and regional governments must invest more in reducing pollution if they want to maintain the Chinese development rate.

However, our results reveal a gradually convergence process in carbon shadow prices although the Chinese government never really implemented a trading system, and the regional carbon shadow prices are very close at the end of the sample years. The sigma convergence of the carbon shadow prices revealed by the decrease in the variation coefficient[3] is clearly demonstrated in Figure 10. The negative trend (–3.6%) is statistically significant (t value = –9.6), revealing a decrease in the disparities among the carbon shadow prices in the Chinese regions over time. In contrast, no convergence processes can be deduced for labor or capital shadow prices during the end of the period as shown in Figure 11. As a result, the structural effect decrease relies strictly on the shadow price of bad output evolution compared to that of labor and capital stock.

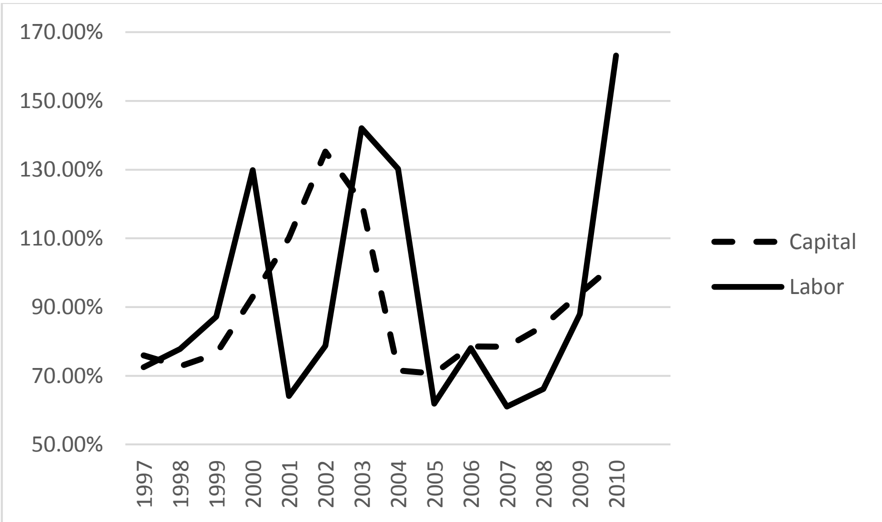
[3] The variation coefficient is defined as the proportion of the standard deviation to the mean.



Note: The total sample includes 30 mainland regions except Tibet, Hong Kong, Macao and Taiwan in China.

Source: authors' calculation.

Figure 10. Variation coefficient of carbon shadow price among 30 Chinese regions



Note: the total sample includes 30 mainland regions except Tibet, Hong Kong, Macao and Taiwan in China.

Source: authors' calculation.

Figure 11. Variation coefficients of labor and capital shadow prices among 30 Chinese regions

4. Conclusion

We re-examined the convergence hypothesis at the macroeconomic level across most mainland provinces (or municipalities) of China based on the weak disposability and VRS assumptions. Compared to other studies, the substantial differences in our analysis are that we use an efficiency change component that imposes a non-positive shadow price on bad outputs but no a priori constants returns to scale assumption or a functional form on technology, and any restrictive assumptions on input price to evaluate the technical gaps and input-mix differences between regions.

We argue that analyses of technological adoption derived from statistical tests on efficiency levels are biased if they rely on an implicit CRS assumption. In fact, this assumption appears too restrictive if productivity or efficiency comparisons are established among regions with dissimilar sizes. In that context, it appears crucial to model a VRS technology that explicitly includes bad outputs. Incorporating the latter under a VRS technology, we show that not only some eastern provinces but also underdeveloped regions such as Qinhai or Ningxia or Yunnan serve as benchmarks for China. The results show that structural inefficiency predominates the technical effect in the growth convergence process among Chinese regions. Therefore, we conclude that, regarding the convergence issue, the bad output deepening effect plays a major role. In fact, we find that the structural effect mainly depends on the pollution cost convergence but is not influenced by the relative prices of labor or capital stock evolution. Moreover, the ascending pollution cost estimated through the shadow price of carbon dioxide emissions implies the unsustainability of Chinese economic growth. The regional unbalanced carbon shadow prices indicate that the Chinese government cannot ignore this issue and must make concessions to seek an equilibrium point between economic benefits and the costs of pollution in national and regional efficiency improvements.

In this paper, the carbon shadow prices are generated from each evaluated Chinese region, and the individual prices vary with the provinces. Since carbon dioxide emission is the main element of greenhouse gas and decreasing these emissions is a global action, international comparative research on carbon tax and its trading among countries should be based on a global pricing system. To build a unique pricing scheme for carbon dioxide emissions, the proposed model might be further extended to a Law of One Shadow Price model, which means the same pricing for decreasing carbon must be applied to all regions.

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Appendix: Inefficiencies scores (%)

Regions	Inefficiency scores	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
	Overall	1.13	1.12	1.06	0.98	0.93	0.70	0.53	0.43	0.38	0.14	0.07	0.08	0.00	0.00
Beijing	Technical	0.20	0.18	0.15	0.16	0.09	0.15	0.05	0.08	0.04	0.00	0.00	0.00	0.00	0.00
	Structural	0.93	0.94	0.91	0.82	0.84	0.55	0.48	0.35	0.34	0.14	0.07	0.08	0.00	0.00
	Overall	1.12	1.10	1.09	1.13	1.15	0.96	0.82	0.72	0.53	0.47	0.37	0.32	0.18	0.31
Tianjin	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	1.12	1.10	1.09	1.13	1.15	0.96	0.82	0.72	0.53	0.47	0.37	0.32	0.18	0.31
	Overall	3.21	3.12	3.08	2.92	2.93	3.12	3.15	3.25	3.57	3.53	3.54	3.56	3.45	3.33
Hebei	Technical	1.79	1.87	1.92	1.92	1.92	1.96	1.96	1.98	2.07	2.09	2.18	2.31	2.37	2.30
	Structural	1.42	1.25	1.16	1.00	1.01	1.16	1.19	1.27	1.51	1.44	1.36	1.25	1.08	1.03
	Overall	5.07	5.18	4.60	4.46	4.83	5.47	5.40	4.90	4.46	4.57	4.23	3.97	3.51	3.43
Shanxi	Technical	1.65	1.56	1.60	1.91	1.93	1.89	1.91	1.78	1.74	1.77	1.79	1.88	1.98	2.02
	Structural	3.42	3.62	3.00	2.55	2.91	3.57	3.49	3.12	2.71	2.80	2.44	2.09	1.54	1.42
	Overall	2.03	1.83	1.86	1.87	1.94	1.86	2.05	2.21	2.27	2.41	2.50	2.93	2.87	2.93
Neimenggu	Technical	1.30	1.27	1.31	1.30	1.32	1.31	1.39	1.48	1.41	1.44	1.44	1.43	1.44	1.55
	Structural	0.74	0.57	0.55	0.57	0.61	0.55	0.66	0.72	0.87	0.96	1.06	1.50	1.43	1.38
	Overall	3.93	3.70	3.62	3.90	3.70	3.54	3.35	3.16	2.99	3.01	2.92	2.82	2.48	2.44
Liaoning	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	3.93	3.70	3.62	3.90	3.70	3.54	3.35	3.16	2.99	3.01	2.92	2.82	2.48	2.44
	Overall	1.87	1.63	1.59	1.45	1.48	1.32	1.25	1.08	1.08	1.05	0.94	0.92	0.74	0.80
Jilin	Technical	1.08	0.85	0.83	0.80	0.75	0.80	0.72	0.76	0.77	0.80	0.76	0.76	0.67	0.70
	Structural	0.78	0.78	0.77	0.65	0.73	0.52	0.53	0.31	0.31	0.25	0.18	0.17	0.07	0.10
	Overall	2.41	2.17	2.11	2.01	1.84	1.57	1.51	1.35	1.22	1.17	1.13	1.17	0.99	0.97
Heilongjiang	Technical	0.66	0.77	0.69	0.76	0.70	0.64	0.61	0.51	0.44	0.40	0.45	0.43	0.42	0.45
	Structural	1.75	1.40	1.43	1.24	1.14	0.93	0.90	0.84	0.78	0.78	0.68	0.74	0.57	0.53
	Overall	1.36	1.32	1.30	1.27	1.26	1.08	1.01	0.79	0.83	0.41	0.24	0.29	0.19	0.31
Shanghai	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	1.36	1.32	1.30	1.27	1.26	1.08	1.01	0.79	0.83	0.41	0.24	0.29	0.19	0.31
	Overall	0.92	0.86	0.71	0.48	0.36	0.41	0.44	0.72	1.25	1.13	1.06	0.98	0.79	0.87
Jiangsu	Technical	0.92	0.86	0.71	0.39	0.23	0.22	0.26	0.15	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	0.00	0.00	0.00	0.09	0.13	0.19	0.18	0.57	1.25	1.13	1.06	0.98	0.79	0.87
	Overall	0.44	0.37	0.33	0.46	0.42	0.40	0.46	0.51	0.56	0.62	0.68	0.65	0.52	0.44
Zhejiang	Technical	0.44	0.37	0.33	0.46	0.42	0.40	0.46	0.51	0.52	0.57	0.63	0.57	0.50	0.41
	Structural	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.05	0.05	0.07	0.02	0.03
	Overall	1.44	1.53	1.51	1.50	1.55	1.42	1.35	1.10	0.83	0.85	0.90	1.05	0.98	0.84
Anhui	Technical	0.37	0.38	0.36	0.34	0.33	0.30	0.29	0.18	0.09	0.08	0.07	0.09	0.09	0.10
	Structural	1.06	1.15	1.15	1.16	1.22	1.12	1.07	0.92	0.74	0.77	0.83	0.96	0.89	0.74
	Overall	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fujian	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Overall	0.82	0.80	0.79	0.77	0.79	0.63	0.58	0.58	0.52	0.42	0.41	0.38	0.31	0.38
Jiangxi	Technical	0.69	0.65	0.63	0.59	0.60	0.51	0.49	0.53	0.45	0.42	0.42	0.38	0.31	0.38
	Structural	0.13	0.15	0.16	0.18	0.19	0.12	0.09	0.05	0.07	0.00	0.00	0.00	0.00	0.01
	Overall	1.83	1.59	1.35	0.83	1.30	1.40	1.80	2.33	3.31	3.43	3.57	3.77	3.46	3.47
Shandong	Technical	1.22	1.16	1.01	0.83	1.05	1.18	1.36	1.45	1.35	1.34	1.37	1.14	0.90	0.94
	Structural	0.61	0.43	0.35	0.00	0.25	0.22	0.43	0.88	1.96	2.09	2.20	2.63	2.56	2.53
	Overall	1.61	1.68	1.66	1.57	1.66	1.71	1.40	2.07	2.21	2.36	2.46	2.38	2.16	2.04
Henan	Technical	1.32	1.39	1.39	1.38	1.41	1.45	1.40	1.60	1.77	2.01	2.26	2.33	2.09	2.02
	Structural	0.29	0.28	0.26	0.18	0.25	0.26	0.00	0.47	0.44	0.35	0.20	0.05	0.08	0.01
	Overall	1.82	1.70	1.68	1.54	1.41	1.35	1.30	1.20	1.04	1.07	1.09	0.98	0.86	0.91
Hubei	Technical	1.14	1.15	1.20	1.14	1.13	1.15	1.15	1.11	1.01	1.04	1.04	0.94	0.84	0.88
	Structural	0.68	0.55	0.48	0.40	0.28	0.20	0.15	0.09	0.02	0.03	0.05	0.04	0.02	0.03
	Overall	1.07	1.08	0.70	0.54	0.67	0.60	0.58	0.66	0.93	0.92	0.94	0.81	0.66	0.52
Hunan	Technical	0.74	0.73	0.62	0.54	0.63	0.60	0.58	0.66	0.75	0.76	0.73	0.65	0.55	0.51
	Structural	0.33	0.34	0.08	0.00	0.05	0.00	0.00	0.00	0.19	0.17	0.21	0.16	0.10	0.01
	Overall	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Guangdong	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Overall	0.45	0.46	0.43	0.44	0.44	0.28	0.26	0.32	0.20	0.21	0.24	0.19	0.12	0.19
Guangxi	Technical	0.33	0.32	0.27	0.26	0.24	0.17	0.13	0.25	0.20	0.19	0.19	0.14	0.09	0.20
	Structural	0.12	0.14	0.16	0.17	0.20	0.12	0.12	0.06	0.00	0.02	0.06	0.05	0.02	-0.01
	Overall	0.41	0.44	0.44	0.46	0.52	0.29	0.33	0.17	0.00	0.02	0.10	0.12	0.01	0.05
Hainan	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	0.41	0.44	0.44	0.46	0.52	0.29	0.33	0.17	0.00	0.02	0.10	0.12	0.01	0.05
Chongqing	Overall	1.79	1.81	1.45	1.20	1.04	1.18	1.22	1.23	0.90	1.01	1.12	1.36	1.31	0.98
and	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sichuan	Structural	1.79	1.81	1.45	1.20	1.04	1.18	1.22	1.23	0.90	1.01	1.12	1.36	1.31	0.98
	Overall	1.90	2.00	1.82	1.75	1.67	1.50	1.60	1.56	1.35	1.46	1.41	1.22	1.16	1.02
Guizhou	Technical	1.46	1.52	1.40	1.37	1.29	1.26	1.33	1.31	1.19	1.22	1.14	1.00	0.98	0.91
	Structural	0.44	0.47	0.42	0.39	0.37	0.24	0.28	0.25	0.16	0.24	0.26	0.22	0.17	0.10

	Overall	1.03	1.00	0.89	0.83	0.89	0.86	1.01	1.08	0.98	1.04	0.97	0.95	0.86	0.76
Yunnan	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	1.03	1.00	0.89	0.83	0.89	0.86	1.01	1.08	0.98	1.04	0.97	0.95	0.86	0.76
	Overall	1.37	1.35	1.19	1.07	1.20	1.15	1.08	1.15	1.08	1.21	1.20	1.32	1.26	1.42
Shaanxi	Technical	1.28	1.24	1.04	0.90	1.04	1.06	1.01	1.12	1.07	1.21	1.20	1.31	1.26	1.42
	Structural	0.09	0.11	0.14	0.17	0.16	0.09	0.07	0.04	0.01	0.00	0.00	0.01	0.00	0.00
	Overall	1.42	1.42	1.40	1.41	1.41	1.24	1.14	1.05	0.90	0.82	0.81	0.80	0.64	0.68
Gansu	Technical	1.23	1.21	1.17	1.17	1.15	1.09	0.99	0.97	0.88	0.82	0.80	0.78	0.66	0.69
	Structural	0.19	0.21	0.22	0.23	0.26	0.15	0.15	0.08	0.01	0.00	0.01	0.03	-0.02	-0.01
	Overall	0.63	0.65	0.68	0.65	0.71	0.52	0.40	0.28	0.14	0.14	0.09	0.15	0.04	0.06
Qinhai	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Structural	0.63	0.65	0.68	0.65	0.71	0.52	0.40	0.28	0.14	0.14	0.09	0.15	0.04	0.06
	Overall	0.81	0.82	0.81	0.80	1.00	0.91	0.97	0.73	0.58	0.55	0.52	0.58	0.49	0.59
Ningxia	Technical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.01
	Structural	0.81	0.82	0.81	0.80	1.00	0.91	0.97	0.73	0.58	0.55	0.52	0.58	0.43	0.58
	Overall	1.55	1.59	1.52	1.52	1.53	1.36	1.22	1.14	1.04	1.06	1.01	1.12	1.16	1.24
Xinjiang	Technical	0.71	0.70	0.72	0.77	0.79	0.81	0.76	0.78	0.81	0.85	0.84	0.92	1.05	1.06
	Structural	0.83	0.89	0.80	0.75	0.74	0.55	0.46	0.35	0.23	0.21	0.17	0.20	0.11	0.18
	Overall	43.44	42.31	39.67	37.81	38.65	36.82	36.22	35.76	35.15	35.07	34.53	34.86	31.19	30.99
China	Technical	18.54	18.17	17.34	17.00	17.04	16.96	16.85	17.23	16.55	17.00	17.31	17.06	16.26	16.54
	Structural	24.90	24.13	22.33	20.81	21.61	19.86	19.37	18.53	18.60	18.07	17.22	17.80	14.93	14.45

Source: authors' calculation.

