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Abstract

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 total factor productivity (TFP) in Chinese mainland provinces but suffered from methodological weaknesses by assuming constant returns to scale (CRS) for the production frontier and/or incorrectly modeling variables returns to scale (VRS) technology taking into account bad output such as carbon dioxide emissions. Our paper offers a right 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.

JEL Classification: O47, O44, O33, D24.

Highlights:
The paper explores the growth convergence process among 30 Chinese regions including a bad output like carbon dioxide emission.
Regional efficiency changes are decomposed into a technical catching-up effect and a structural effect measuring convergence among input/output mixes.
Carbon dioxide emission is introduced as an undesirable output for which we estimate the shadow price.
As a main result, we find that the environmental growth convergence among regions has mainly relied on the structural effect.

Keywords: Growth Convergence, Catching-up, Undesirable Output, Carbon Dioxide Emissions, Shadow Price, Weak Disposability.

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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. The neoclassical standard theory assuming perfect capital mobility and identical technology 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 advance of the 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. The 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 the main source of productivity growth is from technical progress which determined by 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

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

across regions. Some papers incorrectly modeled technologies with bad outputs although the researchers used variable returns to scale (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.

Introduced by Chung et al. (1997), the Malmquist-Luenberger index is a popular productivity index that incorporates undesirable output production with directional distance function. 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.

- Figure 1 about here -

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.

- Figure 2 about here -

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.

- Figure 3a about here -

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.

- Figure 3b about here -

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.

- Figure 3c about here -

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:

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

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

The whole country (W) is composed of K regions $(k = 1, \ldots K)$. 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:

$$T^W = \sum_{k=1}^{K} T \quad (3)$$

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

$$T_{CRS}^W = \sum_{k=1}^{K} T_{CRS} = T_{CRS} \quad (4)$$

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

$$T_{VRS}^W = \sum_{k=1}^{K} T_{VRS} = K \times T_{VRS} \quad (5)$$

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

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

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

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

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).

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

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

Concerning the directional distance function, we use the aggregate output vector to construct the direction of the translation; i.e., $(\mathbf{g}_{\mathbf{x}}, \mathbf{g}_{\mathbf{y}^{\mathrm{G}}}, \mathbf{g}_{\mathbf{y}^{\mathrm{B}}}) = \left(0, \sum_{k \in W} \mathrm{y}_{\mathrm{k}}^{\mathrm{G}}, \sum_{k \in W} \mathrm{y}_{\mathrm{k}}^{\mathrm{B}}\right)$. 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):

Primal directional distance function under a VRS technology

$$\vec{D}_{T_{VRS}}(\mathbf{x}_o, \mathbf{y}_o^{\mathbf{G}}, \mathbf{y}_o^{\mathbf{B}}; 0, \sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{G}}, \sum_{k\in W}\mathbf{y}_{\mathbf{k}}^{\mathbf{B}}) = \max_{z,\theta,\lambda} \lambda$$

$$s.t. \sum_{k\in W} z_k y_{k,m}^G \geq y_{o,m}^G + \lambda \sum_{k\in W} y_{k,m}^G \quad \forall m = 1,\cdots,M$$

$$\sum_{k\in W} z_k y_{k,\mathrm{p}}^B \leq y_{o,p}^B - \lambda \sum_{k\in W} y_{k,p}^B \quad \forall p = 1,\cdots,P \qquad \text{(LP1)}$$

$$\sum_{k\in W} z_k x_{k,n} \leq \theta x_{o,n} \quad \forall n = 1,\cdots,N$$

$$\sum_{k\in W} z_k = \theta$$

$$z_k \geq 0 \quad \forall k = 1,\ldots,K$$

$$\theta \leq 1$$

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:

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

and computed by the following LP.:

Primal directional distance function under an aggregate VRS technology

$$\vec{D}_{T^W_{VRS}}(\sum_{k\in W}\mathbf{x}_k, \sum_{k\in W}\mathbf{y}^{\mathbf{G}}_k, \sum_{k\in W}\mathbf{y}^{\mathbf{B}}_k; 0, \sum_{k\in W}\mathbf{y}^{\mathbf{G}}_{\mathbf{k}}, \sum_{k\in W}\mathbf{y}^{\mathbf{B}}_{\mathbf{k}}) = \max_{z,\theta,\lambda} \lambda$$

$$s.t.\;\; K\sum_{k\in W} z_k y^G_{k,m} \geq \sum_{o\in W} y^G_{o,m} + \lambda \sum_{k\in W} y^G_{k,m} \quad \forall m = 1,\cdots,M$$

$$\begin{aligned}
&K\sum_{k\in W} z_k y^B_{k,\mathrm{p}} \leq \sum_{o\in W} y^B_{o,p} - \lambda \sum_{k\in W} y^B_{k,p} \quad \forall p = 1,\cdots,P \\
&K\sum_{k\in W} z_k x_{k,n} \leq \theta \sum_{o\in W} x_{o,n} \quad \forall n = 1,\cdots,N \\
&\sum_{k\in W} z_k = \theta \\
&z_k \geq 0 \;\; \forall k = 1,\dots,K \\
&\theta \leq 1
\end{aligned} \tag{LP2}$$

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

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

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:

Dual directional distance function under a VRS technology

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

- Figure 4 about here -

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:

Dual directional distance function under an aggregate VRS technology

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

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 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 9: 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).

$$CO_2 = \sum_{n=1}^{8} CO_2^n = \sum_{n=1}^{8} E_n * NCV_n * CEF_n * COF_n * 44/12 \tag{11}$$

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.

