



KOCHI UNIVERSITY OF TECHNOLOGY

Social Design Engineering Series

SDES-2014-9

Decomposition of productivity considering multi-environmental pollutants in Chinese industrial sector

Hidemichi Fujii

Graduate School of Fisheries Science and Environmental Studies, Nagasaki University

Jing Cao

Tsinghua University

Shunsuke Managi

Graduate School of Environmental Studies, Tohoku University

20th October, 2014

School of Economics and Management
Research Center for Social Design Engineering
Kochi University of Technology

KUT-EMS working papers are preliminary research documents published by the School of Economics and Management jointly with the Research Center for Social Design Engineering at Kochi University of Technology. To facilitate prompt distribution, they have not been formally reviewed and edited. They are circulated in order to stimulate discussion and critical comment and may be revised. The views and interpretations expressed in these papers are those of the author(s). It is expected that most working papers will be published in some other form.

Decomposition of productivity considering multi-environmental pollutants in Chinese industrial sector

Hidemichi Fujii

Jing Cao

Shunsuke Managi

Abstract

The objective of this study is to calculate and decompose productivity incorporating multi-environmental pollutants in Chinese industrial sectors from 1992 to 2008. We apply a weighted Russell directional distance model to calculate productivity from both the economic and environmental performance. Main findings are, 1) Chinese industrial sectors increased productivity, with the main contributing factors being labor saving prior to 2000. 2) The main contributing factors for productivity growth in coastal areas include both economic and environmental performance improvement. While central and west regions improved productivity due to economic development, they have a trade-off relationship between economic and environmental performance.

Fujii: Graduate School of Fisheries Science and Environmental Studies, Nagasaki University, 1-14 Bunkyo-machi, Nagasaki 852-8521, Japan. Tel: +81-95-819-2756, Fax: +81-95-819-2756, E-mail: hidemichifujii@nagasaki-u.ac.jp

Cao: Tsinghua University, 128 Shunde Building, Beijing, China. Tel: 86-10-62792726, E-mail: caojing@sem.tsinghua.edu.cn

Managi: Graduate School of Environmental Studies, Tohoku University, 6-6-20

Aramaki-Aza-Aoba, Aoba-ku, Sendai, 980-8579, Japan. Tel: +81-22-795-3216, Fax: +81-22-795-4309, E-mail: managi.s@gmail.com

Queensland University of Technology, Level 8, Z Block, Gardens Point, 2 George St, Brisbane QLD 4000, Australia.

Note: Managi is Corresponding author.

JEL Classification Number: O47, Q53, Q56

Date: July 15, 2014

1. Introduction

Since 1990, the economic development of China has produced an average 10.2% growth rate and it is forecast that this rapid upward trend in economic growth will continue. Along with such impressive economic development and rapid industrialization, many environmental problems have arisen, including industrial pollution, which has attracted much attention (Zhang *et al.*, 2010).

Productivity improvement is the main driver of economic growth, but rapid growth can increase pollutant emissions due to the greater use of resources. Consequently, there is a conflict between economic growth and environmental concerns. In research on growth theory, analyses of economic growth and the environment have shown the importance of productivity increases and found that improved productivity decreases the input demand for pollution levels (Akao and Managi, 2007). Thus, emission reductions should be considered for continuous productivity progress.

There are a few Chinese studies on productivity considering environment. Fujii *et al.* (2011) apply directional distance function and Luenberger productivity indicator to estimate total factor productivity (TFP) change considering wastewater and CO₂ emissions in iron and steel firms. Cao (2007) uses a time-series input-output table, and measures the Green TFP using estimated health damages from undesirable pollutions following the Jorgenson Divisia

index method.

This study measures productivity change in Chinese industrial sectors by provinces. We apply the weighted Russell directional distance model (WRDDM) to measure productive inefficiency using production technology following Chen *et al.* (2011) and Barros *et al.* (2011). They proposed a measure based on directional distance function, which is evaluated in linear form, and hence processes the attractive advantages of easy computation and easy extension of incorporating the additional undesirable outputs into the programming problems. Our main objective is to estimate the contribution of each input/output considering environmental pollutions in Chinese industrial sector. Those points are not considered in the previous study. We further apply nonparametric test for equality densities by Li et al. (2009) to understand the difference of TFP differences.

The rest of this paper is organized as follows. In Section 2, we explain environmental pollution problem from industrial sector and environmental policy in China. In Section 3, we introduce our methodology. Using China's provincial panel data from 1992-2008, we analyze the productivity change considering environmental pollution in Chinese industrial sectors in Section 4. Section 5 presents our conclusion and discusses the policy implications.

2. Environmental Pollution from Chinese Industrial Sector

Facing the bottleneck of sustainable development, China has identified air pollution as a high-priority issue that it must address immediately (Managi and Kaneko, 2010). China became the world's largest sulfur dioxide (SO₂) emitter in 2005 (Su et al., 2011), and it is now evident that many of the existing air pollution problems are the result of these significant SO₂ emissions. Furthermore, industrial sectors discharge large amounts of soot and dust substances into the air (Fujii et al., 2013).

Meanwhile, water pollution by industrial wastewater is another big problem in China, especially in the northern part of China, where the water resource shortage problem is severe (Wang *et al.*, 2008). To solve water pollution problems, the Chinese government has enforced more strict environmental regulations and a levy system to promote wastewater management in Chinese industrial sectors. According to Shao (2010), the Chinese government has enacted more than 130 policies related to environmental protection since 1979 to curb the deterioration of water environments and to improve the surface water quality.

Environmental protection has become one of the high priority targets for the Chinese government. In China's ninth five-year plan, the Chinese government enforced a strong environmental policy to decrease industrial pollution. For instance, China forced more than

80,000 small, polluted enterprises in 15 heavy-polluting industries to shut down or stop production lines during 1997-2000 (Zhang and Wen, 2008).

Figure 1 shows that wastewater, waste gas, and solid waste discharge amount from industrial sectors in China from 1992 to 2008. Even though many environmental regulations and policies were enforced, environmental pollution has rapidly increased since 2000, especially waste gas and solid waste (see Figure 1). According to Fujii et al. (2013), this pollution increase was mainly due to the rapidly expanding production scale in Chinese industrial sector. After joining the World Trade Organization (WTO) in 2001, China has gradually become a world factory for manufacturing commodities (Hoa, 2010). However, pollution per value-added (Environmental efficiency) has been improved between 1992 and 2008. Wastewater, waste gas, and solid waste emissions per value added decreased by more than 80%, 40%, and 60% respectively, during this period.

< Figure 1. about here >

3. Methodology

Weighted Russell Directional Distance Model (WRDDM)

Weighted Russell directional distance model (WRDDM) is developed by Chen *et al.* (2011) and Barros *et al.* (2011). Let inputs be denoted by $x \in R_+^N$, good outputs by $y \in R_+^M$, and bad or undesirable outputs by $b \in R_+^L$. The directional distance function seeking to increase the desirable outputs and decrease the undesirable outputs and inputs directionally can be defined by the following:

$$\vec{D}(x, y, b|g) = \sup\{\beta: (x + \beta g_x, y + \beta g_y, b + \beta g_b) \in T\} \quad (1)$$

Where the vector $g = (-g_x, g_y, -g_b)$ determines the directions in which inputs, desirable outputs, and undesirable outputs are scaled. The vector specifies for inefficient samples the way to improve productivity towards the frontier production line. The technology reference set $T = \{(x, y, b): x \text{ can produce } (y, b)\}$ satisfies strong disposability of desirable outputs and inputs, and weak disposability of undesirable outputs.