Chapter 3

Aggregate Green Productivity Growth in OECD's Countries

In chapter 2, we examine environmental growth convergence in China and separate reginal efficiency changes into technical and structural effects. Now we turn to analyze the environmental productivity evolution over time for 30 OECD countries. Compared to the case of China, OECD countries are benefit from their economic conditions and environmental policies. We attempt to investigate whether economic growth in OECD countries is motivated by their environmental policies. Based on WDA approach, we decompose the aggregate productivity growth into technology progress, technical effect and structural effect under a CRS technology. The structural one has not been quantified by the previous literature.

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 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 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 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:

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

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:

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

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:

$$\begin{aligned}
TFP^{t,t+1} &= \frac{1}{2}[D^{t}(\mathbf{x}^{t},\mathbf{v}^{t},\mathbf{w}^{t};\mathbf{g}_{v}^{t},\mathbf{g}_{w}^{t}) - D^{t}(\mathbf{x}^{t+1},\mathbf{v}^{t+1},\mathbf{w}^{t+1};\mathbf{g}_{v}^{t+1},\mathbf{g}_{w}^{t+1}) + \\
&D^{t+1}(\mathbf{x}^{t},\mathbf{v}^{t},\mathbf{w}^{t};\mathbf{g}_{\mathbf{v}}^{t},\mathbf{g}_{\mathbf{w}}^{t}) - D^{t+1}(\mathbf{x}^{t+1},\mathbf{v}^{t+1},\mathbf{w}^{t+1};\mathbf{g}_{v}^{t+1},\mathbf{g}_{w}^{t+1})] \\
EC^{t,t+1} &= D^{t}(\mathbf{x}^{t},\mathbf{v}^{t},\mathbf{w}^{t};\mathbf{g}_{v}^{t},\mathbf{g}_{w}^{t}) - D^{t+1}(\mathbf{x}^{t+1},\mathbf{v}^{t+1},\mathbf{w}^{t+1};\mathbf{g}_{v}^{t+1},\mathbf{g}_{w}^{t+1}) \\
TP^{t,t+1} &= \frac{1}{2}[D^{t+1}(\mathbf{x}^{t},\mathbf{v}^{t},\mathbf{w}^{t};\mathbf{g}_{\mathbf{v}}^{t},\mathbf{g}_{\mathbf{w}}^{t}) - D^{t}(\mathbf{x}^{t},\mathbf{v}^{t},\mathbf{w}^{t};\mathbf{g}_{\mathbf{v}}^{t},\mathbf{g}_{\mathbf{w}}^{t}) + \\
&D^{t+1}(\mathbf{x}^{t+1},\mathbf{v}^{t+1},\mathbf{w}^{t+1};\mathbf{g}_{\mathbf{v}}^{t+1},\mathbf{g}_{\mathbf{w}}^{t+1}) - D^{t}(\mathbf{x}^{t+1},\mathbf{v}^{t+1},\mathbf{w}^{t+1};\mathbf{g}_{v}^{t+1},\mathbf{g}_{w}^{t+1})]
\end{aligned} \tag{8}$$

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.

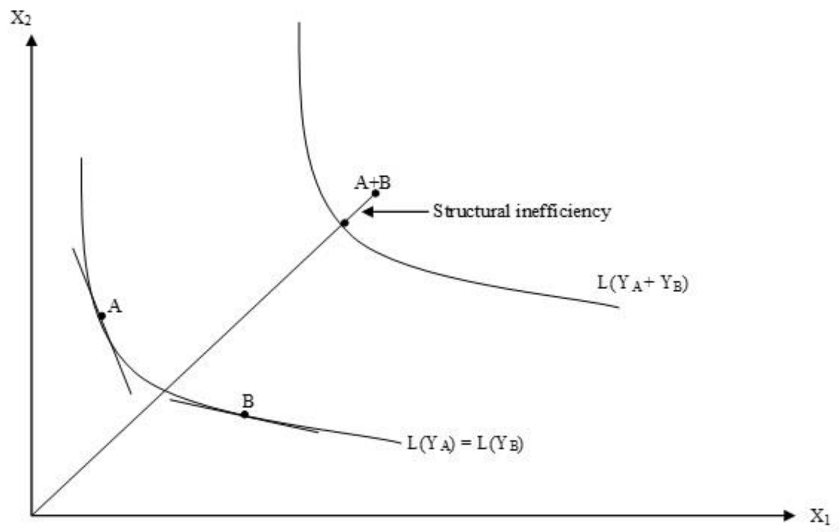

Figure 1: Illustration of structural efficiency

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:

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

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

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

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:

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

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 bad 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.

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

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:

$$
\begin{aligned}
&D^t(\sum_{k=1}^{K}\mathbf{x}_k^t,\sum_{k=1}^{K}\mathbf{v}_k^t,\sum_{k=1}^{K}\mathbf{w}_k^t;\mathbf{g_v^t},\mathbf{g_w^t}) = \max_{\delta_G^t,\lambda}\ \delta_G^t \\
s.t.\ &K\sum_{k=1}^{K}\lambda_k v_{m,k}^t \geq \sum_{k=1}^{K} v_{m,k}^t + \delta_G^t g_{v,m}^t \quad \forall m=1,\cdots,M \\
&K\sum_{k=1}^{K}\lambda_k w_{j,k}^t = \sum_{k=1}^{K} w_{j,k}^t - \delta_G^t g_{w,j}^t \quad \forall j=1,\cdots,J \\
&K\sum_{k=1}^{K}\lambda_k x_{n,k}^t \leq \sum_{k=1}^{K} x_{n,k}^t \quad \forall n=1,\cdots,N \\
&\lambda_k \geq 0 \quad \forall k=1,\ldots,K
\end{aligned}
\qquad \text{(LP2)}
$$

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.

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

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 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.

Regions	Capital Stock	Labor Force	Real GDP	CO2
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%

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

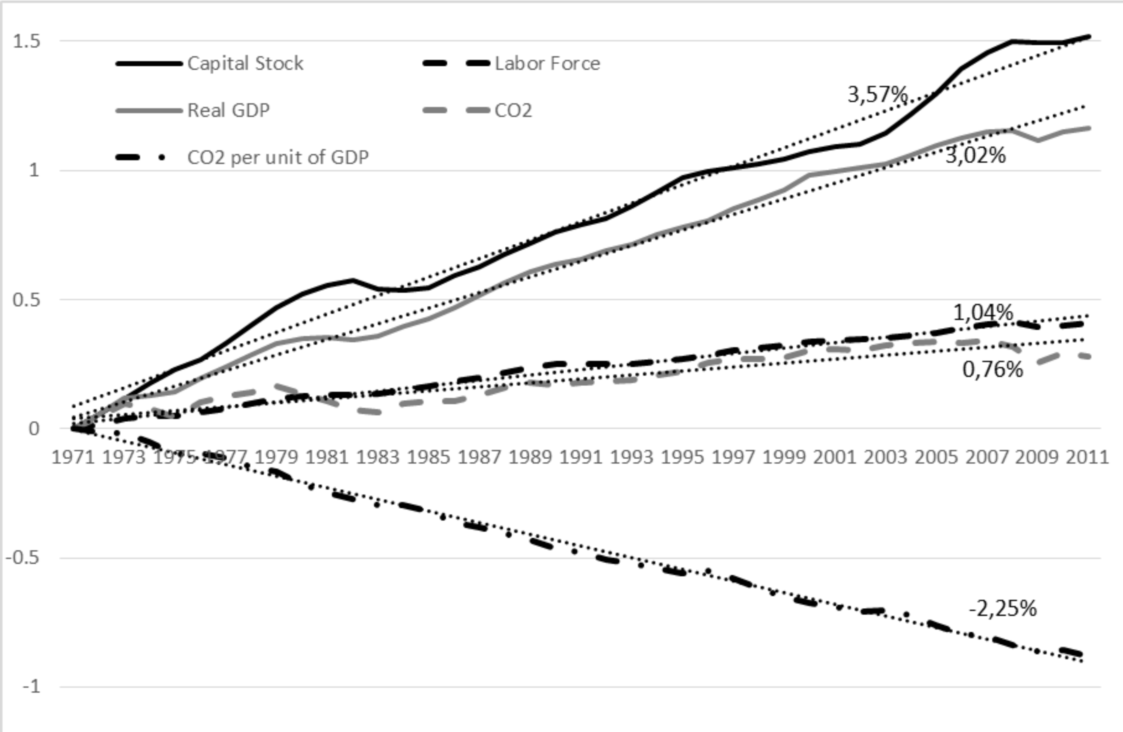

Figure 2: Evolutions of input and output indexes for the OECD (in logarithm terms)

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.