- Table 1 about here -

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 technological 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.

- Figure 5 about here -

On average, the technical inefficiency score is about 17.1% for China (total aggregation of regions) meaning that if all provinces adopted the best productive practices and aligned on the VRS benchmark, the TFP for China could improve nearly 17.1%. 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. As shown in our results, this zone has great potential technical catching-up compared to the eastern provinces. Finally, Figure 6 shows that no significant productivity catching-up effect operates within the three mainland economic zones.

- Figure 6 about here -

Structural inefficiency is nearly 19.5% (cf. Figure 5), meaning that if all regions adopted common input or output mixes, the TFP level of China would improve the same amount. This level of structural inefficiency shows that the input/output deepening effect plays a major role in the convergence process. In Figure 7, this inefficiency component is distributed among eastern, inland, and western regions by 8.6%, 6.7%, and 4.2%, respectively. 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.

- Figure 7 about here –
- Table 2 about here –

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.

- Figure 8 about here -

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.

- Figure 9 about here -

The average Chinese carbon shadow price is about 864 yuan/ton in 2010 while the regional estimates show a significant difference at the beginning of the sample years. 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, which 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[2] 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.

- Figure 10 about here -
- Figure 11 about here –

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.

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

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6. Vitae

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

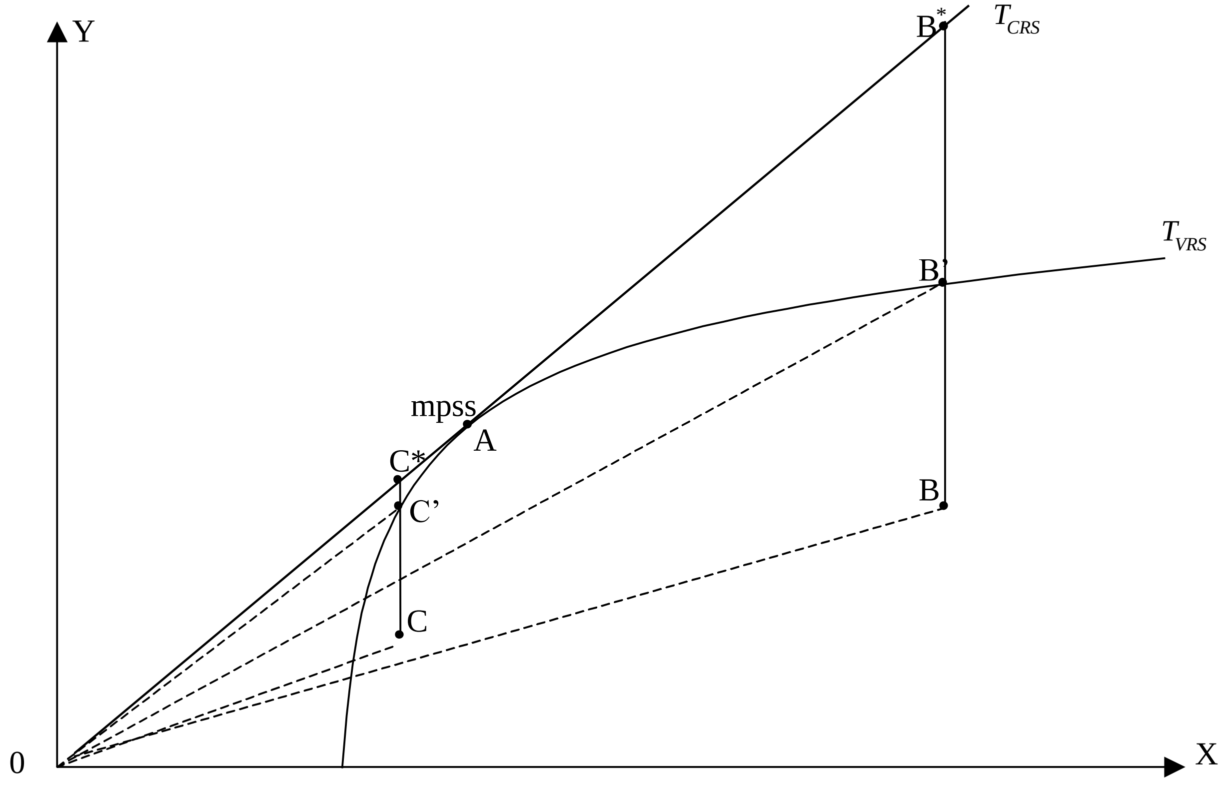

Figure 2. Technical progress and technical catching-up

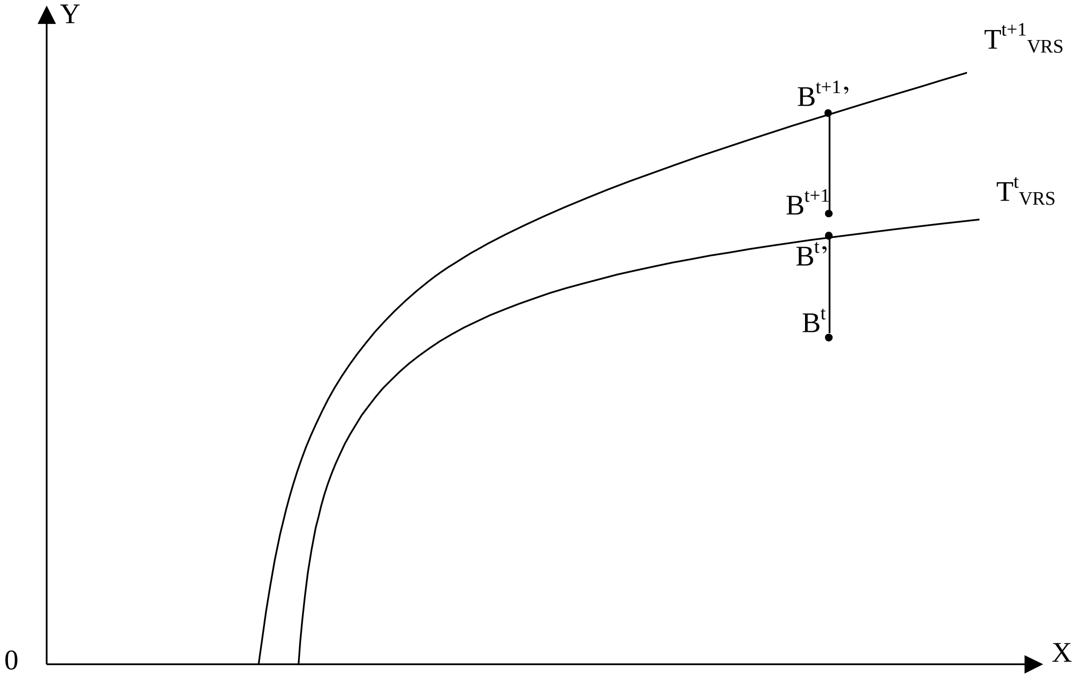

Figure 3a. Illustration of structural efficiency

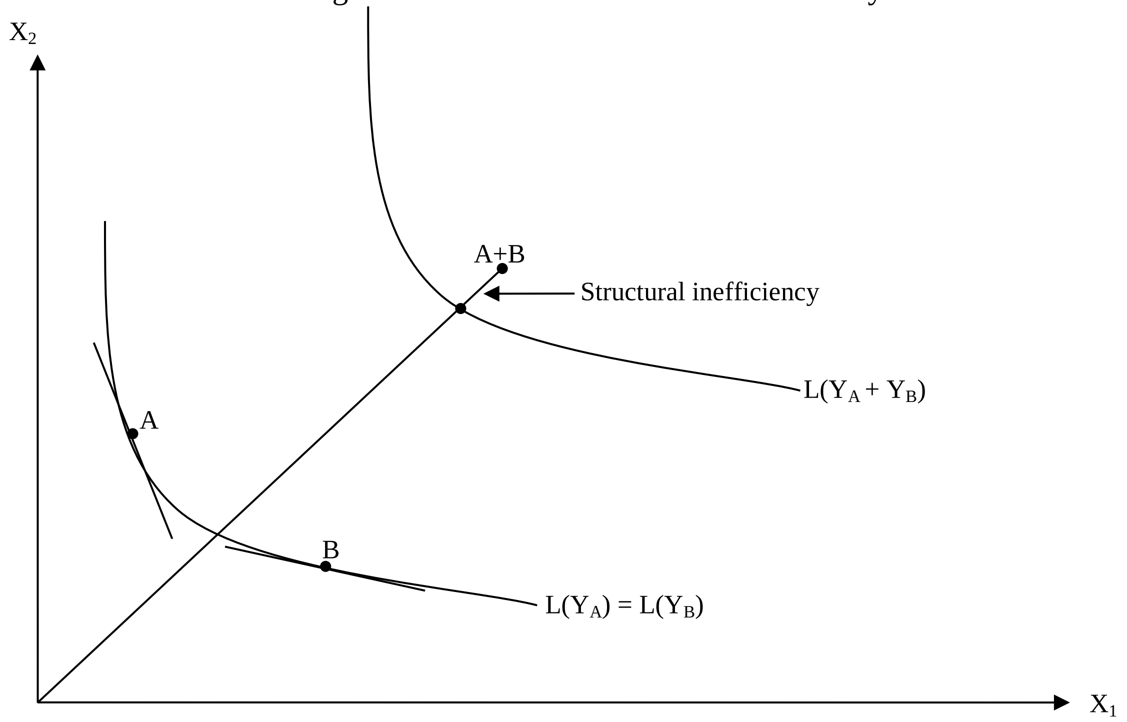

Figure 3b. The measurement of structural efficiency

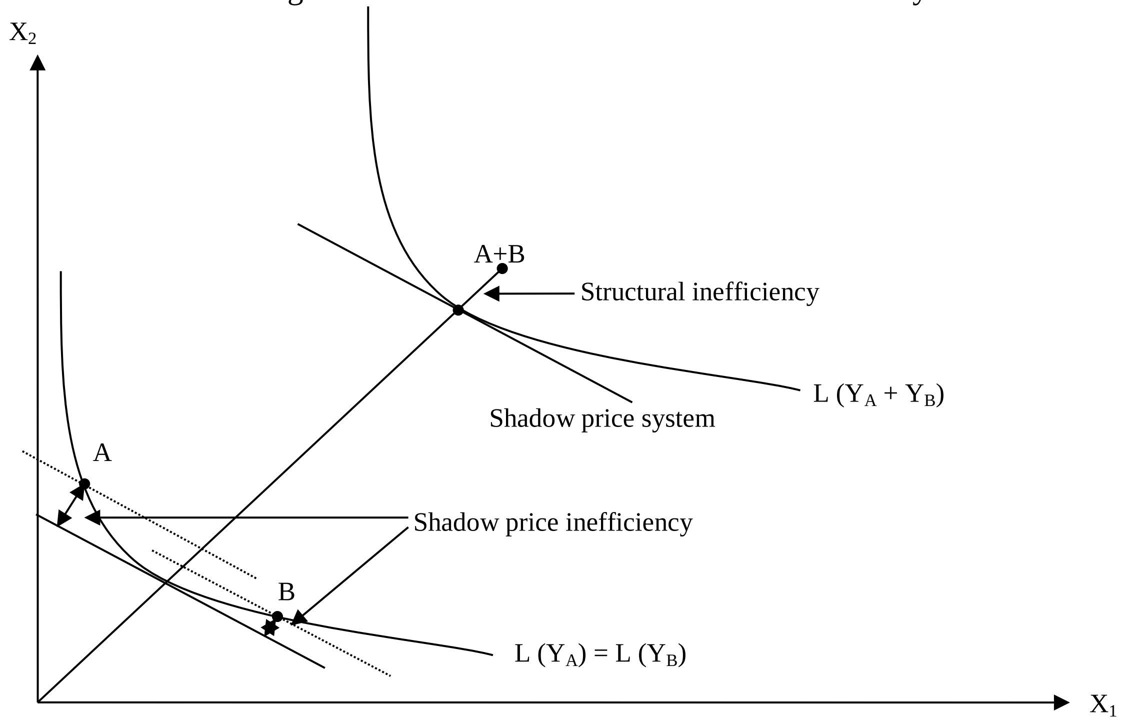

Figure 3c. The measurement of structural efficiency

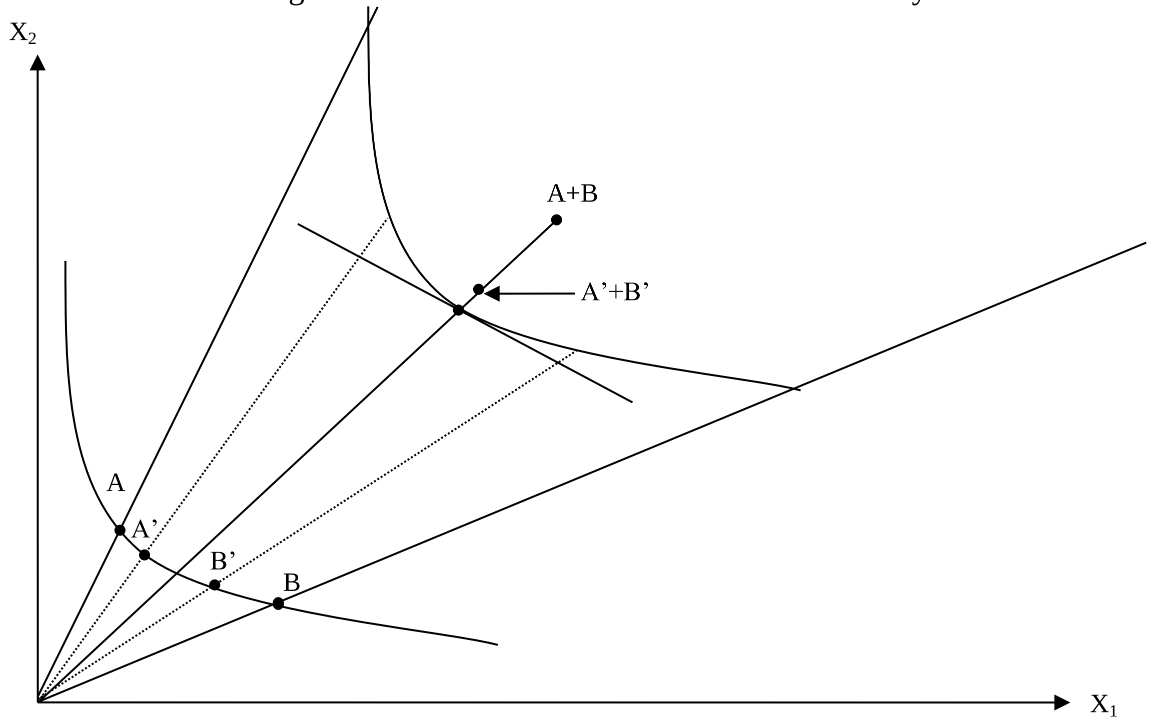