Suppose there are $j = 1, 2, \dots, k, \dots, J$ decision-making units (DMUs) in the dataset. Each DMU uses inputs $x = (x_1, x_2, \dots, x_N) \in R_+^N$ to jointly produce desirable outputs $y = (y_1, y_2, \dots, y_M) \in R_+^M$ and undesirable outputs $b = (b_1, b_2, \dots, b_L) \in R_+^L$. Following Aparicio

et al. (2013) and Fujii et al. (2014), the WRDDM for inefficiency calculation with variable returns to scale of DMU k can be described as follows:

$$\vec{D}(x, y, b|g) = \text{maximize} \left(\frac{1}{N} \sum_{n=1}^N \beta_n^k + \frac{1}{M} \sum_{m=1}^M \beta_m^k + \frac{1}{L} \sum_{l=1}^L \beta_l^k \right) \quad (2)$$

subject to

$$\sum_{j=1}^J z_k y_{mj} \geq y_{mk} + \beta_m^k g_{ymk} \quad (2a)$$

$$\sum_{j=1}^J z_k b_{lj} = b_{lk} + \beta_l^k g_{blk} \quad (2b)$$

$$\sum_{j=1}^J z_k x_{nj} \leq x_{nk} + \beta_n^k g_{xnk} \quad (2c)$$

$$\sum_{j=1}^J z_k = 1 \quad (2d)$$

$$Z_j \geq 0, \quad j = 1, 2, \dots, k, \dots, J \quad (2e)$$

where β_m^k, β_l^k , and β_n^k are the individual inefficiency measures for desirable outputs, undesirable outputs, and inputs, respectively. Z_k is the intensity variable to shrink or expand the individual observed activities of DMU k for the purpose of constructing convex combinations of the observed inputs and outputs. To estimate productivity change indicators,

we set directional vector = $(g_{xnk}, g_{ymk}, g_{blk}) = (-x_{nk}, y_{mk}, -b_{lk})$.¹ This type of directional vector assumes that an inefficient province can decrease productive inefficiency while increasing desirable outputs and decreasing undesirable outputs and/or inputs in proportion to the initial combination of actual inputs and outputs.

One of the strong points of the WRDDM is that it is able to determine the effect of each variable's contribution to inefficiency. This contribution effect cannot be determined in conventional productive inefficiency analysis. The contribution effects enable us to discuss how and why each province successfully decreased its productive inefficiency. Under this vector combination, the WRDDM with variable returns to scale is shown as follows:

$$\vec{D}(x_k, y_k, b_k | g) = \text{maximize} \left(\frac{1}{N} \sum_{n=1}^N \beta_n^k + \frac{1}{M} \sum_{m=1}^M \beta_m^k + \frac{1}{L} \sum_{l=1}^L \beta_l^k \right) \quad (3)$$

subject to

$$\sum_{j=1}^J z_k y_{mj} \geq y_{mk} (1 + \beta_m^k) \quad (3a)$$

$$\sum_{j=1}^J z_k b_{lj} = b_{lk} (1 - \beta_l^k) \quad (3b)$$

$$\sum_{j=1}^J z_k x_{nj} \leq x_{nk} (1 - \beta_n^k) \quad (3c)$$

$$\sum_{j=1}^J z_k = 1 \quad (3d)$$

$$Z_j \geq 0, \quad j = 1, 2, \dots, k, \dots, J \quad (3e)$$

One of the strong points of the WRDDM is that it is able to determine each variable's contribution effect for inefficiency. This contribution effect cannot be determined in conventional productive inefficiency analysis. The contribution effects enable us to discuss how and why each province successfully decreased its productive inefficiency.

TFP Change Estimation and Decomposition

In order to analyze changes in efficiency over time, aggregated indices such as the *Malmquist Index* and *Luenberger Productivity Indicator* have been developed (Chambers, 1998). We employ the *Luenberger Productivity Indicator* as a TFP measure because the *Luenberger Productivity Indicator* has advantage for productivity change estimation with additive distance function model than *Malmquist productivity index* (Balk *et al.*, 2008). Change in the *Luenberger Productivity Indicator* (TFP) is further decomposed into technical change and efficiency change.² TFP is computed with the results of the WRDDM and derived as follows:

$$TFP_t^{t+1} = \frac{1}{2} \{ \vec{D}^{t+1}(x_k^t, y_k^t, b_k^t) - \vec{D}^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) + \vec{D}^t(x_k^t, y_k^t, b_k^t) - \vec{D}^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) \} \quad (4a)$$

$$TECHCH_t^{t+1} = \frac{1}{2} \{ \vec{D}^{t+1}(x_k^t, y_k^t, b_k^t) + \vec{D}^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) - \vec{D}^t(x_k^t, y_k^t, b_k^t) - \vec{D}^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) \} \quad (4b)$$

$$EFFCH_t^{t+1} = \vec{D}^t(x_k^t, y_k^t, b_k^t) - \vec{D}^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) \quad (4c)$$

$$TFP_t^{t+1} = TECHCH_t^{t+1} + EFFCH_t^{t+1} \quad (4d)$$

where x_t represents the input for year t , x_{t+1} is the input for year $t+1$, y_t is the desirable output for year t , and y_{t+1} is the desirable output for year $t+1$. b_t is the undesirable output for year t , and b_{t+1} is the undesirable output for year $t+1$. $\vec{D}^t(x_k^t, y_k^t, b_k^t)$ is the inefficiency score of year t based on the frontier curve in year t . Similarly, $\vec{D}^{t+1}(x_k^t, y_k^t, b_k^t)$ is the inefficiency of year t based on the frontier curve in year $t+1$.

We obtain aggregated TFP from technological and efficiency changes from (4a) – (4d) where all components of directional distance functions are estimated by (3a) – (3e). The TFP score indicates the productivity change as compared to the benchmark year. The TFP includes all categories of productivity change, which can be broken down into Technical Change (TECHCH) and Efficiency Change (EFFCH). TECHCH shows shifts in the production

frontier, while EFFCH measures changes in the position of a production unit relative to the frontier.

Here, we decompose TFP using the inefficiency score of each variable's contribution effect for inefficiency. Let us describe the each variable's contribution effect for inefficiency as follows.

$$\text{maximize } \left(\frac{1}{N} \sum_{n=1}^N \beta_n^k + \frac{1}{M} \sum_{m=1}^M \beta_m^k + \frac{1}{L} \sum_{l=1}^L \beta_l^k \right) = \vec{D}_x(x_k^t, y_k^t, b_k^t) + \vec{D}_y(x_k^t, y_k^t, b_k^t) + \vec{D}_b(x_k^t, y_k^t, b_k^t) \quad (5)$$

Where $\vec{D}_x(x^t, y^t, b^t)$ represents the contribution effect of input variables for inefficiency score, $\vec{D}_y(x, y, b)$ represents the contribution effect of desirable output variables for inefficiency score, and $\vec{D}_b(x, y, b)$ represents the contribution effect of undesirable output variables for inefficiency score. Then, we can obtain following equation:

$$\vec{D}^t(x_k^t, y_k^t, b_k^t | g) = \vec{D}_x(x_k^t, y_k^t, b_k^t) + \vec{D}_y(x_k^t, y_k^t, b_k^t) + \vec{D}_b(x_k^t, y_k^t, b_k^t) \quad (6)$$