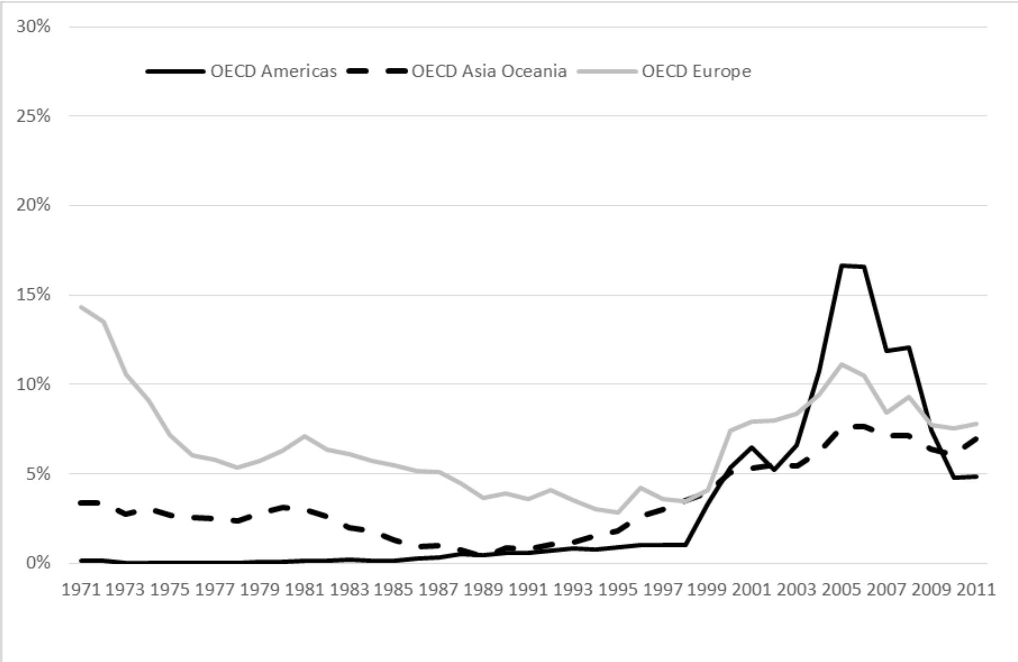

Figure 3: Technical inefficiency scores for groups

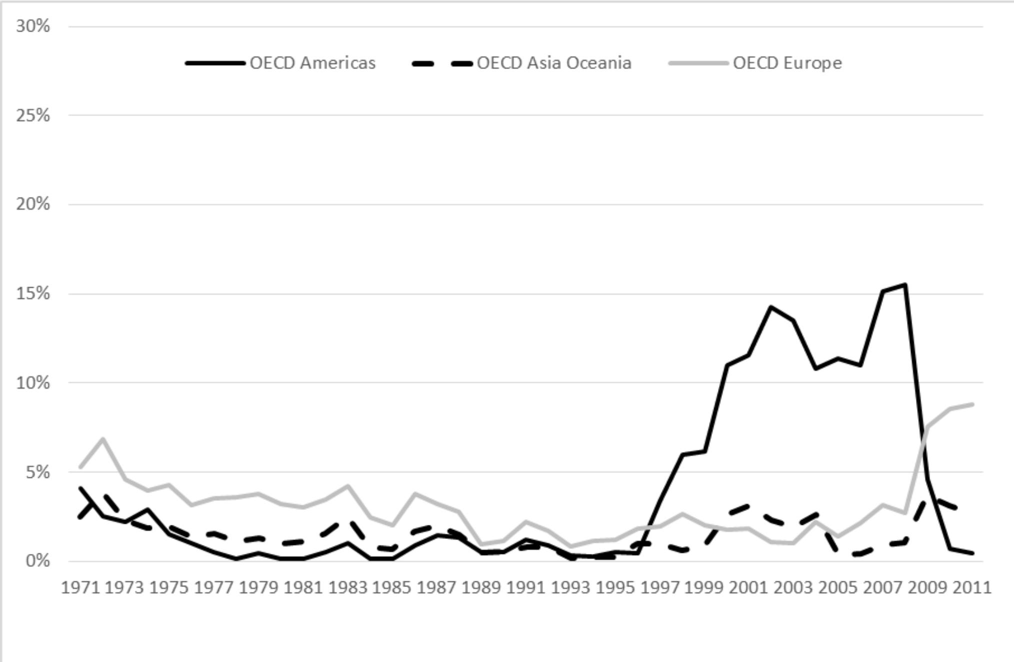

Figure 4: Structural inefficiency scores for groups

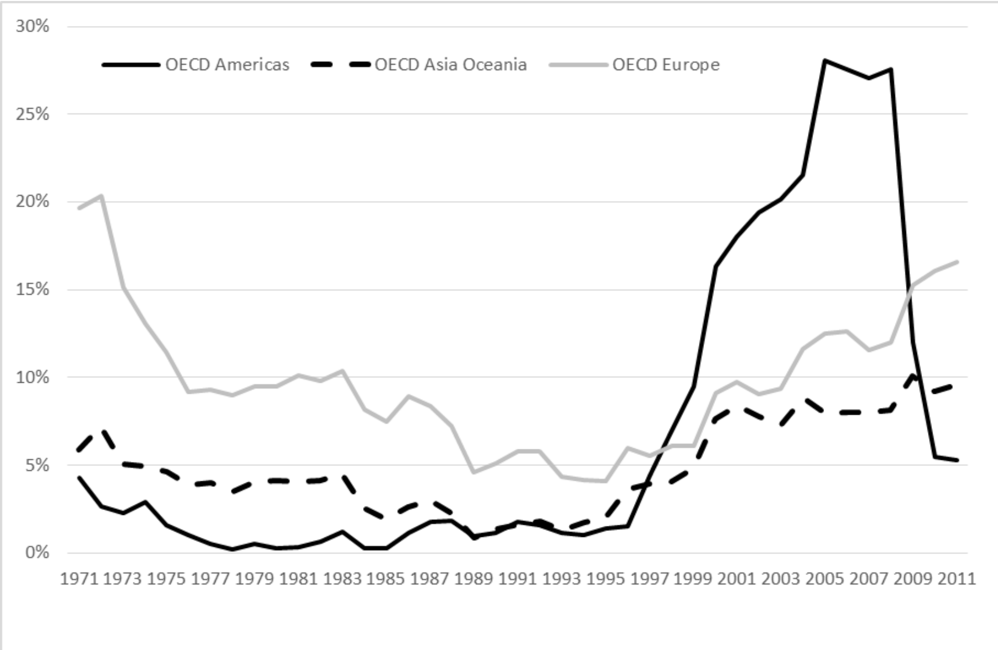

Figure 5: Overall inefficiency scores for groups

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.

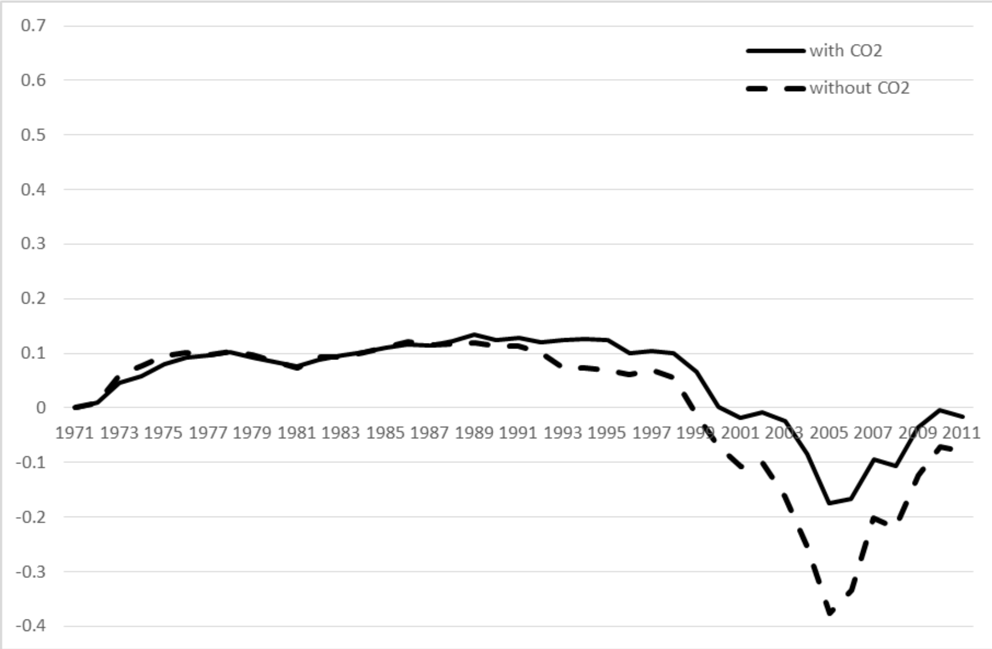

Figure 6: Technical efficiency index for the OECD (in logarithm terms)

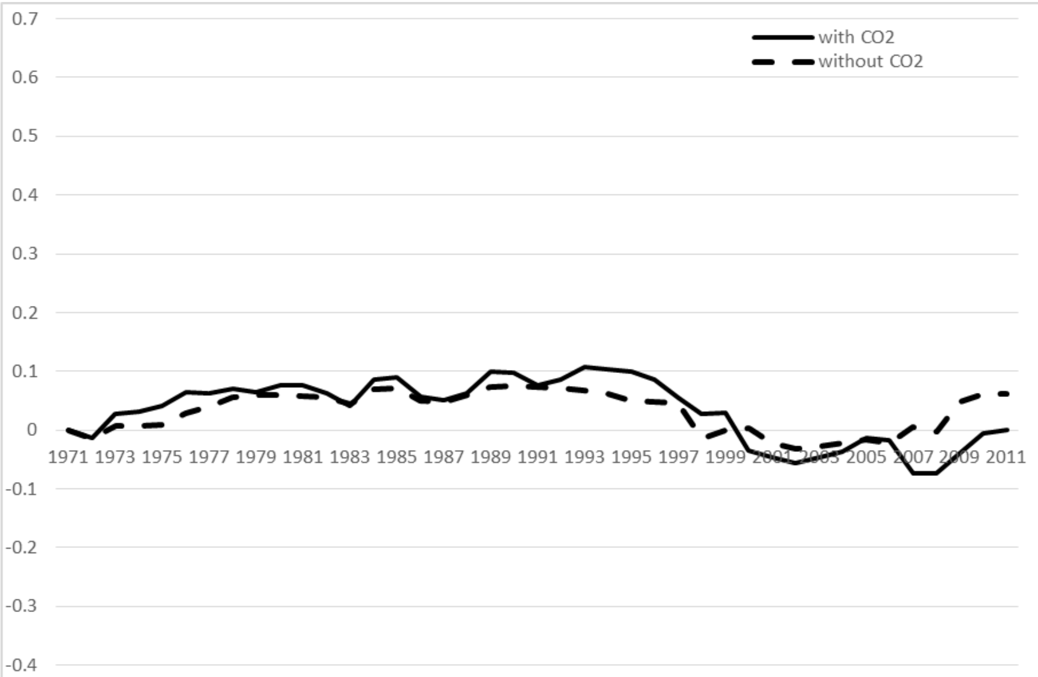

Figure 7: Structural efficiency index for the OECD (in logarithm terms)

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 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.

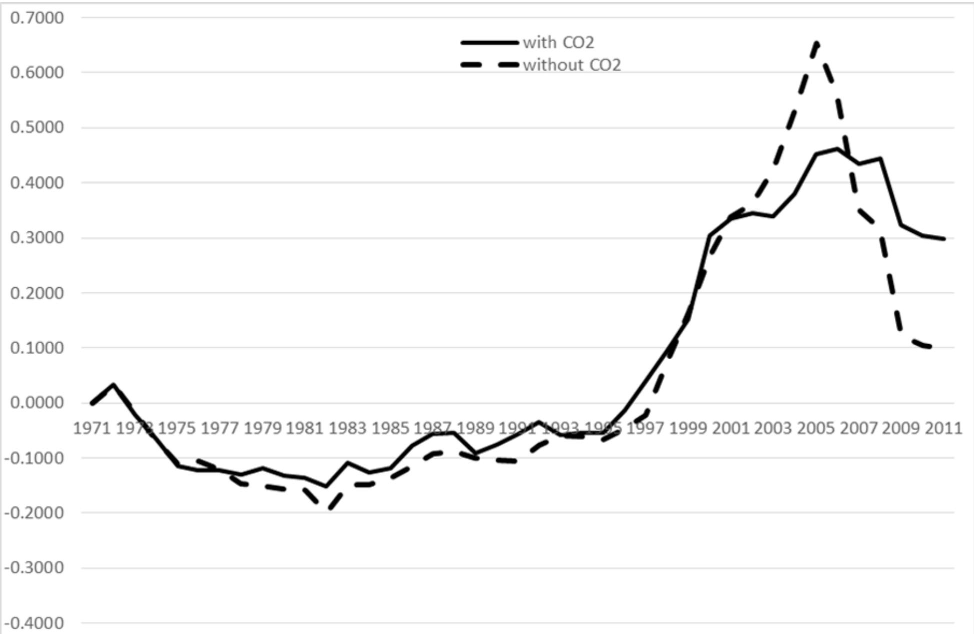

Figure 8: Technical progress index for the OECD (in logarithm terms)

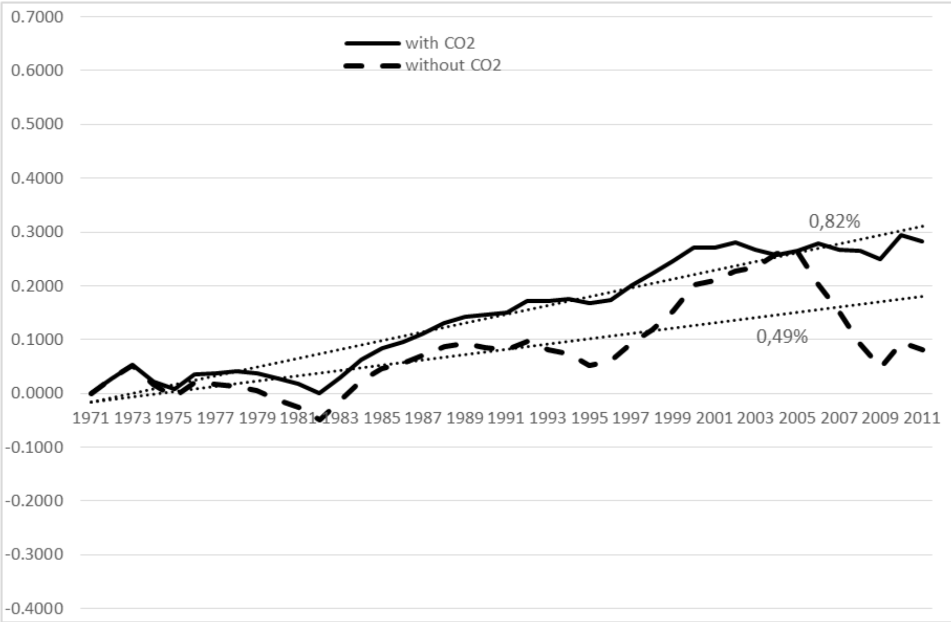

Figure 9: TFP index for the OECD (in logarithm terms)

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.

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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Chapter 4

Worldwide Carbon Shadow Prices during 1990–2011

Carbon shadow prices indicate the amount of economic value that producers have to give up for a certain amount of carbon emission reduction. In this chapter, we concentrate our research on carbon shadow prices at a worldwide level. Following Kuosmanen's (2005) WDA approach, in the first stage, we propose a robust estimation for global carbon shadow prices that can reduce the influence of potential outliers belonging to the production set. In the second stage, we attempt to evaluate the impact of intergovernmental environmental agreements on carbon shadow prices, such as the Kyoto Protocol.

1. Introduction

According to record of the U.S. National Centers for Environmental Information, 2014 was the warmest year ever, globally. Global warming threatens the survival of people all over the world, and scientists attribute climate change to emissions of greenhouse gases, such as carbon dioxide emissions. Carbon emissions have no real prices, but the opportunity costs for producers can be shown by carbon shadow prices—the amount of revenue that producers have to give up for a certain amount of carbon emission abatement—which provides useful information for environmental regulators. Nowadays, governments make great efforts to reduce carbon emissions and carry out different pricing approaches for carbon taxes. A popular approach is to set a gradually decreasing upper limit on carbon emissions and to allow exchanges of emissions permits in the market (Kossoy et al., 2015). Thus, the right to emit carbon dioxide changes from being a public good that is neither rivalrous nor excludable to a private good that is both rivalrous and excludable. When an amount of carbon emissions has a real price, is the price reasonable or fair to each producer? Lee et al. (2014) find that the carbon shadow price increases as the abatement level increases over time in South Korean electricity generating plants. Molinos-Senante et al. (2015) argue that the estimation of the carbon shadow price for non-power enterprises can provide incentives for reducing greenhouse gas emissions. The objective of this paper is to investigate the carbon shadow price at the worldwide level for its economic implications and references for global carbon pricing.

To estimate the shadow prices of undesirable outputs, both parametric and non-parametric methods, such as translog and quadratic functional forms or data envelopment analysis (DEA), tend to be used in the literature. Zhou et al. (2015) compare carbon abatement costs among Shanghai industrial sectors using the parametric and non-parametric approaches, with both the Shephard input/output and directional distance functions. Their results indicate that the type of distance functions plays a tiny role in estimating carbon shadow prices. However, the choice between parametric and non-parametric approaches affects the final prices significantly.

Compared to the parametric approach, a non-parametric framework based on activity analysis modeling makes it possible to explore the entire production technology, incorporating environmental elements without any particular specifications of functional forms. Zhou et al. (2008) classify two groups in modeling pollution-generating technologies among activity analysis models: one uses data transformation or treats undesirable outputs as inputs based on free disposability assumption while the other uses original data based on a weak disposability assumption. The latter approach is introduced by Färe et al. (1989), such that desirable and undesirable outputs can only be decreased proportionately by a uniform abatement factor. Kuosmanen et al. (2005) propose an improvement by setting non-uniform abatement factors for variable returns to scale (VRS) models; Kuosmanen and Matin (2011) develop the dual formulation for this model. The applications of Kuosmanen's model is available from Mekaroonreung and Johnson (2009), Berre et al. (2013), Berre et al. (2014), and Lee and Zhou (2015).

Recently, several pollution-generating technologies have been proposed in non-parametric models and debates have been generated on selecting the right way to model undesirable outputs, such as by-production technology, materials balance principles, and weak G-disposability, etc. Indeed, the choice of modeling technologies including environmental dimensions should be based on different criteria, according to the research question, the level of analysis (micro versus macro), and the types of pollution that are included in the production technology (SO_2, CO_2, NO_X, …).