Figure 4. Non-positive shadow price for bad outputs

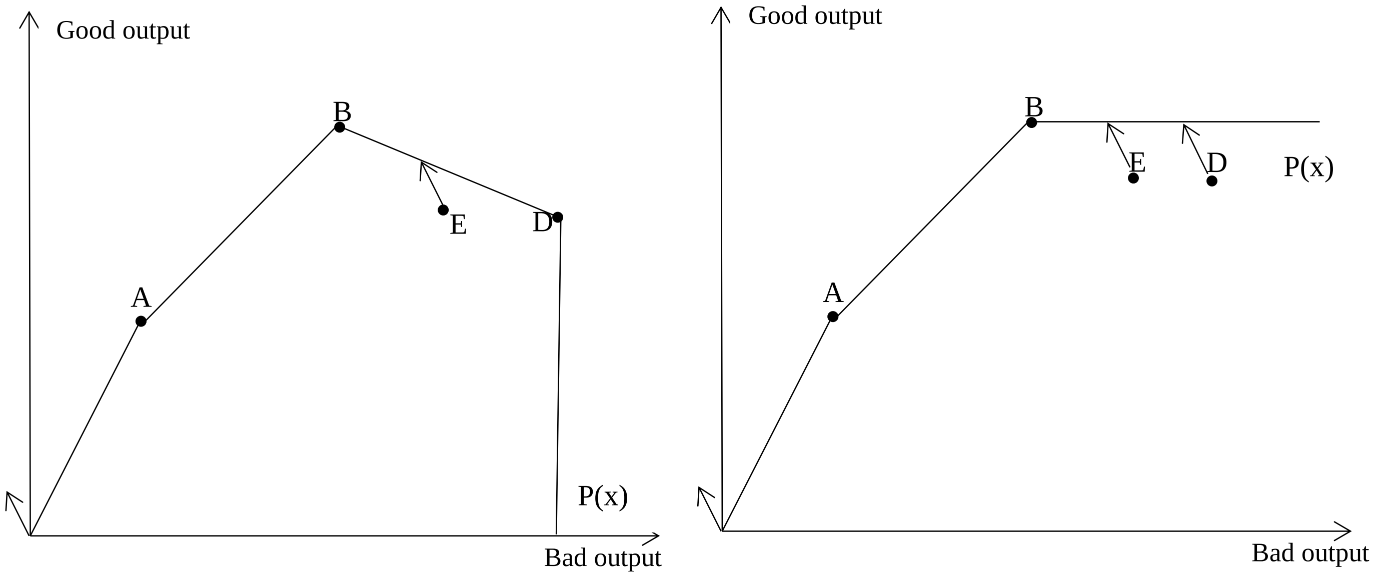

Figure 5. Total inefficiency scores for China

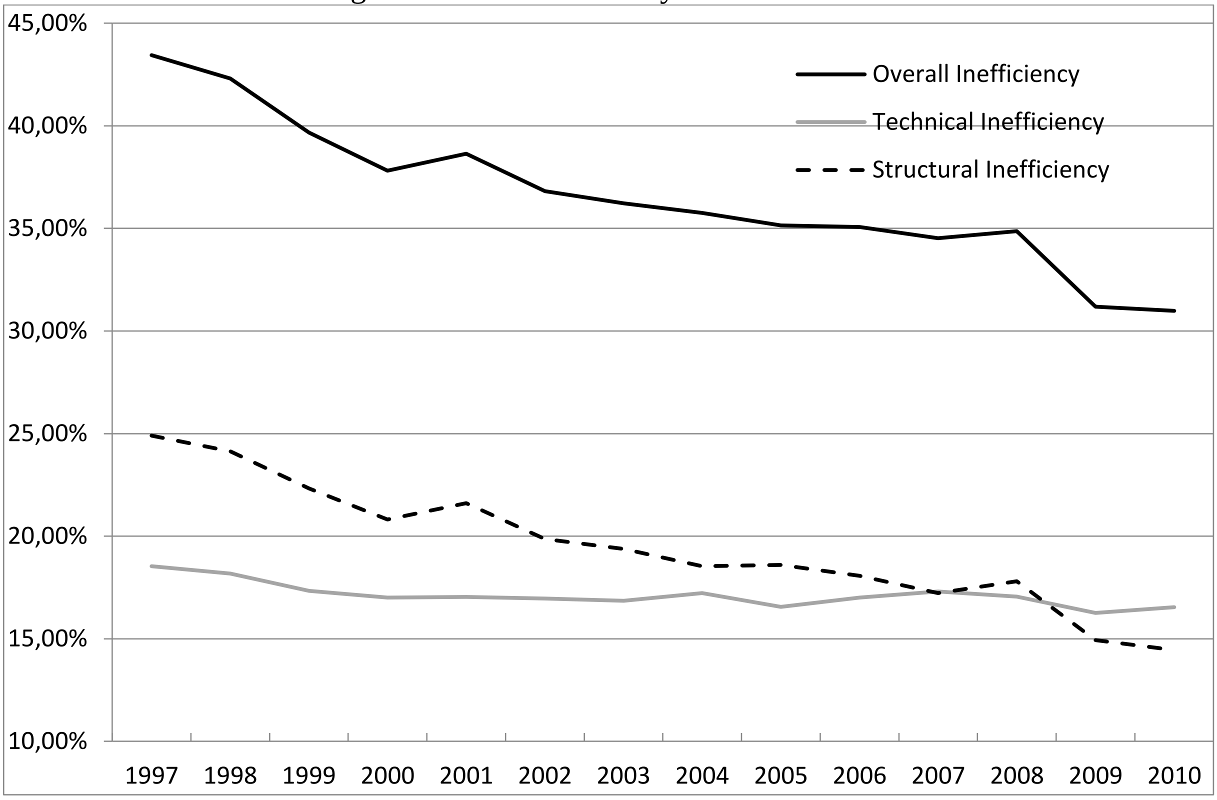

Figure 6. Technical catching-up effect

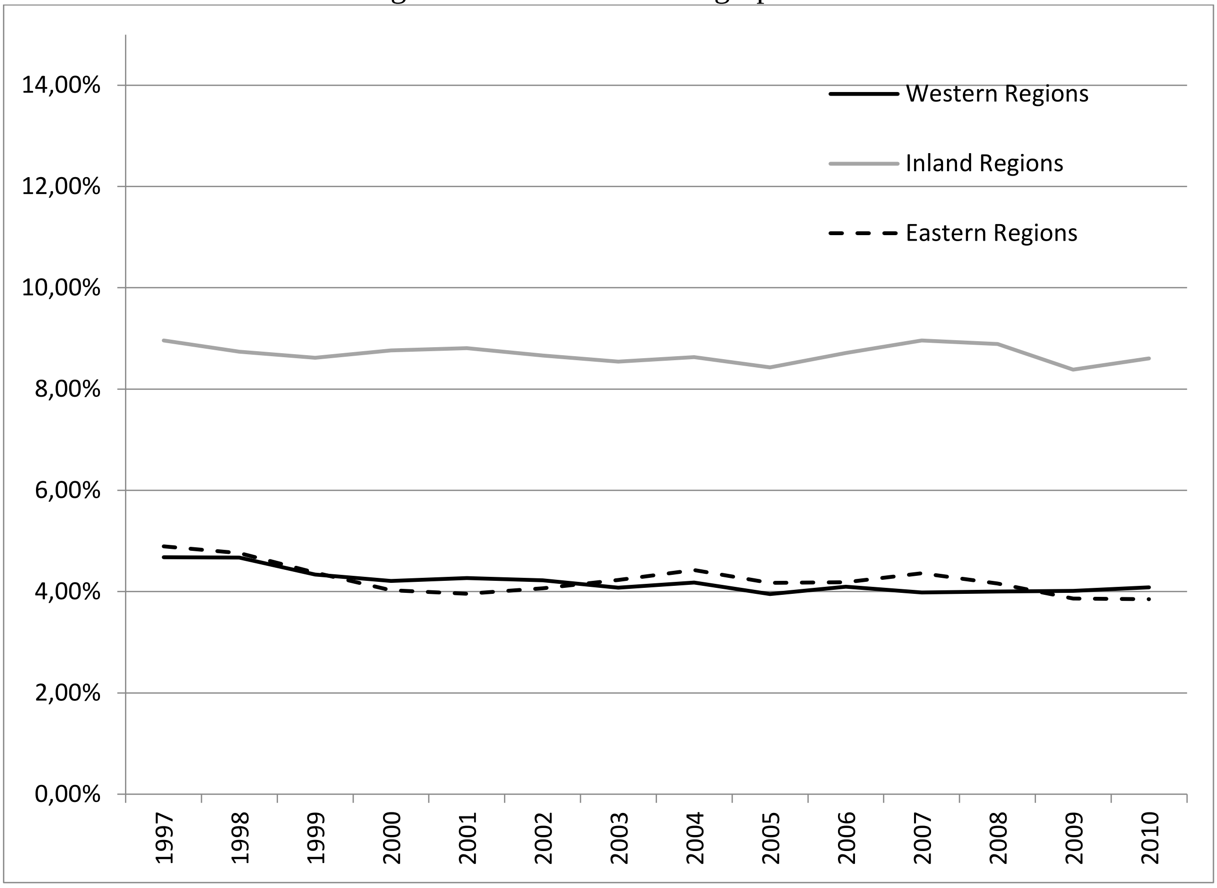

Figure 7. Structural effect

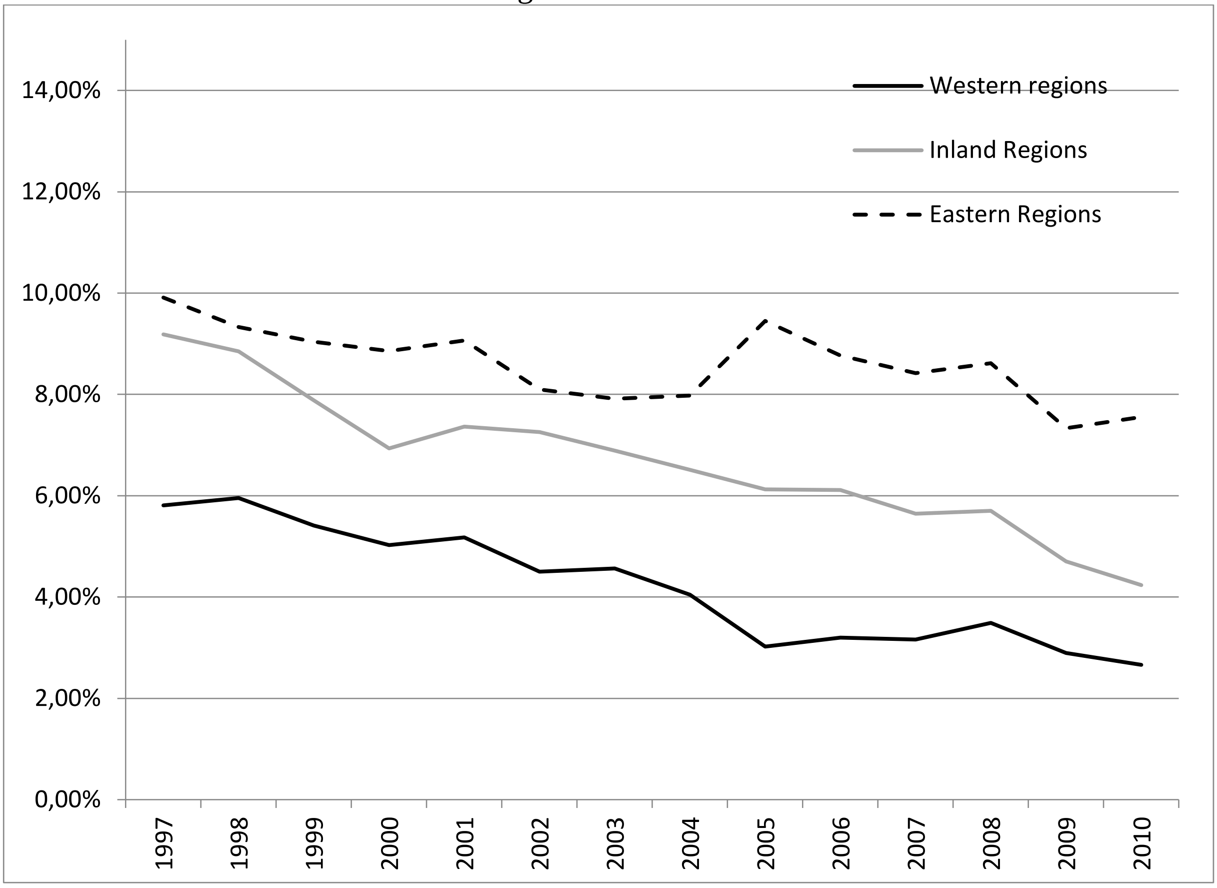

Figure 8. Comparison of inefficiencies with and without CO_2

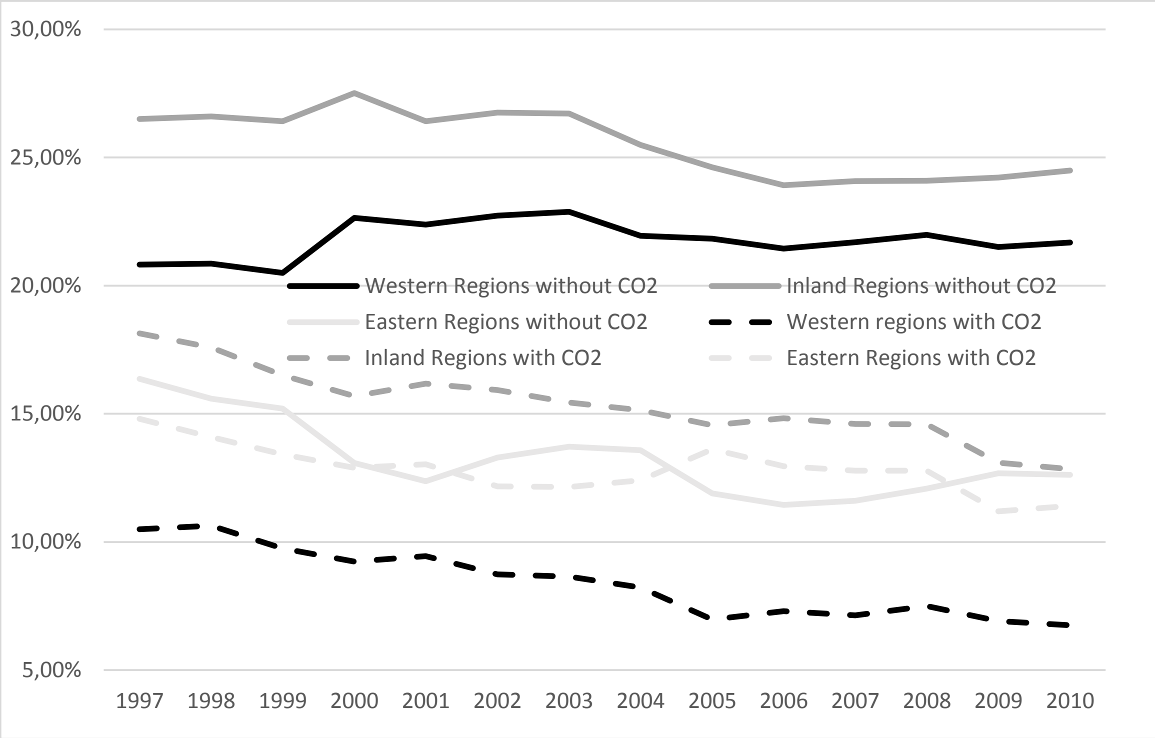

Figure 9. Shadow prices of carbon dioxide (yuan/ton)