From equation (14) and (18), we have the following TFP decomposition form:

$$\text{TFP}_t^{t+1} = \frac{1}{2} \{ \vec{D}^{t+1}(x_t, y_t, b_t) - \vec{D}^{t+1}(x_{t+1}, y_{t+1}, b_{t+1}) + \vec{D}^t(x_t, y_t, b_t) - \vec{D}^t(x_{t+1}, y_{t+1}, b_{t+1}) \}$$

$$\begin{aligned}
&= \frac{1}{2} \{ \vec{D}_x^{t+1}(x^t, y^t, b^t) - \vec{D}_x^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_x^t(x^t, y^t, b^t) - \vec{D}_x^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \\
&+ \frac{1}{2} \{ \vec{D}_y^{t+1}(x^t, y^t, b^t) - \vec{D}_y^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^t(x^t, y^t, b^t) - \vec{D}_y^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \\
&+ \frac{1}{2} \{ \vec{D}_b^{t+1}(x^t, y^t, b^t) - \vec{D}_b^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_b^t(x^t, y^t, b^t) - \vec{D}_b^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \\
&= \text{TFP}_{t,x}^{t+1} + \text{TFP}_{t,y}^{t+1} + \text{TFP}_{t,b}^{t+1} \tag{7}
\end{aligned}$$

Where

$$\text{TFP}_{t,x}^{t+1} = \frac{1}{2} \{ \vec{D}_x^{t+1}(x^t, y^t, b^t) - \vec{D}_x^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_x^t(x^t, y^t, b^t) - \vec{D}_x^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \tag{7a}$$

$$\text{TFP}_{t,y}^{t+1} = \frac{1}{2} \{ \vec{D}_y^{t+1}(x^t, y^t, b^t) - \vec{D}_y^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^t(x^t, y^t, b^t) - \vec{D}_y^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \tag{7b}$$

$$\text{TFP}_{t,b}^{t+1} = \frac{1}{2} \{ \vec{D}_b^{t+1}(x^t, y^t, b^t) - \vec{D}_b^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_b^t(x^t, y^t, b^t) - \vec{D}_b^t(x^{t+1}, y^{t+1}, b^{t+1}) \} \tag{7c}$$

where $\text{TFP}_{t,x}^{t+1}$ represents a contribution effect of input variables for TFP change. $\text{TFP}_{t,y}^{t+1}$ represents a contribution effect of desirable output variables for TFP change. $\text{TFP}_{t,b}^{t+1}$ represents a contribution effect of undesirable output variables for TFP change. Here we explain the meaning of contribution effect change by using $\text{TFP}_{t,x}^{t+1}$. Increasing of $\text{TFP}_{t,x}^{t+1}$ is caused by following two cases. In the first case, contribution effect of input variables is improved. In this case, we can understand $\text{TFP}_{t,x}^{t+1}$ growth represents how much TFP increases due to improvement of input use.

In the second case, inefficiency of input becomes smaller than inefficiency of desirable output or undesirable output. This case shows that inefficiency of input improves rapidly relative to desirable output or undesirable output. In this case, $TFP_{t,x}^{t+1}$ will increase and $TFP_{t,y}^{t+1}$ or $TFP_{t,b}^{t+1}$ decrease. This is because WRDDM evaluates each variable's contribution effect (such as $\vec{D}_x^t(x^t, y^t, b^t)$) by maximizing relative inefficiency among input, desirable output, and undesirable output. Therefore, we need to check carefully why each contribution effect of TFP change is changed, especially focusing on the substitution of contribution effects of each variable. From equation (4b), (4c), and (7), we can also decompose the TECHCH indicator and EFFCH indicator by the following decomposition formula:

$$TECHCH_t^{t+1} = TECHCH_{t,x}^{t+1} + TECHCH_{t,y}^{t+1} + TECHCH_{t,b}^{t+1} \quad (8)$$

$$EFFCH_t^{t+1} = EFFCH_{t,x}^{t+1} + EFFCH_{t,y}^{t+1} + EFFCH_{t,b}^{t+1} \quad (9)$$

Technological Innovation

It should be noted that the technical progress change index for any particular state between two adjacent years merely depicts the shift in the production frontier for that province. A value of technical change index greater than unity does not necessarily imply that the

province under consideration did actually push the frontier outward. Thus in order to determine the provinces that were shifting the frontier or were “innovators” (see Färe *et al.*, 1994), the following three conditions are required to be fulfilled for a given province:.

$$TECHCH_t^{t+1} > 0 \quad (10a)$$

$$\vec{D}^t(x^{t+1}, y^{t+1}, b^{t+1}) < 0 \quad (10b)$$

$$\vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 0 \quad (10c)$$

By using the WRDDM result, we can distinguish the technological innovator from the economic and environment point of view. Technological innovator of economic performance need to fulfill the following conditions. The technological innovator of economic performance (Innovator_{Econ}) achieves more efficient input use and value added production from t year to t+1 year:

$$TECHCH_{t,x}^{t+1} + TECHCH_{t,y}^{t+1} > 0 \quad (11a)$$

$$\vec{D}_x^t(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^t(x^{t+1}, y^{t+1}, b^{t+1}) < 0 \quad (11b)$$

$$\vec{D}_x^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) + \vec{D}_y^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 0 \quad (11c)$$

Additionally, the technological innovators of environmental performance need to fulfill the following conditions. Similarly, the technological innovator of environmental performance ($\text{Innovator}_{\text{Env}}$) achieves more efficient environmental pollutant emissions management from t year to $t+1$ year.

$$TECHCH_{t,b}^{t+1} > 0 \quad (12a)$$

$$\vec{D}_b^t(x^{t+1}, y^{t+1}, b^{t+1}) < 0 \quad (12b)$$

$$\vec{D}_b^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 0 \quad (12c)$$

4. Result

Data

To understand the differences of regional characteristics, we make three groups which is coastal, central and western area (see Appendix). Tibet is excluded because some relevant data are not available. Data for Chongqing, which was separated from Sichuan in 1997, is merged with data for Sichuan. Thus, our data sample is 29 provinces over 1992 to 2008.³

Data for the study were collected from two main sources: the China Environmental

Statistical Yearbook (CESY) and the China Statistical Yearbook (CSY). The data covers the seventeen year period from 1992 to 2008. The main variables used in the analysis are value added (yuan) as desirable output⁴; amount of labor (number of persons) and net value of fixed assets (yuan)⁵ as market input; wastewater discharge amount (tonnes), waste gas emissions (m³), and solid waste discharge amount (tonnes) as the undesirable output. We consider the wastewater, waste gas, and solid waste emissions are major and important measure to evaluate industrial environmental performance and many previous studies use these three variables (e.g. Managi and Kaneko, 2010). All financial data variables are deflated as 1995 year price.⁶

CESY does not cover the entire sample collected in the CSY. Thus, data coverage in the CESY is different with that in CSY. Therefore, productivity estimation using both CSY and CESY data directly is not consistent because of the mismatch of data coverage. To overcome this problem, we adjust the data from CESY so as to be able to compare the data to the CSY. Sales data are included in both the CESY and the CSY. Therefore, we calculate an adjustment coefficient by taking the ratio of sales data in the CESY and that in the CSY.⁷ We then multiply the adjustment coefficients to expand the data coverage of CESY, which vary by year and province.⁸ This adjustment technique follows procedures by Managi and Kaneko (2009).

In this study, all pollutants data from CESY is expanded by using adjustment coefficient.

Estimated pollution data (E_{adj}) is calculated as $E_{jt,adj} = SALE_{jt,CSY} \times (E_{jt,CESY} / SALE_{jt,CESY})$ by using emission data from CESY (E_{CESY}), sale data from CESY ($SALE_{CESY}$) and sale data from CSY ($SALE_{CSY}$) in province j year t . We apply this data expansion approach for wastewater emissions, waste gas emissions, and solid waste emissions data, separately.