In detail, weak disposability emphasizes the symbiosis between good and bad outputs, which suggests that pollution is difficult to abandon. Some pollutions are easily disposed of by the introduction of additional equipment. For example, most sulfides and nitrides are soluble in water, and a simple chemical treatment may deal with them effortlessly. Even if some of them are difficult to dissolve in water, they can be removed by inexpensive approaches (e.g., nitric oxide can be oxidized to nitric dioxide, which is soluble in water). Consequently, these pollutions can be at a null level in the final production. At this time, the traditional weak disposability assumption is not relevant, and results may not provide useful and precise information for environmental regulators. However, some other types of pollution, such as carbon dioxide, are difficult to dispose of, and therefore the weak disposability assumption seems more appropriate. Murty and Russell (2002) introduce the by-production approach, combining two sub-technologies, namely, intended production technology and residual generation technology. Their intersection indicates the right trade-offs in production activities (Murty et al., 2012). On the basis of the laws of thermodynamics/mass conservation, material balance principles require the balance of materials' bounds between physical inputs and outputs using weak G-disposability. These two last approaches (by-production and material balance) require detailed data, such as pollution-generating inputs, that may be not available for country-level analyses, which often retains CO_2 as a bad output linked to GDP. Consequently, the weak disposability assumption still seems an appropriate manner to model the production technology at the macro level.

Reviews of environmental modeling technologies in a non-parametric framework can be found in Zhou et al. (2008), Song et al. (2012), Oude-Lansink and Wall (2014), Zhang and Choi (2014), and Dakpo et al. (2015), etc. Zhou et al. (2014) summarize the literature on shadow price estimation for undesirable outputs. They note that most of the previous papers focusing on the shadow prices of undesirable outputs are conducted at the micro level for energy plants or polluted firms because of data availability and that there is a lack of studies exploring this field across different countries at a macro level. Yörük and Zaim (2005) discover a positive correlation between environmental productivity and climate protocol among OECD countries. Wei et al. (2013) argue that carbon shadow prices are positively correlated with the technology level of thermal power enterprises. However, most papers ignore the relationship between carbon shadow prices and environmental protocol.

That being so, this paper investigates the global carbon shadow prices for 119 countries, both developed and developing, using a robust non-parametric model based on the weak disposability assumption in the first stage. In the second stage, we analyze the impact of the Kyoto Protocol on the evolution of carbon shadow prices. The rest of the paper is structured as follows: Section 2 reviews environmental production technology and proposes a robust DEA model for estimating carbon shadow prices; Section 3 introduces the data and presents the empirical results; Section 4 presents the conclusions.

2. Methodology

2.1. Model specification

In order to measure the worldwide carbon shadow price through a model of pollution-generating technology, we start from the Shephard's definition of weakly disposable technology (Färe & Grosskopf, 2003). Introduced by Shephard (1970, 1974), weak disposability and the null-joint condition are two classical assumptions usually used to model a pollution-generating technology. Weak disposability implies that proportional decreases in good and bad outputs are achievable through a scaling down of production activity through the introduction of an abatement factor, θ . From an economic point of view, desirable and undesirable outputs are joint outputs. In addition, the null-joint condition means that the desirable outputs cannot be made if the undesirable outputs are at the null level.

Let $\mathbf{x}=(x_1,...,x_N)\in R_+^N$ denote the vector of inputs, and $\mathbf{y}=(y_1,...,y_M)\in R_+^M$ and $\mathbf{z}=(z_1,...,z_J)\in R_+^J$ the vectors of desirable and undesirable outputs for a country, respectively. The technology and its corresponding output set are denoted by T and P:

$$T=\left\{(\mathbf{x},\mathbf{y},\mathbf{z}):\mathbf{x}\text{ can produce }(\mathbf{y},\mathbf{z})\right\} \qquad (1)$$

$$P(\mathbf{x})=\left\{(\mathbf{y},\mathbf{z}):(\mathbf{x},\mathbf{y},\mathbf{z})\in T\right\} \qquad (2)$$

Weak disposability and null-jointness assumptions can be defined as:

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

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

The directional distance function measures gaps between the observed production plans (countries) and the production frontier or the benchmark defined by the best practices. The inefficiency scores δ estimate these distances. Based on the Färe and Grosskopf axiomatic (FG), the production technology and directional distance function for an observed sample of K decision-making units (DMUs or countries) are defined by:

$$\hat{T}_{FG}=\left\{\begin{array}{l}(\mathbf{x},\mathbf{y},\mathbf{z}):\mathbf{x}\in R_+^N,\ \mathbf{y}\in R_+^M,\ \mathbf{z}\in R_+^J,\ \theta\sum_{k=1}^{K}\mu_k y_k^m\ge y_{k'}^m,\ m=1,\cdots,M,\ \theta\sum_{k=1}^{K}\mu_k z_k^j=z_{k'}^j,\ j=1,\cdots,J,\\ \sum_{k=1}^{K}\mu_k x_k^n\le x_{k'}^n,\ n=1,\cdots,N,\ \sum_{k=1}^{K}\mu_k=1,\ \mu_k\ge 0\ \ k=1,...,K,\ 0\le\theta\le 1\end{array}\right\} \qquad (5)$$

$$D_{T_{FG}}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z}) = \sup_{\delta}\left\{\ \delta\in\Re_+ :\ (\mathbf{x},\mathbf{y}+\boldsymbol{\delta}\times\mathbf{g_y},\mathbf{z}-\boldsymbol{\delta}\times\mathbf{g_z})\in T_{FG}\ \right\} \qquad (6)$$

Next, the primal non-linear program under a VRS technology is denoted as:

$$\begin{aligned}
&\hat{D}_{T_{FG}}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g_y},\mathbf{g_z}) = \max_{\delta,\mu,\theta} \ \delta \\
s.t.\ &\theta \sum_{k=1}^{K} \mu_k y_k^m \geq y^m + \delta g_y^m \quad \forall m = 1,\cdots,M \\
&\theta \sum_{k=1}^{K} \mu_k z_k^j = z^j - \delta g_z^j \quad \forall j = 1,\cdots,J \\
&\sum_{k=1}^{K} \mu_k x_k^n \leq x^n \quad \forall n = 1,\cdots,N \\
&\sum_{k=1}^{K} \mu_k = 1 \\
&\mu_k \geq 0 \quad \forall k = 1,\ldots,K \\
&0 \leq \theta \leq 1
\end{aligned} \tag{NLP1}$$

The nonzero vector $(\mathbf{0},\mathbf{g_y},\mathbf{g_z})$ suggested by Chung et al. (1997) is intended to maximize desirable outputs and to minimize undesirable outputs simultaneously. To measure the carbon shadow price for each country, we employ output vector as the direction $(\mathbf{0},\mathbf{g_y},\mathbf{g_z}) = (\mathbf{0},\mathbf{y},\mathbf{z})$, starting from a country sample of K DMUs. In NLP1, the production technology is non-linear, and this abatement effort is conventionally unique, shared with all countries under the VRS assumption. The corresponding VRS linearization related to a uniform abatement has been developed correctly by Zhou et al. (2008) and Sahoo et al. (2011). In order to maintain the convexity of the technology, Kuosmanen (2005) proposes non-uniform abatement factors as θ_k. The resulting technology is given by:

$$\hat{T}_{KU} = \left\{ (\mathbf{x},\mathbf{y},\mathbf{z}) : \mathbf{x} \in R_+^N,\ \mathbf{y} \in R_+^M,\ \mathbf{z} \in R_+^J,\ \sum_{k=1}^{K} \theta_k \mu_k y_k^m \geq y_{k'}^m,\ m = 1,\cdots,M,\ \sum_{k=1}^{K} \theta_k \mu_k z_k^j = z_{k'}^j,\ j = 1,\cdots,J, \right. \\ \left. \sum_{k=1}^{K} \mu_k x_k^n \leq x_{k'}^n,\ n = 1,\cdots,N,\ \sum_{k=1}^{K} \mu_k = 1,\ \mu_k \geq 0\ \ k = 1,\ldots,K, 0 \leq \theta_k \leq 1\ \ k = 1,\ldots,K \right\} \tag{7}$$

Kuosmanen technology also leads to a straightforward linearization of Equation 7. Using changes of variables $\mu_k = \lambda_k + \sigma_k$ and $\lambda_k = \theta_k \mu_k$, the primal linear program under a VRS technology is defined as:

$$
\begin{aligned}
&\hat{D}_{T_{KU}}(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_{\mathbf{y}},\mathbf{g}_{\mathbf{z}}) = \max_{\delta,\lambda,\sigma}\ \delta \\
s.t.\ &\sum_{k=1}^{K}\lambda_k y_k^m \geq y^m + \delta g_y^m \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k z_k^j = z^j - \delta g_z^j \quad \forall j = 1,\cdots,J \\
&\sum_{k=1}^{K}(\lambda_k + \sigma_k)x_k^n \leq x^n \quad \forall n = 1,\cdots,N \\
&\sum_{k=1}^{K}(\lambda_k + \sigma_k) = 1 \\
&\lambda_k \geq 0 \quad \forall k = 1,\ldots,K \\
&\sigma_k \geq 0 \quad \forall k = 1,\ldots,K
\end{aligned}
\qquad \text{(LP1)}
$$

Kuosmanen and Podinovski (2009) argue that their model can provide new economic insights into weak disposability while Shephard's model violates the convexity axiom.

2.2. Shadow prices of undesirable outputs

Thanks to a non-parametric DEA approach, the shadow prices of outputs and inputs (ω_y, ω_x) can be deduced from marginal values related to the constraints in the primal model even when the information of market prices is incomplete. These marginal values have no economic sense as absolute values, but their ratio may be interpreted as input marginal productivities, which can be derived from the Lagrangian method (Equation 8).

$$
\frac{\omega_x}{\omega_y} = -\frac{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_{\mathbf{y}},\mathbf{g}_{\mathbf{z}})/\partial x}{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_{\mathbf{y}},\mathbf{g}_{\mathbf{z}})/\partial y} \qquad (8)
$$

In the same manner, the ratio of shadow prices of carbon emissions to GDP can be understood as the opportunity cost of reducing one extra unit of carbon emissions by giving up a certain unit of GDP. This ratio may provide useful information for producers and regulators to make trade-offs between economic benefits and environmental impacts in terms of negative externality. Although the shadow prices of undesirable outputs can usually be obtained by using the Lagrangian method (cf. Equation 9), the duality can bridge the gap between the production technologies and may provide more explicit economic representations than the primal model can.

$$\frac{\omega_z}{\omega_y} = -\frac{\partial D_T(\mathbf{x}, \mathbf{y}, \mathbf{z}; \mathbf{0}, \mathbf{g_y}, \mathbf{g_z}) / \partial z}{\partial D_T(\mathbf{x}, \mathbf{y}, \mathbf{z}; \mathbf{0}, \mathbf{g_y}, \mathbf{g_z}) / \partial y} \qquad (9)$$

Kuosmanen and Matin (2011) develop the dual formulation of LP1 to derive the shadow prices of bad outputs, which provides an economic interpretation for weak disposability. In Kuosmanen's initial model, the shadow prices of bad outputs are unconstrained, allowing negative and positive values. Consequently, bad outputs are allowed to involve benefits or costs in production activity that could generate ambiguous economic signals. We therefore change the equality sign to inequality ($\leq$) in the second constraint of LP1, meaning that bad outputs can only produce costs (negative revenues).

Finally, we compute the corresponding constrained dual model for each country (k') as:

$$\begin{aligned}
&\hat{D}(\mathbf{x}_{k'}, \mathbf{y}_{k'}, \mathbf{z}_{k'}; \mathbf{0}, \mathbf{g_y}, \mathbf{g_z}) = \min_{\phi, \pi_x, \pi_y, \pi_z} [\ \phi - \ (\sum_{m=1}^{M} \pi_y^m y_{k'}^m - \sum_{j=1}^{J} \pi_z^j z_{k'}^j - \sum_{n=1}^{N} \pi_x^n x_{k'}^n)] \\
s.t.\ &\sum_{m=1}^{M} \pi_y^m y_k^m - \sum_{j=1}^{J} \pi_z^j z_k^j - \sum_{n=1}^{N} \pi_x^n x_k^n \leq \phi \quad \forall k = 1, \cdots, K \\
&-\sum_{n=1}^{N} \pi_x^n x_k^n \leq \phi \quad \forall k = 1, \cdots, K \\
&\sum_{m=1}^{M} \pi_y^m g_y^m + \sum_{j=1}^{J} \pi_z^j g_z^j = 1 \qquad\qquad\qquad\qquad \text{(LP2)} \\
&\pi_y^m \geq 0 \quad \forall m = 1, ..., M \\
&\pi_z^j \geq 0 \quad \forall j = 1, ..., J \\
&\pi_x^n \geq 0 \quad \forall n = 1, ..., N
\end{aligned}$$

The shadow prices of inputs and good and bad outputs—defined by ω_x, ω_y, and ω_z—can be directly computed from LP2 by the estimated values of π_x, π_y, and π_z (Equations 10 and 11). In LP2, the objective function is to minimize the profit inefficiency of the evaluated country (k') by minimizing the difference between optimal shadow profit ϕ and the shadow profit for k' derived from the best shadow prices and observed inputs and outputs $(\sum_{m=1}^{M}\pi_y^m y_{k'}^m - \sum_{j=1}^{J}\pi_z^j z_{k'}^j - \sum_{n=1}^{N}\pi_x^n x_{k'}^n)$ (Berre et al., 2013).

$$\frac{\hat{\omega}_x}{\hat{\omega}_y} = -\frac{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_\mathbf{y},\mathbf{g}_\mathbf{z})/\partial x}{\partial D_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_\mathbf{y},\mathbf{g}_\mathbf{z})/\partial y} = \frac{\pi_x}{\pi_y} \qquad (10)$$

$$\frac{\hat{\omega}_z}{\hat{\omega}_y} = -\frac{\partial \hat{D}_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_\mathbf{y},\mathbf{g}_\mathbf{z})/\partial z}{\partial \hat{D}_T(\mathbf{x},\mathbf{y},\mathbf{z};\mathbf{0},\mathbf{g}_\mathbf{y},\mathbf{g}_\mathbf{z})/\partial y} = \frac{\pi_z}{\pi_y} \qquad (11)$$

A methodological point deserves discussion at this stage. It is well known that when linear programs are degenerate, several shadow prices are obtained and multiple solutions exist. This is generally a problem because we cannot decide easily which solution must be kept. Our approach, developed in the next section, circumvents this obstacle through a sub-sampling approach. While a large number of replications are computed, we can expect that the average shadow prices calculated from their empirical distributions are representative.