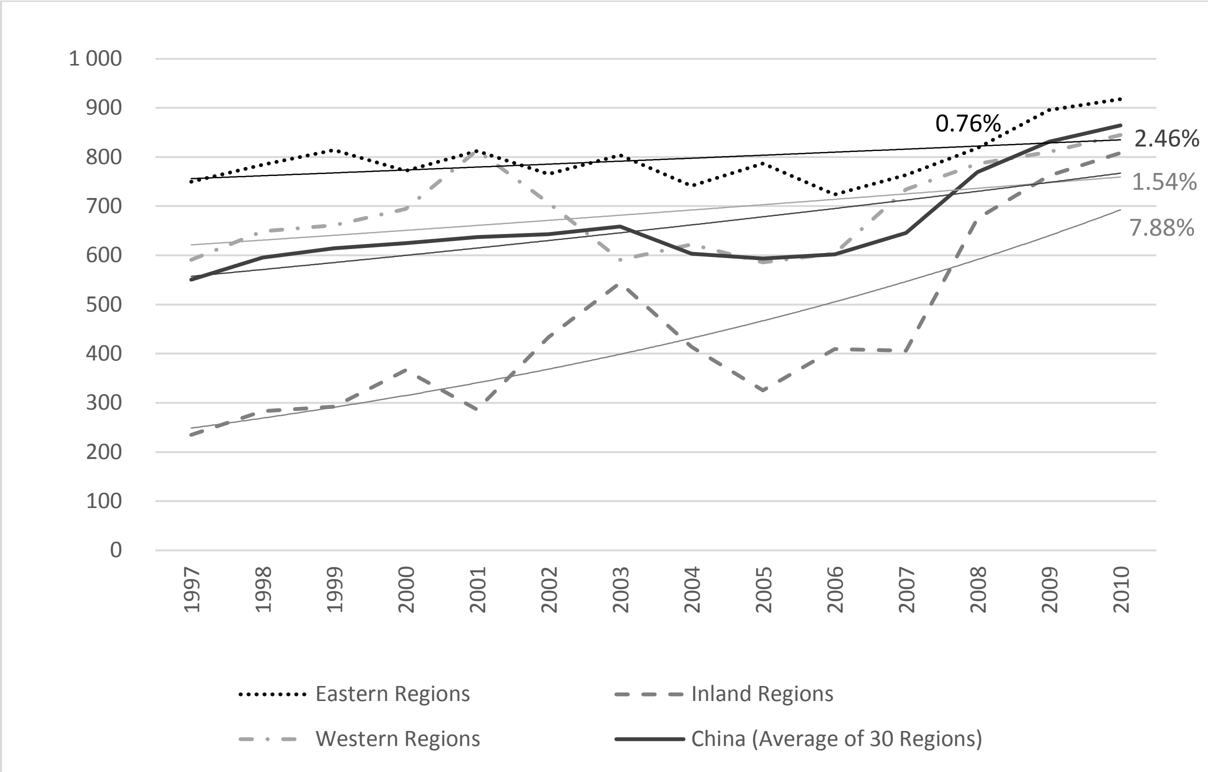

Figure 10. Variation coefficient of carbon shadow price among 30 Chinese regions

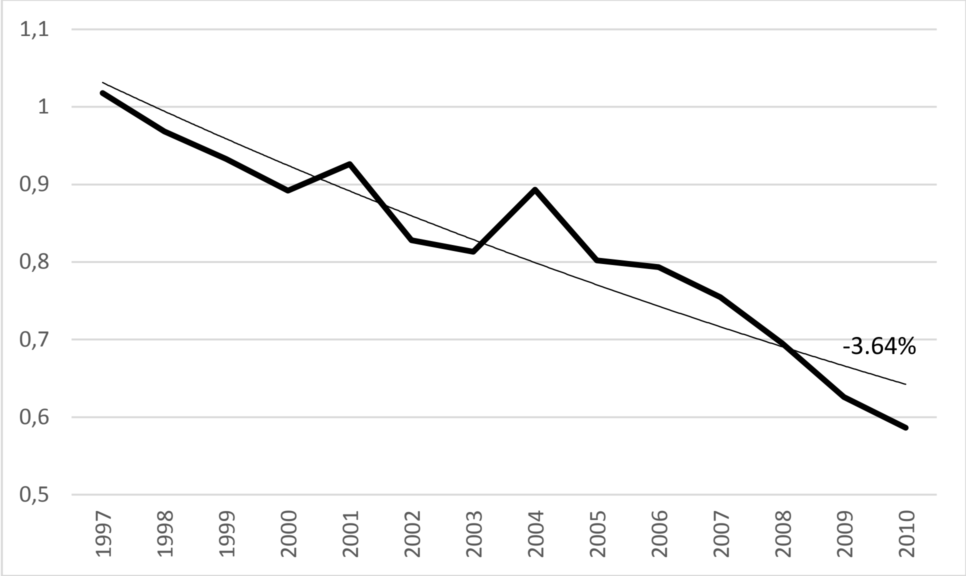

Figure 11. Variation coefficients of labor and capital shadow prices among 30 Chinese regions

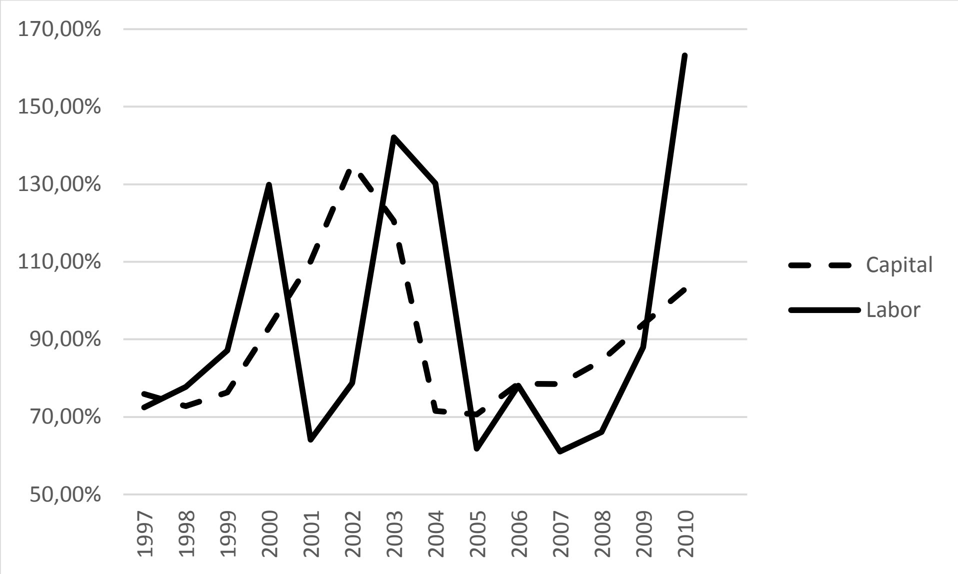

Table 1 Average growth rates of inputs and outputs
(Estimated trends over the period 1997–2010)

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%

Table 2 Average growth rates in % of inefficiency scores
(Estimated trends over the period 1997–2010)

Regions	Overall		Technical		Structural	
	coefficient	t-value	coefficient	t-value	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

Appendix 1: 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
Yunnan	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
	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