Productivity Change and Contribution Effect

Figure 2 represents the provincial average inefficiency score from 1992 to 2008, where provincial names are described in Appendix 1. Tianjin, Shanghai, Shandong, Guangdong, and Hainan have zero inefficiency in Figure 2, which shows that the production performance of manufacturing sectors in these five provinces are efficient from 1992 to 2008. Additionally, Beijing, Heilongjiang, Yunnan, and Qinghai have low inefficiency scores, suggesting they also achieved efficient performance in our examined time-range. Thus, the production frontier line of Chinese manufacturing sectors mainly consists of these nine provinces.

<Figure 2. about here>

Figure 3 through Figure 5 show the accumulative changes of TFP, TECHCH, and EFFCH

indicators from 1992 to 2008. We set 1992 as the baseline year, then the three indicators equal zero in 1992. A positive TFP score indicates that a Chinese industrial sector achieved productivity improvement. In Figure 3 through Figure 5, the line chart indicates the accumulative 29 provincial average score of TFP, TECHCH, and EFFCH indicators compared in 1992. And the bar chart shows the accumulative contribution effect of each factor with respect to the TFP, TECHCH, and EFFCH change. The results as indicated in the bar chart are equal to those in the line chart. To compare the results in each Figure, we can distinguish the main contributor for TFP, TECHCH, and EFFCH change according to the individual pollutant and economic variables.

Then, we consider the result of productivity change. According to Figure 3, the Chinese industrial sector increases TFP by nearly 40% from 1992 to 2008. The rapid TFP increase from 1992 to 1993 and decline after 1993 are caused by price deregulation policy in China.⁹ After 1995, TFP increases again and the main contributors are labor force saving, value added increase, and environmental pollution managements. Contribution effect from Labor force saving mainly affects TFP to increase in 1990's and early 2000's. Figure 3 shows contribution effect of capital input has a negative effect on TFP change from 1997. From these two results, we suppose that the Chinese manufacturing sector increases TFP by utilizing modern

production equipment that allows production input substitution from labor force to capital equipment.

In Figure 3, the contribution effect of value added has a negative effect on TFP in the 1990's, which is caused by the performance of inefficient provinces. This is because value added factor has a significantly negative effect on EFFCH indicator in Figure 5, which shows that the inefficiency gap between efficient and inefficient province becomes larger due to the slow speed of value added increase in inefficient provinces. One interpretation of this result is that, differences of production technology are affected by the technological spillover from developed countries through the foreign direct investment (FDI) (Zhao and Zhang, 2010). Regional distribution of FDI is diversified in China, and the main FDI target is the coastal areas which has easy access to international trade. So, high-technology and high-profit ratio manufacturing sectors (e.g. electric products, precision equipment) are developed in coastal areas even though west and central provinces mainly produce conventional manufacturing sectors (e.g. mining sector). We support this situation reflecting value added gap between efficient provinces (mainly coastal area) and inefficient provinces (mainly central and west area).

We do not observe this negative effect of value added factor except 1995 for TECHCH

indicator in Figure 4, which suggests the value added keep increasing year by year in efficient provinces. Thus, the negative effect of value added into TFP is caused by low profitable performance in inefficient provinces in the late 1990's.

After 2000, the contribution effect of value added positively affected China's TFP improvement. China's WTO entry in 2000 stimulated a massive expansion of export-oriented manufacturing sectors. China's labor-intensive manufacturing has achieved a comparative advantage on a global scale, and the size of the production scale further improved the production efficiencies. China also includes a GDP target of 7-7.5% in the 10th, 11th and 12th Five year Plan, and very few provinces report GDP growth lower than this plan target, as local government officer's promotion is closely linked with such GDP target, thereby achieving an aggregate GDP growth at 10.1% for the period of 2000-2010 (National Bureau of Statistics, 2011).

Another interpretation of this result is that the Chinese government set the political target and provided certain preferred policies for promoting high-technology industry that produces high profit ratio products in China's Tenth Five-Year Plan (for 2001 through 2005). For instance, the Chinese government increased the value added tax and consumption rebates on high-tech commodity exports, mostly around 13%-16%, thereby increasing the comparative

advantages on these products. High-tech industries also enjoyed preferred treatment on tax payments, such as reducing enterprise income tax from 25% to 15%.

Contribution effects of industrial wastewater managements also contribute improving TFP gradually from 1992 to 2008 in Figure 3. From Figure 4, the TECHCH indicator rapidly increased from 2004 due to industrial wastewater management effects. Meanwhile the EFFCH indicator dramatically decreased after 2004 due to the shift in the production frontier line from Figure 5. This result is caused by a rapid decrease in pollutant emission, especially wastewater discharge, in Shanghai, which creates a production frontier line. Thus, rapid industrial wastewater reductions in Shanghai contributed to the increase in the TECHCH indicator. At the same time, EFFCH indicator decreases due to the gap of environmental pollutant management in this period because other inefficient provinces do not catch up the reduction speed in Shanghai. Shanghai spent about 3% of GDP on environmental investment, setting up “non-coal-using” zones, phasing out inefficient public and taxi vehicles, helping to reduce particulate matters by 25% in 2004. Shanghai also improved efficiency on wastewater treatment through marketization of urban water infrastructure with public-private joint venture approach, along with huge subsidies on the service fee and preferential policies (e.g. providing free or cheaper land to the investor) (Zhong et.al, 2008). While in other provinces,

due to the expansion of manufacturing and rising fossil fuel demand, many local governments failed to achieve the 10th Five Year Plan targets on environmental protection.

<Figure 3, 4, 5 about here>

Comparison of Regional Characteristics of TFP, Contribution Effect, and Innovator

In this section, we discuss the regional differences of TFP change and innovators of technological frontier. Table 1 and Table 2 show accumulated TFP change and contribution effect of each variable by region from 1992 to 2008. We also show the result of testing equality of multivariate densities in Table 1 and Table 2 to test the statistical differences between each TFP indicators among regions. This study used nonparametric methods to obtain TFP and contribution effects. In this case, we are not able to know the distribution of score in advance and, therefore, we need to apply the nonparametric equality test called nonparametric test for equality densities which was introduced by Li et al. (2009). This nonparametric equality test would be best to analyze the difference of distribution when analyzing TFP and contribution effects. This equality testing employ bootstrap resampling to obtain the finite-sample distribution of the statistic. In this paper, we set the bootstrap

algorithm was repeated 1,000 times.

From Table 1, coastal areas more rapidly increase TFP than central and west regions from 1992 to 2008. TFP_b scores in coastal areas are much higher than those in west and central areas. Another finding is that, the contribution effect of labor increase more rapidly in coastal areas than in others. This result implies two situations: (1) industrial structure in coastal areas shifted faster from labor intensive industry (conventional sector) to capital intensive industry (modern and high-technology industry) than other region, (2) coastal areas successfully improve labor productivity by inducing modern production equipment (input substitution effect). These results show that central and west region achieved more rapid value added increasing than coastal area from 1992 to 2008. One interpretation of this result is that there is large gap of profitability performance between coastal area and the other regions at the initial condition (1992 year) because coastal area produce high-tech product while west and central region are mainly produce conventional product (e.g. textile, wood product) .

< Table 1. about here>

Table 2 represent how many times provinces in each area become technological innovator

by economic point of view ($\text{Innovator}_{\text{Econ}}$), environmentally point of view ($\text{Innovator}_{\text{Env}}$), and both point of view (Innovator). We also show the accumulated FDI, accumulated patent application, and accumulated patent granted from 1992 to 2008. Technological innovations in both economic and environmental performance mainly occurred in coastal provinces. Technological innovation mainly occurred through new technology invention, which is reflected by patent application or patents granted. From Table 2, both patent application and patents granted are higher in coastal areas than in others. One interpretation of this difference is the regional distribution gap of FDI. FDI has an important role to promote patent invention and technological innovation in developing countries (Wooster and Diebel, 2010; Managi and Bwalya, 2010). Thus, the technological innovation in coastal areas might occur due to the FDI from developed countries.