2.3. Estimation approach: A robust DEA model

The directional distance function defined in (6) makes it possible to evaluate gaps between the observed production plan and the relevant production frontier defined by best practices. As the true frontier is unknown, this distance function in a general multi-output, multi-input framework is gauged through LP1 or LP2. Owing to their non-parametric nature, these linear programs permit the avoidance of eventual bias effects on efficiency scores and shadow prices resulting from the arbitrary choice of the functional forms of technology necessary for econometric methods. However, this enveloping technique has a major drawback: it is difficult to incorporate statistical noise into the empirical estimations. Therefore, estimated shadow prices may be significantly influenced by potential outliers belonging to the production set. This issue can be resolved through successive sub-sampling frontier estimations rather than only one traditional full frontier. Consequently, in our empirical analysis, the presence of potential outliers is taken into account by applying an estimation strategy proposed by Kneip et al. (2008) and Cazals et al. (2002), from which consistent estimators can be derived. More precisely, partial frontiers are constructed from a large number of Monte-Carlo replications ($b=1,\cdots,B$), by selecting different random sub-samples of size I ($I\in K$) with replacement and based on the initial observed DMUs. Their corresponding production sets are now defined as:

$$\hat{T}_{KU}^{b}=\left\{(\mathbf{x},\mathbf{y},\mathbf{z}):\mathbf{x}\in R_{+}^{N},\ \mathbf{y}\in R_{+}^{M},\ \mathbf{z}\in R_{+}^{J},\ \sum_{k=1}^{I}\lambda_k y_k^m \geq y_{k'}^m,\ m=1,\cdots,M,\ \sum_{k=1}^{I}\lambda_k z_k^j \leq z_{k'}^j,\ j=1,\cdots,J,\right.$$
$$\left.\sum_{k=1}^{I}(\lambda_k+\sigma_k)x_k^n \leq x_{k'}^n,\ n=1,\cdots,N,\ \sum_{k=1}^{I}(\lambda_k+\sigma_k)=1,\ \lambda_k\geq 0\ \ k=1,...,I,\ \sigma_k\geq 0\ \ k=1,...,I\right\} \quad (12)$$

This leads to defining the directional distance function relative to each sub-sample (b) as:

$$\hat{\delta}_{k'}^{b}(y_{k'}^m, z_{k'}^j, x_{k'}^n)=\max\left\{\delta:(y_{k'}^m+\delta y_{k'}^m, z_{k'}^j-\delta z_{k'}^j, x_{k'}^n)\in\hat{T}_{KU}^{b}\right\} \quad (13)$$

Finally, robust values of the shadow prices of inputs and good and bad outputs are obtained from their empirical distributions as:

$$\begin{aligned}\hat{\pi}_x&=\frac{1}{B}\sum_{b=1}^{B}\hat{\pi}_x^b\\ \hat{\pi}_y&=\frac{1}{B}\sum_{b=1}^{B}\hat{\pi}_y^b\\ \hat{\pi}_z&=\frac{1}{B}\sum_{b=1}^{B}\hat{\pi}_z^b\end{aligned} \quad (14)$$

This robust frontier approach is characterized by the number of replications (B) and the size (I) of the sub-samples. The number of the Monte-Carlo replications has to be large enough to check the sensitivity of the final results. If the sub-sample size reaches infinity, one gets back to the shadow prices of LP2 because each country of the entire sample has a high probability of selection into the sub-technology. By contrast, with too small values for I, the referent production set might be inappropriate. As a result, through a relevant choice between these two parameters, the robust frontier approach implies a trade-off between a pertinent definition of the technology and a control of the outlier bias effects.

3. Data and results

3.1. Data

In order to estimate global carbon shadow prices, we try to integrate as large a number as possible of country samples from all over the world. Our data covers 119 countries in 12 groups for the period from 1990 to 2011: 20 countries from Africa (Angola, Benin, Botswana, Cameroon, Côte d'Ivoire, Democratic Republic of the Congo, Ethiopia, Gabon, Ghana, Kenya, Morocco, Mozambique, Nigeria, Republic of the Congo, Senegal, Sudan, Togo, Tunisia, Zambia, and Zimbabwe), 10 countries from Asia (Bangladesh, Brunei Darussalam, Malaysia, Mongolia, Nepal, Pakistan, Philippines, Singapore, Sri Lanka, and Thailand), 4 countries from the BRI(C)S (Brazil, India, Russian Federation, and South Africa), 5 countries from CIVET (Colombia, Egypt, Indonesia, Turkey, and Viet Nam), 11 countries from the Middle East (Bahrain, Islamic Republic of Iran, Iraq, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, and Yemen), 14 countries from the Non-OECD Americas (Argentina, Bolivia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Panama, Peru, Trinidad and Tobago, Uruguay, and Venezuela), 21 countries from Non-OECD Europe and Eurasia (Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Malta, Republic of Moldova, Romania, Serbia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan), 3 countries from the OECD Americas (Canada, Chile, and Mexico), 5 countries from OECD Asia Oceania (Australia, Israel, Japan, New Zealand, and Republic of Korea), 24 countries from OECD Europe (Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom), and the two biggest carbon emitters, China, and the United States of America (USA), respectively.

We use two inputs, one desirable output, and one undesirable output: capital stock, labor force, real GDP, and carbon dioxide emissions, respectively. Capital stock is measured using the perpetual inventory method at current purchasing power parities in 2005 US million dollars. The labor force is measured as number of persons employed, in millions. Real GDP is measured as output-side at current purchasing power parities in 2005 US million dollars. Carbon emissions are based on sectoral approach in million tons. The first three are taken from the Penn World Table 8.1 (Feenstra et al., 2015) and the last from fuel combustion highlights (International Energy Agency, 2014).

Table 1 shows the average growth rates of inputs and outputs. China, the Middle East, CIVET, and Asia have the top four growth rates of capital stock (all higher than 6%), possibly because of their proactive investment policies and good financing environment. We note that a negative growth in labor force appears only in Non-OECD Europe and Eurasia (-0.34%) and that the global trend is increasing, at 1.43%. The growth rates of real GDP in the Middle East, China, and Africa, the three highest, respectively, are all above 5%. China has the highest growth rate of carbon emissions (5.91%) and has been the largest emitter, rather than the USA, since 2008. Although the USA has a high level of carbon emissions, it is increasing at only 0.6%. Europe has negative growth in carbon emissions (-0.15%) thanks to effective and efficient environmental policies. We also notice that Non-OECD Europe and Eurasia has a negative trend in carbon emissions (-1.78%), reflecting the economic downturn after the collapse of the former Soviet Union.

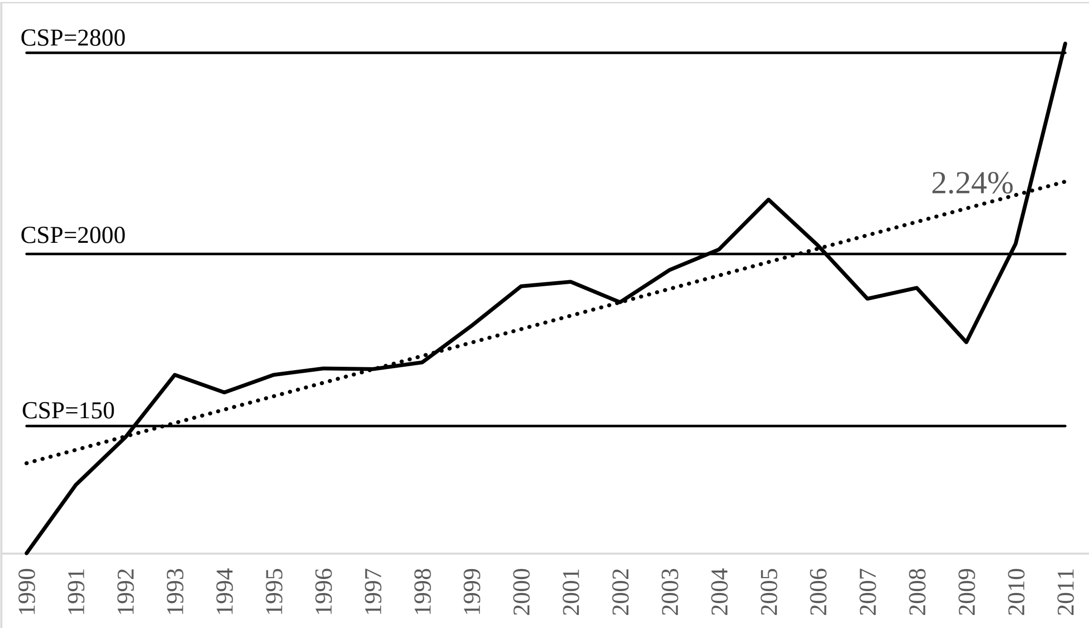
Regions	**Capital Stock**	**Labor Force**	**Real GDP**	**CO_2**
Africa	4.95%	2.68%	5.65%	3.28%
Asia	6.28%	2.26%	4.18%	4.62%
BRI(C)S	2.78%	1.73%	3.95%	1.43%
CIVET	7.24%	1.77%	3.85%	4.62%
Middle East	7.61%	3.68%	8.49%	4.83%
Non-OECD Americas	5.16%	2.05%	4.61%	3.17%
Non-OECD Europe and Eurasia	2.03%	-0.34%	2.44%	-1.78%
OECD Americas	3.20%	1.98%	3.15%	1.78%
OECD Asia Oceania	4.05%	0.41%	2.03%	1.52%
OECD Europe	3.73%	0.75%	2.91%	-0.15%
China	11.05%	1.00%	6.72%	5.91%
USA	3.73%	0.93%	2.72%	0.60%
Total	4.68%	1.43%	3.69%	2.02%

Table 1. Average growth rates of inputs and outputs 1990–2011

3.2. Empirical results

Because we may have introduced outliers into production technology owing to the disparate scales of national economies and carbon emissions among countries, a robust frontier approach is implemented. We simulate $B = 1000$ replications with a sub-sample size $I = 90$ out of the 119 countries in the initial sample. The robust shadow prices are computed by the mean values of the 1000 replications in the first stage.

In Figure 1, the evolution of the carbon shadow price at a worldwide level is measured by the average value of each group in logarithm terms. The carbon shadow price is significantly increasing, at an annual rate of 2.24% (t-value=6.81). This first result is in line with Table 1, which clearly shows that the growth rate of real GDP is around twice as high as that for CO_2. This suggests that pollution issues have been taken more into account by most of countries, particularly in Non-OECD Europe, OECD Europe, and the USA. The worldwide carbon shadow price is evaluated at around 1213 US dollars per ton in 1990 and experiences a steady fifteen-year growth between 1991 and 2005 to around 2191 US dollars per ton in 2005. A significant decrease in the carbon shadow price is observed between 2005 and 2009, followed by a substantial rise for 2009–2011; its mean value is around 2845 US dollars per ton in 2011.



CSP: Carbon shadow price ($/ton)

Figure 1. Shadow prices of carbon emissions at worldwide level (in logarithmic terms)

The kernel densities of carbon shadow prices are plotted in Figure 2. In most regions, carbon shadow prices are distributed around 600 US dollars per ton in 1990 and 2400 US dollars per ton in 2011. The right side shift of the kernel density peaks between these two periods confirms the positive growth for carbon shadow prices. Simultaneously, their distribution is significantly more dispersed.

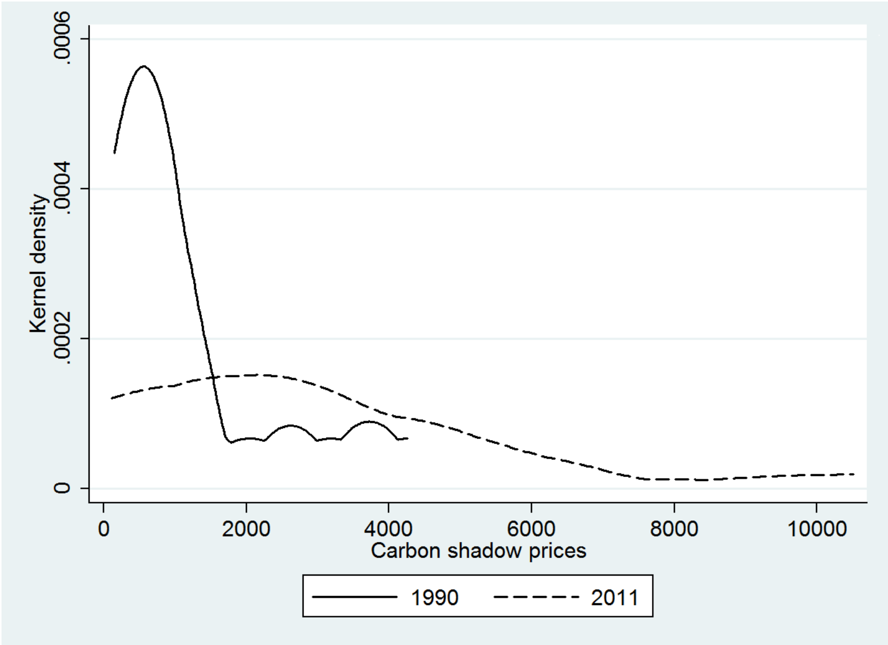
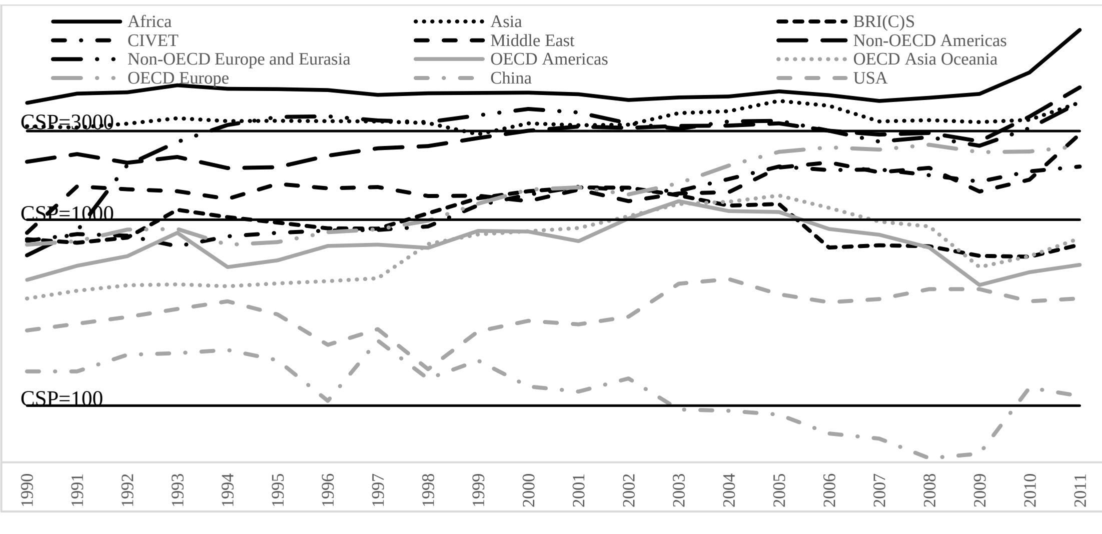


Figure 2. Kernel density of carbon shadow prices

For a specific group of countries, the regional carbon shadow prices show clustering characteristics. In Figure 3, three groups of carbon shadow prices can be easily identified at the beginning of the sample period. The first group includes Africa, Asia, and the Non-OECD Americas, presenting the highest carbon shadow prices. The second group contains China and the USA, which record the lowest carbon shadow prices. These levels indicate that their marginal abatement costs of carbon emission are very low. The third group contains the rest of the regions, with shadow prices between the first and the second groups' levels.