<Table 2. about here>

Figure 6 shows the scatter plot of accumulated TFP_b and $\text{TFP}_y + \text{TFP}_x$ by province. The first quadrant in Figure 6 represent achievement both economic and environmental performance improvement. While, the second and fourth quadrant represent trade-off relationship between

environmental and economic performance. From Figure 6, many coastal provinces achieved combined improvement in economic performance and environmental performance from 1992 to 2008. Meanwhile, west area provinces show a trade-off relationship between economic performance and environmental performance. This trade-off relationship needs to reconcile the Western China Development and local environmental protection.

< Figure 6. about here >

5. Conclusion

This study analyzes productivity change relative to environmental pollution in Chinese industrial sectors from 1992 to 2008. Based on an empirical analysis, the major findings can be summarized as follows: First, Chinese industrial sectors succeeded in increasing productivity. The main contributing factors are industrial wastewater emissions reduction in coastal areas, and economic performance improvement in the central and west regions. Second, Chinese industrial TFP increased by 40% from 1992-2008. The main contributing factors are labor saving and value-added increase. After 2000, industrial wastewater management began to contribute more to the productivity growth due to more stringent

government policies. Third, technological innovation mainly occurred in the coastal provinces, which have a lot of foreign direct investment. Finally, most coastal and central provinces achieved improvement in economic performance and environmental performance from 1992 to 2008. Meanwhile, west area provinces have a trade-off relationship between economic performance and environmental performance.

Our results suggest China's imbalanced progress on productivity growth and environmental protection across regions. It has important policy implications regarding differential policy at regional level and environmental federalism. Innovations, FDI and patent applications are mainly concentrated in the coastal areas; this may also contribute to the overall efficiency improvement in the coastal areas.

On the other side, the western area is growing due to conventional economic inputs, while may at a loss of environmental efficiency. Given the gaps between the coastal and western regions, policy recommendations may need to consider more preferred policies to support innovative and high profit industries in the western region, such as more favored R&D and patent policies combined with tax-credit and subsidies to facilitate innovations and technology transfer from coastal area to central and western area.

In terms of federalism, considering the quite diverse characteristics of economic patterns

and pollution performance, the central government should allow the local government more power to decide environmental policies to target regional needs. Considering the deteriorative environmental damages, environmental policies and regulations need to be strengthened in the western area to avoid “pollution haven” traps. The 11th and 12th Five Year Plan target were set mostly due to each province’ energy saving and emission abatement potentials and abilities, which in fact cause a gap in terms of targets.

In addition, other economic policies such as western development projects also provide tax credit or subsidy incentives for more heavy pollution industries to shift from coastal area to western area. Therefore, even if the productivity and environmental performance improve in the coastal area, the overall improvements at the national level may be limited. Therefore, the economic policies and environmental policies need to be strengthened to achieve a more balanced production efficiency and environmental protection at the whole national level, and each region develop its own industries with comparative advantage. For instance, the western area can develop more green industries and renewable energy due to its abundant natural resource endowment or national park tourism.

Reference

1. Aparicio, Juan, Jesus T. Pastor, and Subhash C. Ray, “An overall measure of technical inefficiency at the firm and at the industry level: The ‘lost profit on outlay’,” *European Journal of Operational Research* 226 (2013):154-62.
2. Akao, Ken-Ichi and Shunsuke Managi, “The feasibility and optimality of sustainable growth under materials balance,” *Journal of Economic Dynamics and Control* 31 (2007):3778–90.
3. Barros, Carlos P., Shunsuke Managi, and Roman Matousek, “The technical efficiency of the Japanese banks: Non-radial directional performance measurement with undesirable output,” *Omega* 40 (2012):1-8.
4. Balk, Berk M., Rolf Färe, Shawna Grosskopf, and Demitris Margaritis, “Exact relations between Luenberger productivity indicators and Malmquist productivity indexes,” *Economic Theory* 35 (2008):187-90.
5. Cao, Jing, “Measuring green productivity growth for China’s manufacturing sectors: 1991-2000,” *Asian Economic Journal* 21 (2008):425-51.
6. Chen, Po-Chi, Ming-Miin Yu, Ching-Cheng Chang, and Shunsuke Managi, “Non-radial directional performance measurement with undesirable outputs,” *Working Paper. Tohoku*

University 2011.

7. Chambers, Robert G., Yangho Chung, and Rolf Färe, “Profit, directional distance functions, and Nerlovian efficiency,” *Journal of Optimization Theory and Applications* 98 (1998):351–64.
8. Diewert, Erwin W. and Kevin J. Fox, “Notes on the Decomposition of Malmquist Productivity Indexes,” Paper Prepared for the 32nd General Conference of The International Association for Research in Income and Wealth 2012.
9. Färe, Rolf, Shawna Grosskopf, Mary Norris, and Zhongyang Zhang, “Productivity growth, technical progress and efficiency change in industrialized countries,” *American Economic Review* 84 (1994):66–83.
10. Fujii, Hidemichi, Shinji Kaneko, and Shunsuke Managi, “Changes in environmentally sensitive productivity and technological modernization in China's iron and steel industry in the 1990s,” *Environment and Development Economics* 15 (2010): 485-504.
11. Fujii, Hidemichi, Shunsuke Managi, and Shinji Kaneko, “Decomposition analysis of air pollution abatement in China: Empirical study for ten industrial sectors from 1998 to 2009,” *Journal of Cleaner Production* 59 (2013): 22-31.
12. Fujii, Hidemichi, Shunsuke Managi, Roman Matousek, “Indian bank efficiency and

- productivity changes with undesirable outputs: A disaggregated approach,” *Journal of Banking & Finance* 38 (2014): 41-50.
13. Hoa, Tran V., “Impact of the WTO Membership, Regional Economic Integration, and Structural Change on China's Trade and Growth,” *Review of Development Economics* 14(2010):577-91.
 14. Li, Qi, Esfandiar Maasoumi, and Jeffery S. Racine, “A Nonparametric Test for Equality of Distributions with Mixed Categorical and Continuous Data,” *Journal of Econometrics* 148 (2009):186-200.
 15. Managi, Shunsuke and Samuel M. Bwalya, “Foreign direct investment and technology spillovers in Sub-saharan Africa” *Applied Economics Letters* 17 (2010):605-8.
 16. Managi, Shunsuke and Shinji Kaneko, “Environmental performance and returns to pollution abatement in China,” *Ecological Economics* 68 (2009):1643-1651.
 17. Managi, Shunsuke and Shinji Kaneko, *Chinese Economic Development and Environment*, Cheltenham, UK: Edward Elgar Publishing Ltd., 2010.
 18. Managi, S., J.J. Opaluch, D. Jin, and T.A. Grigalunas. (2004). "Technological Change and Depletion in Offshore Oil and Gas." *Journal of Environmental Economics and Management* 47 (2): 388-409.
 19. Managi, S., J.J. Opaluch, D. Jin, and T.A. Grigalunas. (2005). "Environmental Regulations

- and Technological Change in the Offshore Oil and Gas Industry." *Land Economics* 81 (2): 303-319.
20. Managi, S., Hibki, A. and T. Tsurumi (2009). "Does Trade Openness Improve Environmental Quality?" *Journal of Environmental Economics and Management* 58 (3): 346-363.
 21. Managi, S. and S. Kumar. (2009). "Trade-Induced Technological Change: Analyzing Economic and Environmental Outcomes " *Economic Modelling* 26(3): 721-732.
 22. National Bureau of Statistics, *China Statistical Yearbook 2011*, China Statistics Press, Beijing, China, 2011.
 23. O'Donnell, Christopher J., "An aggregate quantity framework for measuring and decomposing productivity change," *Journal of Productivity Analysis*, 38 (2012):255-72.
 24. Shao, Weiyun, "Effectiveness of water protection policy in China: A case study of Jiaxing," *Science of the Total Environment* 408(2010): 690-701.
 25. Wang, Mark, Michael Webber, Brian Finlayson, and Jon Barnett, "Rural industries and water pollution in China," *Journal of Environmental Management* 86 (2008):648-659.
 26. Wooster, Rossitza B. and David S. Diebel, "Productivity Spillovers from Foreign Direct Investment in Developing Countries: A Meta-Regression Analysis," *Review of Development Economics* 14 (2010):640-55.
 27. Zhang Kun-min and Zong-guo Wen, "Review and challenges of policies of environmental

- protection and sustainable development in China,” *Journal of Environmental Management* 88(2008): 1249-61.
28. Zhang, Xiao-jian, Chao Chen, Jian-qing Ding, Aixin Hou, Yong Li, Zhang-bin Niu, Xiao-yan Su, Yan-juan Xu, and Edward A Laws, “The 2007 water crisis in Wuxi, China: Analysis of the origin,” *Journal of Hazardous Materials* 182 (2010):130-35.
29. Zhongxiu Zhao and Kevin H. Zhang, “FDI and Industrial Productivity in China: Evidence from Panel Data in 2001–06,” *Review of Development Economics* 14 (2010):656-65.
30. Zhong, Lijin, Arthur P.J. Mol, and Tao Fu, “Public-private partnerships in China’s urban water sector,” *Environmental Management* 41 (2008):863-877.

Note

1. We note that solution on for inefficiency depends simultaneously on all the observed inputs, outputs and bad outputs with weights of province estimated by WRDDM. Any interpretation of these coefficients has to be conditional on the input and output data for the industrial sector of each province under consideration represented by (x_{nk}, y_{mk}, b_{lk}) .
2. O’Donnell (2012) and Diewert and Fox (2012) pointed out the mix and scale efficiency are key component to determine the TFP for industrial sector. Scale efficiency and mix

efficiency can be estimate by using index approach such as data envelopment analysis.

Meanwhile, this study employ weighted Russell directional distance model, which does not use index approach but distance function, have difficult to estimate mix and scale efficiency. This point is our research limitation.

3. This study only uses provincial level data but not firm level data. This is because firm level data is difficult to correct capital stock data and pollution data. As the composition of industrial sector differs significantly across different provinces, use of a simple measure of value added ignores the role of composition in the production of environmental pollutants. Currently, there is not such composition data available in Chinese province database.
4. Because intermediate input data is not available, we use labor and capital data as input. In this case, total revenue and total production data are not consistent to use as desirable output data. Thus, we use value added data which is calculated by total revenue minus intermediate cost.
5. We estimate capital stock data using net value of fixed asset is taken from China Industry Economy Statistical Yearbook. Net value of fixed assets in current price and therefore only Perpetual Inventory Method can add them up correctly by deflating them in different

price level. However, there is no industrial depreciation ratio data and price index of fixed capital by province in China. Thus, we consider net value of fixed assets as capital stock data. Because we apply time series analysis in this study, we need to deflate monetary data to understand the productivity change score. To satisfy this condition, we deflate monetary data using provincial retail price index which is data openly available on the China Statistical Yearbook. Those points are limitation of study.

6. Following Managi and Kaneko (2009), we use the price index to deflate all monetary data variable is retail price index.
7. We use sales data for adjustment because we have difficulty to correct the product amount data by type of product. Therefore, the sales data was used to determine the production amount. Generally, the amount of pollutant emissions depended upon the input amount of fossil energy and intermediate chemical materials. This is because the production scale became a factor in determining pollutant emissions.
8. Industrial structure is important factor for amount of pollutants associated with a given level of sales. However, we have difficulty to correct entire pollutant emissions data by industry in each province. Thus, we apply data expansion approach using adjustment coefficient calculated by sales data. In this data expansion approach, we assume data

coverage of CESY reflects the industrial structure of whole industrial sector in province.

Additionally, we have another assumption that the industrial firm which is not covered in sample data has same pollution abatement technology with the industrial firms covered in sample data. Under these two assumptions, we can use expanded pollution data with economic data for production function approach. This point is limitation of this study.

9. Chinese government implemented the price deregulation policy from 1992 into manufacturing product, especially steel product price. This price deregulation affected the performance in China's manufacturing sectors.

Table 1. Accumulated weighted TFP change and contribution effect by each variable from 1992 to 2008.

	Weighted TFP	Contribution effect of undesirable output (TFP _b)			Contribution effect of input (TFP _x)		Contribution effect of desirable output (TFP _y)
		Wastewater	Waste gas	Solid waste	Labor	Capital	Value added
Total	0.428	0.106	0.015	0.002	0.193	-0.016	0.128
Coastal area	0.319	0.084	0.019	0.010	0.149	-0.005	0.062
Central area	0.068	0.014	-0.000	-0.007	0.029	-0.007	0.038
West area	0.041	0.008	-0.004	-0.002	0.015	-0.005	0.028
p-value	0.155	0.258	0.176	0.322	0.135	0.211	0.836

Note 1: Weighted average $TFP_t^{t+1} = \sum_j \{TFP_{tj}^{t+1} \times (sale_j^t / \sum_j sale_j^t)\}$ where j shows province and t shows year.

Note 2: p-value is estimated by nonparametric test for equality of multivariate density by Li et al. (2009).

Table 2. Accumulated FDI, patent application, patent granted, and innovators from 1992 to 2008.

	Innovator	Innovator _{Econ}	Innovator _{Env}	FDI	Patent application	Patent granted
Total	27 (5.48%)	28 (5.68%)	19 (3.85%)	346.2	130.25	68.16
Coastal area	19 (3.85%)	16 (3.25%)	15 (3.04%)	758.2	219.87	114.28
Central area	3 (0.61%)	3 (0.61%)	2 (0.41%)	145.9	84.78	43.59
West area	5 (1.01%)	9 (1.83%)	2 (0.41%)	53.3	41.03	22.93
p-value	0.78	0.915	0.566	0.07	0.160	0.165

Note 1: Innovator, Innovator_{Econ}, and Innovator_{Env} are accumulated count data how many times each regional province is identified as innovator out of 29 provinces over 17 years (i.e. $17 \times 29 = 493$). Number of 27 means 27 provinces are innovator and its share is $27/493 = 5.48\%$.

Note 2: FDI (trillion yuan, 1995 price), patent application (1000 items), and patent granted (1000 items) are regional average.

Note 3: p-value is estimated by nonparametric test for equality of multivariate density by Li et al. (2009).