CSP: Carbon shadow price ($/ton)

Figure 3. Shadow prices of carbon emissions (in logarithmic terms)

We find that the three groups evolve into five new bunches of countries at the end of the sample period. First, Africa still has the highest carbon shadow prices. The new second group is composed of Asia, the Non-OECD Americas, and Non-OECD Europe and Eurasia. Their carbon shadow prices are just below the African level. The third group gathers OECD Europe, the Middle East, and CIVET. These three groups have relatively high carbon shadow prices, which indicates that they have less of an impact on global warming. The rest of the regions except China comprises the fourth group. The fourth group and China dominate the lowest carbon shadow prices, which implies that they contribute much of the world's pollution. In other words, they produce GDP without considering environmental costs. However, all countries have to share the pollution and pay for carbon taxes.

We note that the carbon shadow prices of the BRI(C)S, OECD Asia Oceania, and the OECD Americas tend to be of a similar level while OECD Europe is detached from the other OECD groups during this evolution. The growth of carbon shadow prices in OECD Europe indicates that effective and efficient environmental policies has been carried out.

On the whole, developed countries have lower carbon shadow prices, developing regions dominate higher carbon marginal abatement costs, and BRICS countries have a relatively low opportunity cost of carbon abatement. This result is consistent with Maradan and Vassiliev (2005), who point out that the marginal carbon abatement cost is generally higher in developing countries than in developed ones even if carbon shadow prices in some developing countries are lower than those in high-income countries.

The growth rates of carbon shadow prices for each region are displayed in Table 2. Most of the observed regions reveal significantly increasing trends in carbon shadow prices while the BRICS countries record negative growths. These results can be summarized as follows:

1) Favored emerging economies show rapid economic development, and their economic growth is essentially dependent on high energy consumption, implying carbon emissions;

2) countries with higher carbon emissions have lower opportunity costs for reducing pollution; and

3) shadow price distributions show substantial disparities among countries.

Regions	**coefficient**	**t-value**
Africa	1.00%	1.69
Asia	0.79%	2.65
BRI(C)S	-0.97%	-1.01
CIVET	5.22%	12.55
Middle East	2.28%	3.70
Non-OECD Americas	3.10%	6.80
Non-OECD Europe and Eurasia	3.56%	2.58
OECD Americas	0.74%	0.76
OECD Asia Oceania	4.43%	4.25
OECD Europe	7.01%	14.97
China	-4.81%	-5.03
USA	2.31%	3.05
Total	2.24%	6.81

Table 2. Average growth rates of carbon shadow prices 1990–2011

As shown in Figure 4, one can observe a sigma convergence of carbon shadow prices over the period 1990–2007. The decline of variation coefficient is around -3.6% per year and is statistically significant (t-value = -14.43). Conversely, a sigma divergence is detected between 2008 and 2011. This phenomenon may be correlated with the global financial crisis triggered in the USA. Woo et al. (2015) argue that environmental efficiency is being affected by the global financial crisis. Our results show that this crisis may potentially affect carbon shadow prices.

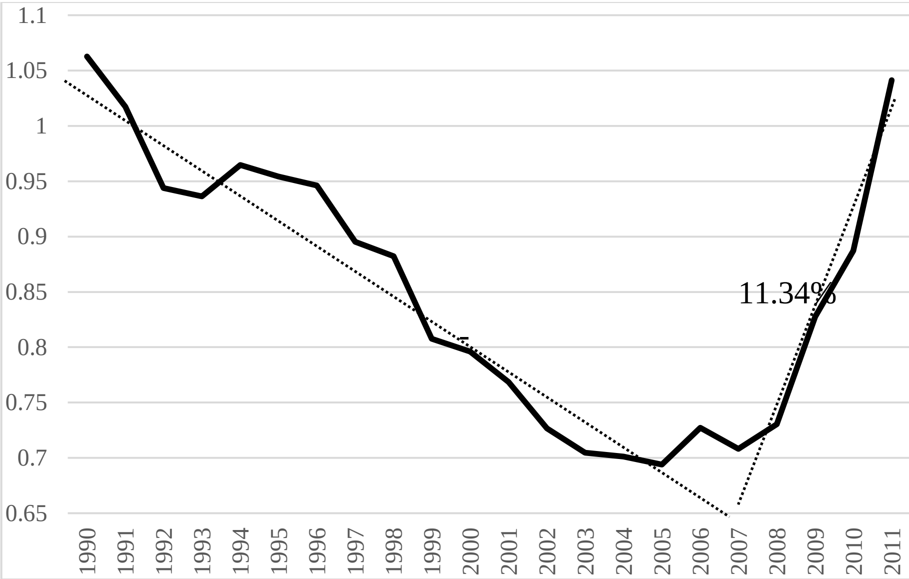


Figure 4. Variation coefficient of shadow prices

Finally, in order to examine the impact of the Kyoto Protocol on the carbon shadow prices, we conduct a regression analysis. Historically, the Kyoto Protocol was adopted at the third session of the conference of the parties (COP 3) in 1997. It was open for signature from 1998 to 1999 and received 84 signatures at that time, but 191 states are now party to it.[4] The effect of the Kyoto Protocol (*KP*) is tested in a fixed effect panel model. According to the date of entry into force, a dummy variable is created for each country and year (cf. Appendix). We add to the regression equation the ratio of carbon emissions to GDP as a control variable (CO_2/GDP), with ε denoting the error term (cf. Equation 15). Time-fixed effects are also introduced through parameter α_t . Consistent with the robust approach we used to compute shadow prices, our estimation strategy is to run a regression per sub-sampling replication and to build confidence intervals for parameters of interest from the empirical distribution of the fixed effects estimators. The

[4] Sourced from the United Nations Framework Convention on Climate Change: http://unfccc.int/kyoto_protocol/status_of_ratification/items/2613.php

regression model is defined by Equation 15, and the results are presented in Table 3 and Figure 5.

$$\ln CSP_{it} = \alpha_t + \beta_0 + \beta_1 \ln(CO_2 / GDP)_{it} + \beta_2 Dummy(KP)_{it} + \varepsilon_{it} \quad (15)$$

Coefficient	**Mean estimation**	**Lower bound (2.5%)**	**Upper bound (97.5%)**	**Significance at 5% level***
β_0	6.521	5.426	7.516	Yes
β_1	-0.048	-0.200	0.096	No
β_2	0.198	-0.060	0.455	No

*A coefficient is significantly different from 0 if the confidence interval does not include 0.

Table 3. Estimates of the Kyoto Protocol equation (15)

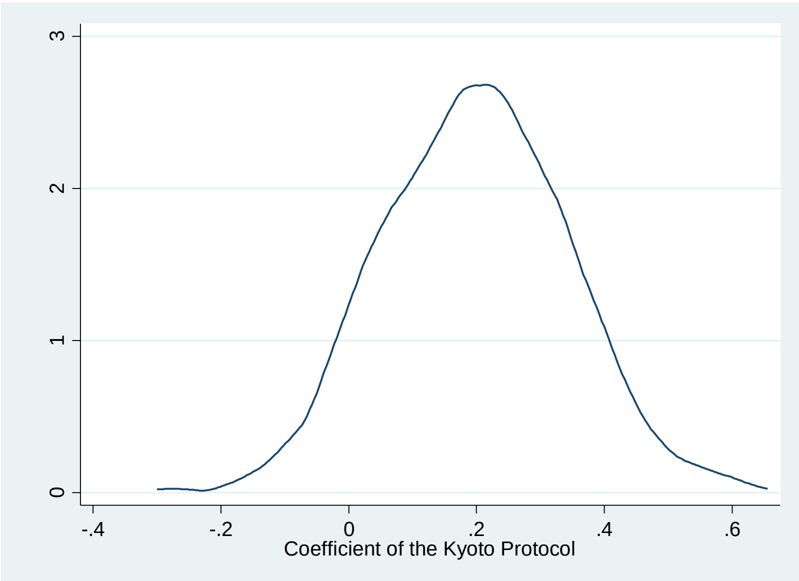


Figure 5. Kernel density of coefficient of the Kyoto Protocol

According to our findings, we conclude that the implementation of the Kyoto Protocol has not a very effective impact on the evolution of carbon shadow prices. The kernel density of β_2 displayed in Figure 5 shows that the distribution of the parameters is mostly positive, but we cannot reject the finding that zero belongs to this distribution at the 5% level. Therefore, we have to conclude that the Kyoto Protocol did not significantly affect the pollution regulations of engaged states. This emphasizes that further cooperation and efforts at carbon reduction among countries, such as the Copenhagen Accord of 2009 and the Paris climate conference of 2015, were necessary.

4. Conclusions

Global warming and carbon pricing were the core issues of the last conference of the parties (COP 21) in Paris in 2015. Most states support the idea of carbon pricing to bring down emissions. A remaining question is the best way that governments can price carbon emissions. Currently, two main types of mechanism can be used: emissions-trading systems, which essentially fix the quota for emissions, leading to an ex-post market price for carbon, and taxes that directly set a price on carbon without constraining ex-ante the volume of emissions. At the moment, given the difficulty of fixing a carbon price, governments favor the first option.

Our analysis is more in line with the second mechanism and could help policy makers to evaluate levels of carbon pricing among different countries and to fix relevant carbon taxes. Through a non-parametric robust frontier, we estimate worldwide carbon shadow prices, incorporating desirable and undesirable outputs, for a sample of 119 countries. According to our empirical results, the carbon shadow price is increasing at a rate of 2.24% per annum, reaching 2845 US dollar per ton in 2011, which suggests that carbon abatement may become increasingly challenging at the worldwide level. However, significant disparities are observed among groups of countries and over time. A significant sigma convergence of carbon shadow prices is observed among regions between 1990 and 2007, while a divergence is detected over the period 2007–2011. This means that economic fluctuations and shocks may affect carbon shadow prices.

In this paper, we conclude that the Kyoto Protocol has had no significant impact on carbon shadow prices. Therefore, countries need to keep engaging in Kyoto resolutions. A new agreement was adopted at the Paris climate conference, which included more countries and ambitious targets. While the necessity of carbon pricing is more and more commonly shared among parties, the main question relates to the uniqueness of the CO_2 tax. Our main conclusion suggests that unique carbon pricing for countries with different levels of economic development and pollution may be unfair or unreasonable. Carbon taxes should be settled according to the respective social capabilities of states.

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Appendix: Implementation dates of the Kyoto Protocol

Country	Entry into force	Country	Entry into force	Country	Entry into force
ALBANIA	30-Jun-05	GEORGIA	16-Feb-05	PERU	16-Feb-05
ANGOLA	6-Aug-07	GERMANY	16-Feb-05	PHILIPPINES	16-Feb-05
ARGENTINA	16-Feb-05	GHANA	16-Feb-05	POLAND	16-Feb-05
ARMENIA	16-Feb-05	GREECE	16-Feb-05	PORTUGAL	16-Feb-05
AUSTRALIA	11-Mar-08	GUATEMALA	16-Feb-05	QATAR	11-Apr-05
AUSTRIA	16-Feb-05	HONDURAS	16-Feb-05	R. KOREA	16-Feb-05
AZERBAIJAN	16-Feb-05	HUNGARY	16-Feb-05	R. MOLDOVA	16-Feb-05
BAHRAIN	1-May-06	ICELAND	16-Feb-05	ROMANIA	16-Feb-05
BANGLADESH	16-Feb-05	INDIA	16-Feb-05	RUSSIAN	16-Feb-05
BELARUS	24-Nov-05	INDONESIA	3-Mar-05	SAUDI ARABIA	1-May-05
BELGIUM	16-Feb-05	IRAN	20-Dec-05	SENEGAL	16-Feb-05
BENIN	16-Feb-05	IRAQ	26-Oct-09	SERBIA	17-Jan-08
BOLIVIA	16-Feb-05	IRELAND	16-Feb-05	SINGAPORE	11-Jul-06
BOSNIA & H.	15-Jul-07	ISRAEL	16-Feb-05	SLOVAKIA	16-Feb-05
BOTSWANA	16-Feb-05	ITALY	16-Feb-05	SLOVENIA	16-Feb-05
BRAZIL	16-Feb-05	JAMAICA	16-Feb-05	SOUTH AFRICA	16-Feb-05
BRUNEI D.	18-Nov-09	JAPAN	16-Feb-05	SPAIN	16-Feb-05
BULGARIA	16-Feb-05	JORDAN	16-Feb-05	SRI LANKA	16-Feb-05
CAMEROON	16-Feb-05	KAZAKHSTAN	17-Sep-09	SUDAN	16-Feb-05
CANADA	16-Feb-05	KENYA	26-May-05	SWEDEN	16-Feb-05
CHILE	16-Feb-05	KUWAIT	9-Jun-05	SWITZERLAND	16-Feb-05
CHINA	16-Feb-05	KYRGYZSTAN	16-Feb-05	SYRIAN A. R.	27-Apr-06
COLOMBIA	16-Feb-05	LATVIA	16-Feb-05	TAJIKISTAN	29-Mar-09
CONGO	13-May-07	LEBANON	11-Feb-07	THAILAND	16-Feb-05
COSTA RICA	16-Feb-05	LITHUANIA	16-Feb-05	TOGO	16-Feb-05
COTE D'IVOIRE	22-Jul-07	LUXEMBOURG	16-Feb-05	TRINIDAD & T.	16-Feb-05
CROATIA	28-Aug-07	MALAYSIA	16-Feb-05	TUNISIA	16-Feb-05
CYPRUS	16-Feb-05	MALTA	16-Feb-05	TURKEY	26-Aug-09
CZECH R.	16-Feb-05	MEXICO	16-Feb-05	TURKMENISTAN	16-Feb-05
D. R. CONGO	21-Jun-05	MONGOLIA	16-Feb-05	UKRAINE	16-Feb-05
DENMARK	16-Feb-05	MOROCCO	16-Feb-05	UK	16-Feb-05
DOMINICAN R.	16-Feb-05	MOZAMBIQUE	18-Apr-05	USA	None
ECUADOR	16-Feb-05	NEPAL	15-Dec-05	URUGUAY	16-Feb-05
EGYPT	12-Apr-05	NETHERLANDS	16-Feb-05	UZBEKISTAN	16-Feb-05
EL SALVADOR	16-Feb-05	NEW ZEALAND	16-Feb-05	VENEZUELA	19-May-05
ESTONIA	16-Feb-05	NIGERIA	10-Mar-05	VIET NAM	16-Feb-05
ETHIOPIA	13-Jul-05	NORWAY	16-Feb-05	YEMEN	16-Feb-05
FINLAND	16-Feb-05	OMAN	19-Apr-05	ZAMBIA	5-Oct-06
FRANCE	16-Feb-05	PAKISTAN	11-Apr-05	ZIMBABWE	28-Sep-09
GABON	12-Mar-07	PANAMA	16-Feb-05		

Sourced from the United Nations Framework Convention on Climate Change

Chapter 5

Further Works

In the last chapter of thesis, we further extend research to two undiscovered areas: one is a law of one shadow price model which imposes a unique constraint on shadow price estimation of bad outputs. Another is extension of by-production model, we point out some possible improvements on this model and a preliminary simulation result for comparing with WDA model is included.