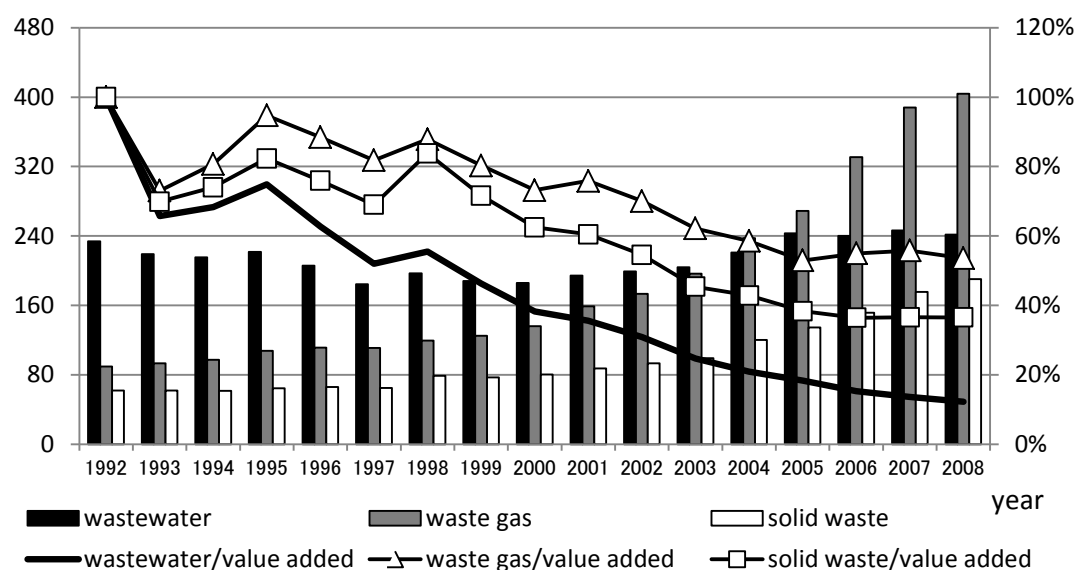


Figure 1. Pollution Emission and environmental efficiency in China

(Source: China Environmental Yearbook)

Note 1: Bar charts show the amount of pollution in China (left axis).

Note 2: Unit: wastewater: 100 million ton, waste gas: 100 billion m3, solid waste: 10 million ton.

Note 3: Line charts show the change of environmental efficiency (right axis, standardized as 1992=1).

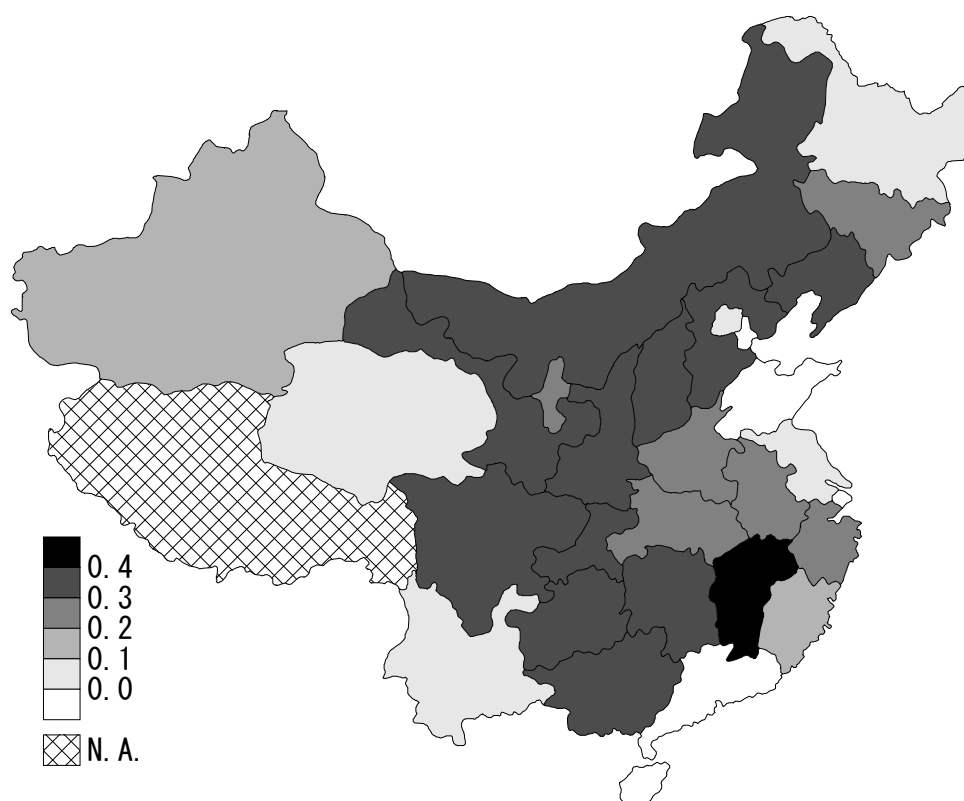


Figure 2. Average inefficiency score from 1992 to 2008 by province

Note: Average inefficiency score of province $j = \sum_{t=1992}^{2008} \{\bar{D}^t(x_j^t, y_j^t, b_j^t)\} / 17$ where j shows province and t shows year.

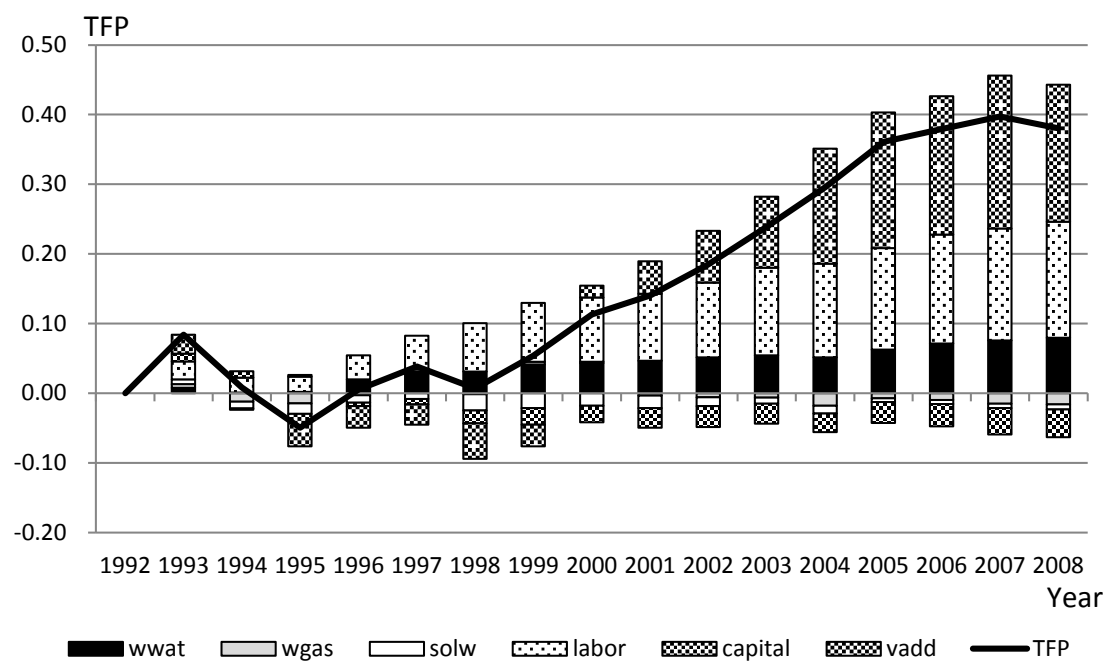


Figure 3. TFP and contribution effect of each variable (29 province average)

Note: $TFP^{t'} = \sum_{t=1992}^{t'-1} \sum_j (TFP_{tj}^{t+1}) / 29$ where j shows province, t and t' show year.