1. A law of one shadow price model

In the traditional DEA models, each DMUs has a specific set of shadow prices for both desirable and undesirable outputs, thus the same good may have different prices in the economy. Kuosmanen et al. (2006) and Leleu (2009) proposed a global constraint model which measures a meta-frontier for all DMUs simultaneously, namely a law of one shadow price model (LOOSP). This global constraint indicates the same shadow prices of identical goods can be applied to each DMUs in an efficient market. We follow Leleu's approach (2013) and a traditional DEA model under a VRS technology that satisfies free disposability of the inputs, weak disposability for outputs and a positive shadow price for undesirable outputs. Primal and dual LOOSP linear programs based on directional distance function can be figured by:

$$
\begin{aligned}
&\max_{\delta,\lambda,\sigma} \sum_{l=1}^{K} \delta_l \\
&s.t. \ -\sum_{k=1}^{K} \lambda_{k,l}(y_k^m - y_l^m) + \sigma_l y_{m,l} + \delta_l g_y^m \le 0 \ \ \forall m = 1,\cdots,M; \forall l = 1,\cdots,K \\
&\sum_{l=1}^{K}\Big(\sum_{k=1}^{K} \lambda_{k,l}(z_k^j - z_l^j) - \sigma_l z_l^j + \delta_l g_z^j\Big) \le 0 \ \ \forall j = 1,\cdots,J \\
&\sum_{k=1}^{K} \lambda_{k,l}(x_k^n - x_l^n) \le 0 \ \ \forall n = 1,\ldots,N; \forall l = 1,\cdots,K \\
&\sum_{k=1}^{K} \lambda_{k,l} + \sigma_l = 1 \ \ \forall l = 1,\ldots,K \\
&\lambda_{k,l} \ge 0 \ \ \forall k = 1,\ldots,K; \forall l = 1,\ldots,K \\
&\sigma_l \ \ \forall l = 1,\ldots,K
\end{aligned}
\qquad (1)
$$

$$
\begin{aligned}
&\min_{\phi,\pi^{v},\pi^{w},\pi^{x}} \sum_{l=1}^{K}\phi_l \\
s.t.\ &(\sum_{m=1}^{M}\pi_{y,l}^{m}v_{k,l}^{m}-\sum_{j=1}^{J}\pi_{z}^{j}z_{k,l}^{j}-\sum_{n=1}^{N}\pi_{x,l}^{n}x_{k,l}^{n})- \\
&(\sum_{m=1}^{M}\pi_{y,l}^{m}y_{l}^{m}-\sum_{j=1}^{J}\pi_{z}^{j}z_{l}^{j}-\sum_{n=1}^{N}\pi_{x,l}^{n}x_{l}^{n})\le\phi_l\quad\forall k=1,\cdots,K;\forall l=1,\cdots,K \\
&\sum_{m=1}^{M}\pi_{y,l}^{m}g_{y}^{m}+\sum_{j=1}^{J}\pi_{z}^{j}g_{z}^{j}=1\quad\forall l=1,\cdots,K \\
&\sum_{m=1}^{M}\pi_{y}^{m}y_{l}^{m}-\sum_{j=1}^{J}\pi_{z}^{j}z_{l}^{j}+\phi_l\ge 0\quad\forall l=1,\cdots,K \\
&\pi_{y,l}^{m}\ge 0\quad\forall m=1,...,M;\forall l=1,\cdots,K \\
&\pi_{z}^{j}\ge 0\quad\forall j=1,...,J \\
&\pi_{x,l}^{n}\ge 0\quad\forall n=1,...,N;\forall l=1,\cdots,K
\end{aligned}
\tag{2}
$$

Kuosmanen et al. (2006) argue that the LOOSP emphasizes the coordinating function of prices in the allocation of resources and hence naturally relates the efficiency of individual firms to the efficiency at the aggregate level of the industry or sector as a whole. By means of this one price method, we may adopt a unique (global) opportunity cost of undesirable outputs in terms of the loss of desirable outputs from environmentally friendly viewpoint. Take carbon emissions as an example, reducing carbon emissions is a global action, the same pricing scheme may help archiving an international consensus and imposing carbon tax for all countries. The LOOSP may become a new activity analysis model with bad outputs. We plan to apply this approach in the future work.

2. By-production method

Initially Murty et al. (2012) employ an improved output-oriented Färe-Grosskopf-Lovell index to measure efficiency with a hyperbolic measurement, the original nonlinear primal program and a dual formulation with direction distance function under a CRS technology can be defined as follows:

$$
\begin{aligned}
&\min_{\delta,\lambda,\sigma,\gamma} \quad 0.5\Big(\sum_{m=1}^{M}\delta^{m} / M + \sum_{j=1}^{J}\gamma^{j} / J\Big) \\
s.t. &\sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m / \delta^m \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n \quad \forall n = 1,\cdots,N \\
&\sum_{k=1}^{K}\sigma_k z_k^j \leq \gamma^j z_{k'}^j \quad \forall j = 1,\cdots,J \qquad (3)\\
&\sum_{k=1}^{K}\sigma_k x_k^p \geq x_{k'}^p \quad \forall p = 1,\cdots,P \\
&\lambda_k \geq 0 \quad \forall k = 1,\ldots,K \\
&\sigma_k \geq 0 \quad \forall k = 1,\ldots,K
\end{aligned}
$$

$$
\begin{aligned}
&\min_{\pi_y,\pi_z,\pi_x,\pi_{xp}} \quad \Big(\sum_{n=1}^{N}\pi_x^n x_{k'}^n - \sum_{m=1}^{M}\pi_y^m y_{k'}^m + \sum_{j=1}^{J}\pi_z^j z_{k'}^j - \sum_{p=1}^{P}\pi_{xp}^p x_{k'}^p\Big) \\
s.t. &\sum_{m=1}^{M}\pi_y^m y_k^m - \sum_{n=1}^{N}\pi_x^n x_k^n \leq 0 \quad \forall k = 1,\cdots,K \\
&\sum_{p=1}^{P}\pi_{xp}^p x_k^p - \sum_{j=1}^{J}\pi_z^j z_k^j \leq 0 \quad \forall k = 1,\cdots,K \\
&\sum_{m=1}^{M}\pi_y^m g_y^m = 0.5 / M \\
&\sum_{j=1}^{J}\pi_z^j g_z^j = 0.5 / J \qquad (4)\\
&\pi_y^m \geq 0 \quad \forall m = 1,\ldots,M \\
&\pi_z^j \geq 0 \quad \forall j = 1,\ldots,J \\
&\pi_x^n \geq 0 \quad \forall n = 1,\ldots,N \\
&\pi_{xp}^p \geq 0 \quad \forall n = 1,\ldots,P
\end{aligned}
$$

where δ^m and γ^j are non-radial efficiency scores for good and bad outputs, π_x, π_{xp}, π_y and π_z denote shadow prices of all inputs, pollution generating inputs, good and bad outputs associated to each constraint in linear programs. In the first sub-technology, it is a classical DEA model with all inputs and good outputs. In the second sub-technology, the disposability is inversed for the pollution generating inputs and bad outputs. Due to the nonlinearity with the above model based on a Färe-Grosskopf-Lovell index, we can extend it to a linear one with directional distance function as follows:

$$
\begin{aligned}
&\max_{\delta,\lambda,\sigma,\gamma} \quad 0.5\left(\sum_{m=1}^{M}\delta^{m} / M + \sum_{j=1}^{J}\gamma^{j} / J\right) \\
&s.t.\ \sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n \quad \forall n = 1,\cdots,N \\
&\sum_{k=1}^{K}\sigma_k z_k^j \leq z_{k'}^j - \gamma^j g_z^j \quad \forall j = 1,\cdots,J \\
&\sum_{k=1}^{K}\sigma_k x_k^p \geq x_{k'}^p \quad \forall p = 1,\cdots,P \\
&\lambda_k \geq 0 \quad \forall k = 1,\dots,K \\
&\sigma_k \geq 0 \quad \forall k = 1,\dots,K \\
&\delta^m \geq 0 \quad \forall m = 1,\cdots,M \\
&\gamma^j \geq 0 \quad \forall j = 1,\cdots,J
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
&\min_{\pi_y,\pi_z,\pi_x,\pi_{xp}} \quad \left(\sum_{n=1}^{N}\pi_x^n x_{k'}^n - \sum_{m=1}^{M}\pi_y^m y_{k'}^m + \sum_{j=1}^{J}\pi_z^j z_{k'}^j - \sum_{p=1}^{P}\pi_{xp}^p x_{k'}^p\right) \\
&s.t.\ \sum_{m=1}^{M}\pi_y^m y_k^m - \sum_{n=1}^{N}\pi_x^n x_k^n \leq 0 \quad \forall k = 1,\cdots,K \\
&\sum_{p=1}^{P}\pi_{xp}^p x_k^p - \sum_{j=1}^{J}\pi_z^j z_k^j \leq 0 \quad \forall k = 1,\cdots,K \\
&\sum_{m=1}^{M}\pi_y^m g_y^m \geq 0.5 / M \\
&\sum_{j=1}^{J}\pi_z^j g_z^j \geq 0.5 / J \\
&\pi_y^m \geq 0 \quad \forall m = 1,\dots,M \\
&\pi_z^j \geq 0 \quad \forall j = 1,\dots,J \\
&\pi_x^n \geq 0 \quad \forall n = 1,\dots,N \\
&\pi_{xp}^p \geq 0 \quad \forall n = 1,\dots,P
\end{aligned}
\tag{6}
$$

We remark a potential pitfall in the Murty et al. (2012) approach. One can observe that efficiency scores δ^m and γ^j are not constrained in the original model while the objective function is using Färe-Grosskopf-Lovell index at a summation level. Therefore it does not prevent to get negative values for the individual efficiency scores even if the average one is maximized. In order to avoid existence of negative values, we suggest a positive constraint on efficiency scores.

Moreover, we can detect there are two different shadow prices of pollution generating inputs which appear twice both in two sub-technology. Assume that two shadow prices of pollution generating inputs are equivalent, a constraint model of unique shadow prices with directional distance function can be derived as following steps:

$$\min_{\pi_y,\pi_z,\pi_x,\pi_{xp}} \quad ((\sum_{o=1}^{O}\pi_x^o x_{k'}^o + \sum_{p=1}^{P}\pi_x^p x_{k'}^p) - \sum_{m=1}^{M}\pi_y^m y_{k'}^m + \sum_{j=1}^{J}\pi_z^j z_{k'}^j - \sum_{p=1}^{P}\pi_{xp}^p x_{k'}^p)$$
$$s.t.\ \sum_{m=1}^{M}\pi_y^m y_k^m - (\sum_{o=1}^{O}\pi_x^o x_k^o + \sum_{p=1}^{P}\pi_x^p x_k^p) \le 0 \quad \forall k = 1,\cdots,K$$
$$\sum_{p=1}^{P}\pi_{xp}^p x_k^p - \sum_{j=1}^{J}\pi_z^j z_k^j \le 0 \quad \forall k = 1,\cdots,K$$
$$\sum_{m=1}^{M}\pi_y^m g_y^m \ge 0.5/M$$
$$\sum_{j=1}^{J}\pi_z^j g_z^j \ge 0.5/J$$
$$\pi_y^m \ge 0 \quad \forall m = 1,\ldots,M$$
$$\pi_z^j \ge 0 \quad \forall j = 1,\ldots,J$$
$$\pi_x^o \ge 0 \quad \forall o = 1,\ldots,O$$
$$\pi_x^p \ge 0 \quad \forall n = 1,\ldots,P$$
$$\pi_{xp}^p \ge 0 \quad \forall n = 1,\ldots,P \tag{7}$$

we use non-pollution generating x_k^o and pollution generating inputs x_k^p instead of all inputs in the first sub-technology. If we add a new constraint $\pi_x^p = \pi_{xp}^p$ to the above dual program which implies shadow prices of pollution generating inputs are same in both sub-technology, a new dual constraint model is derived as:

$$
\begin{aligned}
&\min_{\pi_y,\pi_z,\pi_x,\pi_{xp}} \quad (\sum_{o=1}^{O}\pi_x^o x_{k'}^o - \sum_{m=1}^{M}\pi_y^m y_{k'}^m + \sum_{j=1}^{J}\pi_z^j z_{k'}^j) \\
&s.t. \ \sum_{m=1}^{M}\pi_y^m y_k^m - \sum_{o=1}^{O}\pi_x^o x_k^o - \sum_{p=1}^{P}\pi_x^p x_k^p \leq 0 \quad \forall k=1,\cdots,K \\
&\sum_{p=1}^{P}\pi_{xp}^p x_k^p - \sum_{j=1}^{J}\pi_z^j z_k^j \leq 0 \quad \forall k=1,\cdots,K \\
&\sum_{m=1}^{M}\pi_y^m g_y^m \geq 0.5/M \\
&\sum_{j=1}^{J}\pi_z^j g_z^j \geq 0.5/J \\
&\pi_y^m \geq 0 \quad \forall m=1,\ldots,M \\
&\pi_z^j \geq 0 \quad \forall j=1,\ldots,J \\
&\pi_x^o \geq 0 \quad \forall o=1,\ldots,O \\
&\pi_{xp}^p \geq 0 \quad \forall n=1,\ldots,P
\end{aligned} \tag{8}
$$