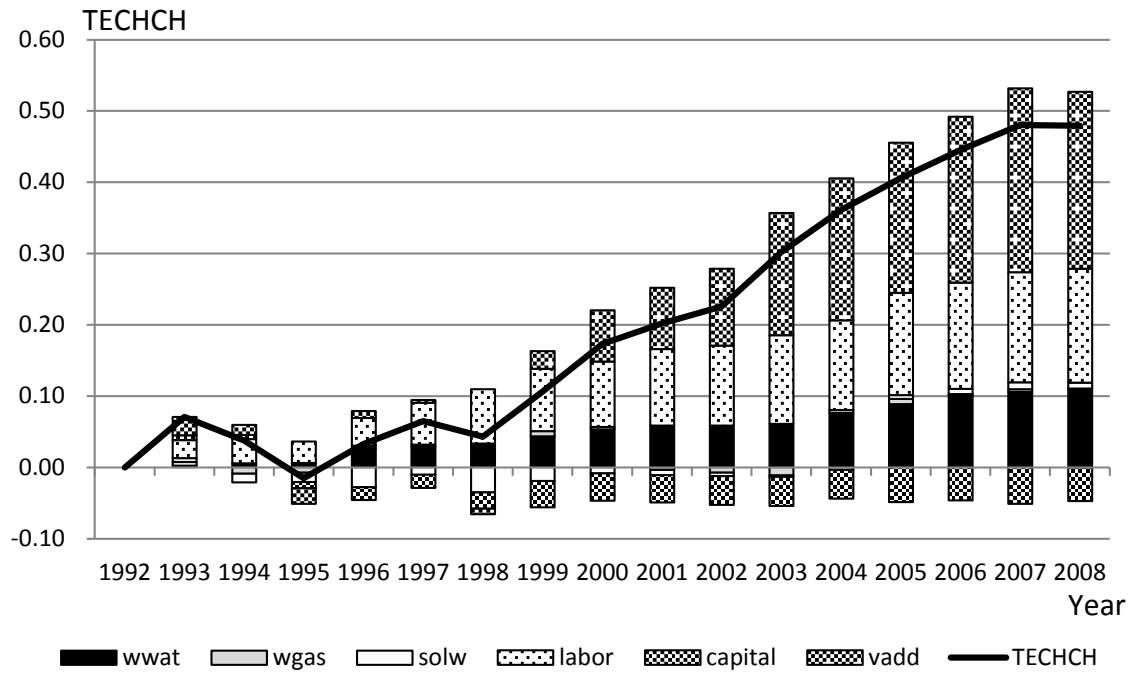


Figure 4. Result of TECHCH change and contribution effect of each variable (29 province average)

Note: $TECHCH^t = \sum_{t=1992}^{t'-1} \sum_j (TECHCH_{tj}^{t+1}) / 29$ where j shows province, t and t' show year.

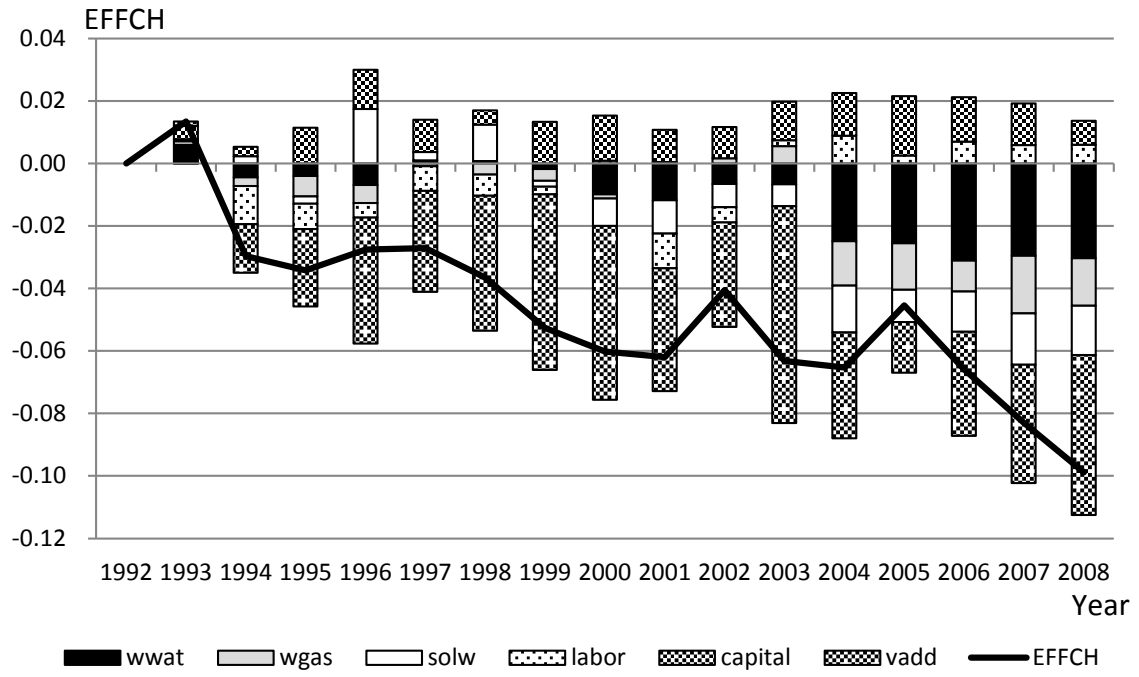


Figure 5. Result of EFFCH change and contribution effect of each variable (29 province average)

Note : $EFFCH^{t'} = \sum_{t=1992}^{t'-1} \sum_j (EFFCH_{tj}^{t+1}) / 29$ where j shows province, t and t' show year.

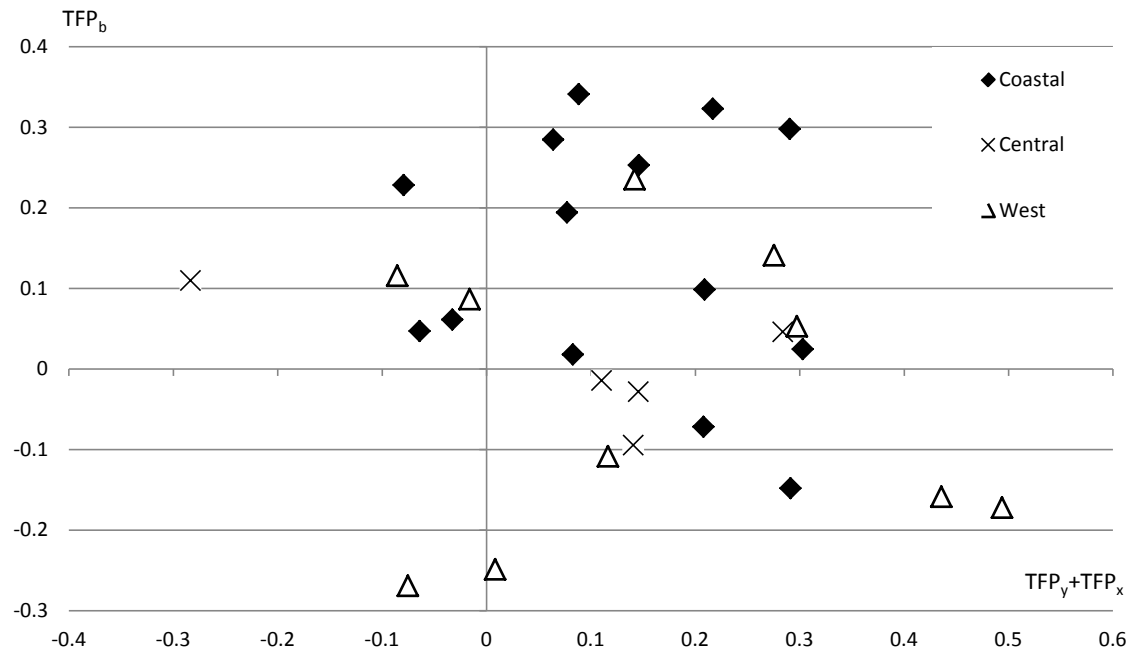


Figure 6. Scatter plot of accumulated TFP_b and TFP_y+TFP_x by province.



Appendix. Provinces of China

Note: Coastal area: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan.

Central area: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan.

West area: Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Inner Mongolia, Guangxi, Xinjiang.

Source: National Bureau of Statistics