Alternatively, the corresponding primal constraint model can be also derived from following steps:

$$
\begin{aligned}
&\max_{\delta,\lambda,\sigma,\gamma} \quad 0.5(\sum_{m=1}^{M}\delta^m / M + \sum_{j=1}^{J}\gamma^j / J) \\
&s.t. \ \sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m \quad \forall m=1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k x_k^o \leq x_{k'}^o \quad \forall o=1,\cdots,O \\
&\sum_{k=1}^{K}\lambda_k x_k^p \leq x_{k'}^p \quad \forall p=1,\cdots,P \\
&\sum_{k=1}^{K}\sigma_k z_k^j \leq z_{k'}^j - \gamma^j g_z^j \quad \forall j=1,\cdots,J \\
&\sum_{k=1}^{K}\sigma_k x_k^p \geq x_{k'}^p \quad \forall p=1,\cdots,P \\
&\lambda_k \geq 0 \quad \forall k=1,\ldots,K \\
&\sigma_k \geq 0 \quad \forall k=1,\ldots,K \\
&\delta^m \geq 0 \quad \forall m=1,\cdots,M \\
&\gamma^j \geq 0 \quad \forall j=1,\cdots,J
\end{aligned} \tag{9}
$$

We decompose all inputs to non-pollution generating and pollution generating inputs and one can notice two constraints $\sum_{k=1}^{K}\lambda_k x_k^p \le x_{k'}^p$ *and* $\sum_{k=1}^{K}\sigma_k x_k^p \ge x_{k'}^p$ in two sub-technologies. With equivalent transformation, we can obtain $\sum_{k=1}^{K}\lambda_k x_k^p \le x_{k'}^p \le \sum_{k=1}^{K}\sigma_k x_k^p$, then $\sum_{k=1}^{K}\lambda_k x_k^p \le \sum_{k=1}^{K}\sigma_k x_k^p$ is derived. If we combine these two constraints together, $\sum_{k=1}^{K}\sigma_k x_k^p - \sum_{k=1}^{K}\lambda_k x_k^p \ge 0$ replaces previous constraints then a new primal constraint model is derived as follows:

$$
\begin{aligned}
&\max_{\delta,\lambda,\sigma,\gamma} \quad 0.5\left(\sum_{m=1}^{M}\delta^m / M + \sum_{j=1}^{J}\gamma^j / J\right) \\
s.t.\ &\sum_{k=1}^{K}\lambda_k y_k^m \ge y_{k'}^m + \delta^m g_y^m \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k x_k^o \le x_{k'}^o \quad \forall o = 1,\cdots,O \\
&\sum_{k=1}^{K}\sigma_k z_k^j \le z_{k'}^j - \gamma^j g_z^j \quad \forall j = 1,\cdots,J \\
&\sum_{k=1}^{K}\sigma_k x_k^p - \sum_{k=1}^{K}\lambda_k x_k^p \ge 0 \quad \forall p = 1,\cdots,P \\
&\lambda_k \ge 0 \quad \forall k = 1,\dots,K \\
&\sigma_k \ge 0 \quad \forall k = 1,\dots,K \\
&\delta^m \ge 0 \quad \forall m = 1,\cdots,M \\
&\gamma^j \ge 0 \quad \forall j = 1,\cdots,J
\end{aligned}
\tag{10}
$$

The primal (8) and dual (10) models are equivalent. Compared to initial by-production model, the main feature in primal model (8) is allowing to use more pollution generating inputs for producing more good outputs. And the dual one (10) is setting identical shadow prices on pollution generating inputs. This model may be further studied.

3. Comparison between by-production and WDA

3.1. Data

In order to compare by-production technology with WDA model, we collect a dataset of two common inputs, one good output, one bad output, and one pollution generating input respectively: capital stock, employment, and GDP are from AMECO database, and energy consumptions and carbon emissions are from International Energy Agency statistics. This dataset includes 24 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States. The net capital stock and GDP are measured as at base year 2010 with purchasing power parities in billions of 2010 Euros. Employment, energy consumptions, and carbon emissions are measured as 1000 persons, kiloton of oil equivalent, and million tons respectively.

3.2. Estimation strategy

We employ a directional distance function as the non-radial measurement based on Färe-Grosskopf-Lovell index for by-production (BP) CRS technology instead of initial nonlinear one. Efficiency scores are constrained for positive values. Alternatively, we provide a classical WDA model under a CRS technology as a baseline. In the WDA model, we keep equal sign for constraint of bad outputs and the non-radial measurement based on Färe-Grosskopf-Lovell index. The by-production and WDA models are defined as follows:

$$
\begin{aligned}
&\max_{\delta,\lambda,\sigma,\gamma} \quad 0.5\left(\sum_{m=1}^{M}\delta^m / M + \sum_{j=1}^{J}\gamma^j / J\right) \\
s.t.\ &\sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n \quad \forall n = 1,\cdots,N \\
&\sum_{k=1}^{K}\sigma_k z_k^j \leq z_{k'}^j - \gamma^j g_z^j \quad \forall j = 1,\cdots,J \\
&\sum_{k=1}^{K}\sigma_k x_k^p \geq x_{k'}^p \quad \forall p = 1,\cdots,P \qquad (11) \\
&\lambda_k \geq 0 \quad \forall k = 1,\ldots,K \\
&\sigma_k \geq 0 \quad \forall k = 1,\ldots,K \\
&\delta^m \geq 0 \quad \forall m = 1,\cdots,M \\
&\gamma^j \geq 0 \quad \forall j = 1,\cdots,J
\end{aligned}
$$

$$
\begin{aligned}
&\max_{\delta,\lambda,\gamma} \quad 0.5\left(\sum_{m=1}^{M}\delta^m / M + \sum_{j=1}^{J}\gamma^j / J\right) \\
s.t.\ &\sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m \quad \forall m = 1,\cdots,M \\
&\sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n \quad \forall n = 1,\cdots,N \\
&\sum_{k=1}^{K}\lambda_k z_k^j = z_{k'}^j - \gamma^j g_z^j \quad \forall j = 1,\cdots,J \qquad (12) \\
&\lambda_k \geq 0 \quad \forall k = 1,\ldots,K \\
&\delta^m \geq 0 \quad \forall m = 1,\cdots,M \\
&\gamma^j \geq 0 \quad \forall j = 1,\cdots,J
\end{aligned}
$$

Instead of comparing results based on the real dataset, we keep data of inputs while we simulate that of two outputs by a Cobb–Douglas production function.

$$Y = AK^a L^b E^c \qquad (13)$$

where *K, L,* and *E* are capital stock, labor, and energy consumption, *a, b,* and *c* are the output elasticities of capital, labor and energy, respectively. In the simulation, inefficiency of outputs are randomly generated and the average inefficiency of simulation is 18%. In order to maintain a CRS technology, we force sum of *a*, *b*, and *c* are equal to 1. Their simulation value are estimated by an OLS regression on the real dataset as follows:

lnA	a	b	c
0.0966	0. 5852	0. 2363	0. 1785

3.3 Results comparison

The scatterplots between inefficiency scores of by-production approach and inefficiency scores of simulation, and between inefficiency scores of WDA approach and inefficiency scores of simulation are shown in Figure1 and Figure2 respectively.

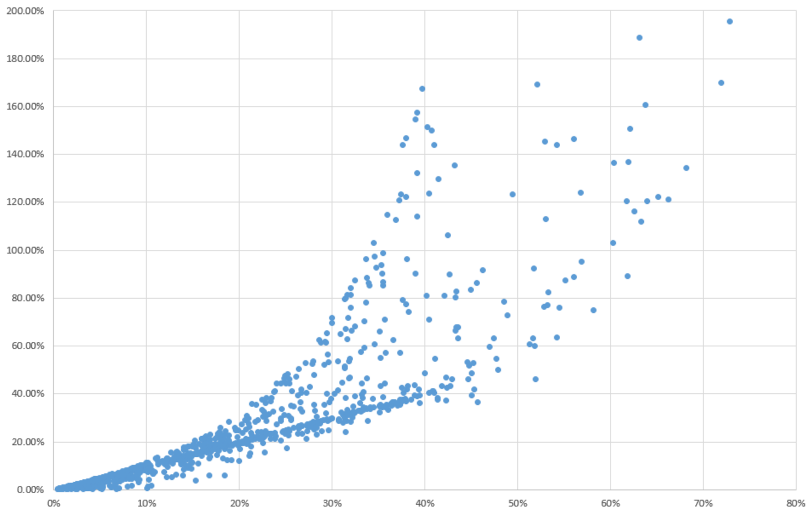

Figure1 Comparison of inefficiency simulation for BP

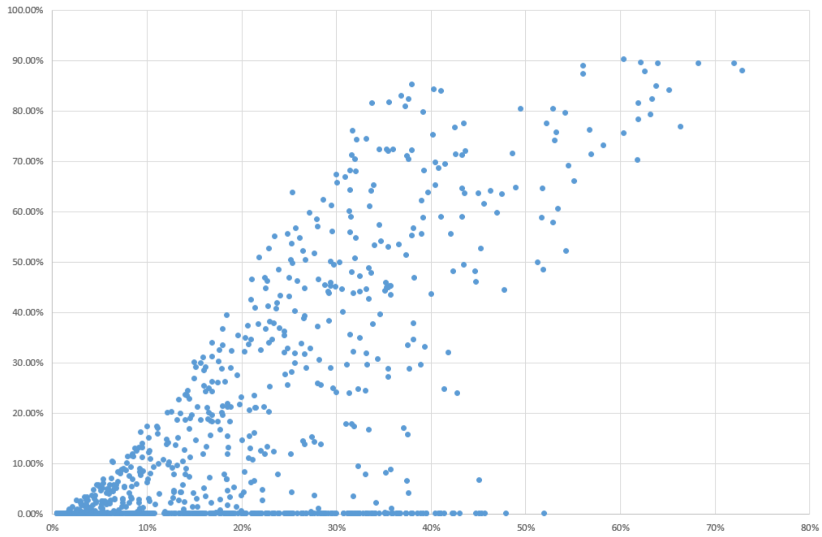

Figure2 Comparison of inefficiency simulation for WDA

We can identify that WDA model has a greater degree of dispersion comparing to that of BP model. Compared to initial settled 18%, the average inefficiency scores are 15.25% in WDA model and 24.65% in BP model. Although some simulation inefficiencies exist in output level, WDA model underestimates inefficiency scores thus points are located at the horizontal axis while we do not detect the same situation in BP model. In this context, we may argue that BP model has a better performance. The further work on BP model and multiple frontiers methods may have broader prospects in future research.

General Conclusion

This thesis introduces undesirable outputs to production technology and attempts to integrate the negative externality of pollution into economic evaluation which is referred to, as green productivity. A nonparametric approach DEA is employed to model the environmental production frontier, which analyzes the environmental impact on economic performance.

The analysis begins by focusing on a developing country, China, which has become the largest carbon emitter since 2008. Chapter 2 re-examines the convergence hypothesis for 30 Chinese regions from 1997 to 2010 based on WDA and VRS assumptions. We propose a novel way of decomposing regional efficiency changes: a technical catching-up process and a structural effect which implies convergence or divergence in input and output mixes. The empirical result reveals that structural inefficiency predominates the technical effect in the growth convergence process, and structural inefficiency is mainly due to the pollution cost convergence among regions. Not only some rich regions but also underdeveloped areas serve as benchmarks for China. We also detect the carbon shadow price increases at 2.5% annually and approaches 864 yuan per ton in 2010 in China. According to these results, we can conclude that the increasing pollution cost estimated through the shadow price of carbon dioxide emissions implies the unsustainability of Chinese current economic growth. The regional unbalanced carbon shadow prices suggest that the Chinese government should seek an equilibrium point between economic benefits and the costs of pollution in national and regional efficiency improvements.

Thereafter, Chapter 3 includes the study of green productivity evolution in developed countries. Incorporating carbon emissions into production frontier 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 the difference-based Luenberger TFP changes into three components; technological progress, technical and structural efficiency changes. Beyond the traditional technical efficiency changes and technological progress, this decomposition captures a structural effect, which 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 empirical results indicate that the traditional TFP index underestimates green growth. Compared to results of Chinese regions in Chapter2, the green growth in productivity performance is driven by the effective and efficient environmental policies of the OECD.

After investigating evolutions of environmental efficiency and productivity in China and OECD countries, the last chapter extends the horizon to a worldwide level: global carbon shadow prices are estimated for 119 countries from all continents during 1990-2011. Our empirical results show that the global carbon shadow price is increasing by around 2.24% per annum and has reached 2845 US dollars per ton in 2011. A significant sigma convergence process of carbon shadow prices among countries is detected during 1990–2007. The relationship between carbon shadow prices and environmental protocol has not been studied yet, we analyze the evolution of carbon shadow prices at a worldwide level by using a sub-sampling approach. This robust approach may circumvent the obstacle of multiple solutions of shadow prices. We discover an insignificant effect of implementation of the Kyoto Protocol on the evolution of global carbon shadow prices.

At the end of this work, we can draw some general conclusions about the main findings in this thesis. First, we argue that environmental elements play a vital role in economic performance among regions which is significantly affected by incorporating undesirable outputs. Not only rich regions, some poor regions with a fine environmental condition may also serve as benchmarks. Studying the impact of environmental element on economic performance can evaluate the cost of the blind pursuit of economic growth, and determine economic, social and environmental sustainability for policy and decision makers. This thesis shows that environmental deterioration has a counteractive effect on the economic performance. Thus governments should not ignore the undesirable outputs in production activity, and protecting environment and reducing undesirable outputs will be advocated by policy and decision makers.

Second, even if regions are technical and price efficient at the individual level, a certain level of inefficiency may appear at the aggregate level. This must be taken into account for a global environmental policy at a worldwide level. Defining a common carbon tax or pricing rules for carbon emission requires international cooperation and integrated evaluation of the impact of pollution in the productivity of countries. Therefore the global environmental protocol may provide a platform for negotiating and implementing emission reduction and carbon tax, such as the Kyoto Protocol, the Copenhagen Accord, and the Paris Climate Conference. Since carbon reduction is an interactive action, our results show that we still have room for structural improvement and efficient resource allocation. This may be beneficial to all participants and intergovernmental cooperation may not only improve our environmental condition but also social wellbeing.

Third, the result implies that developed countries have lower carbon shadow prices while developing regions dominate higher carbon marginal abatement costs. In other words, it is difficult to reduce one unit of carbon emission for a poor country comparing to that for a rich one. We point out that it is unfair to set a unique carbon price for countries with different levels of economic development and pollution. Carbon taxes should be settled according to the respective social capabilities of states. Our research may also help policy and decision makers to investigate opportunity costs of carbon reduction among regions and to design a rational mechanism for carbon taxes which are valuable to each countries.

Finally, we argue that economic sustainable growth can be motivated by effective environmental policies and the green productivity growth is predicated to become a dominant source of economic growth in the 21st century. We believe that the green or low carbon growth will play a vital role in the worldwide economic development model which is the significance of this research.