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China's regional industrial energy efficiency and carbon emissions abatement costs

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Abstract: Evaluating the energy and emissions efficiency, measuring the energy saving and emissions reduction potential, and estimating the carbon price in China at the regional level are considered a crucial way to identify the regional efficiency levels and efficiency promotion potentials, as well as to explore the marginal abatement costs of carbon emissions in China. This study applies a newly developed Data Envelopment Analysis (DEA) based method to evaluate the regional energy and emissions efficiencies and the energy saving and emissions reduction potentials of the industrial sector of 30 Chinese major cities during 2006-2010. In addition, the CO_2 shadow prices, i.e., the marginal abatement costs of CO_2 emissions from industrial sector of these cities are estimated during the same period. The main findings are: (i) The coast area cities have the highest total factor industrial energy and emissions efficiency, but efficiency of the west area cities are lowest, and there is statistically significant efficiency difference between these cities. (ii) Economically well-developed cities evidence higher efficiency, and there is still obviously unbalanced and inequitable growth in the nationwide industrial development of China. (iii) Fortunately, the energy utilization and CO_2 emissions efficiency gaps among different Chinese cities were decreasing since 2006, and the problem of inequitable nationwide development has started to mitigate. (iv) The Chinese major cities could have, on average, an approximately 19% or 17% efficiency increase on energy utilization or CO_2 emissions during 2006-2010. (v) Promoting the industrial energy utilization efficiency is comparatively more crucial for Chinese cities at the current stage, and the efficiency promotion burdens on the west area cities are the heaviest among all Chinese cities. (vi) An N-shaped Environmental Kuznets Curve (EKC) exists between the level of industrial CO_2 emissions efficiency and income, and the inflection point the EKC is located between 12052-12341 US$ of GDP per capita, indicating that an accelerated CO_2 emissions efficiency increase will accrue when this income level is reached. (vii) In 2010, the industrial total energy saving and CO_2 emissions reduction potentials for Chinese major cities were 41 million tce and 143 million tCO_2, respectively. (viii) The average industrial CO_2 emissions abatement cost for Chinese major cities is 45 US$ during 2006-2010, and the existence of large gap on CO_2 shadow prices between different Chinese regions provide a necessity and possibility for establishing a regional carbon emissions trading system in China.

Keywords: CO_2 emissions, energy efficiency, abatement cost, shadow price, DEA

1. Introduction

After 30 years of rapid economic growth, China's GDP has significantly increased by over 80-fold since the implementation of reform and opening-up policy. However, the rapid economic growth also leads to huge amount of energy consumption and related CO_2 emissions. Nowadays, China has overtaken the United States and became the largest energy consumer and CO_2 emitter in the world [1-2]. To realize sustainable development, improve energy efficiency, and control greenhouse gas emissions, the Chinese government has put forward a strategic target of constructing an environment-friendly and resource-saving society, and specifically, in the 11th (2006-2010) and 12th (2011-2015) Five Year Plan (FYP), China has put energy saving and environment protection as one of its highest priority policy, in which the energy intensity (energy consumption per unit of GDP) reduction targets were set to be 20% and 16%, and the total discharge of major pollutants (SO_2 etc.) reduction targets were set to be 10% and 8%, during 2006-2010 and 2011-2015, respectively [3]. In addition, China also proposed a mitigation action plan consists of reducing CO_2 emissions intensity (CO_2 emissions per unit of GDP) by 40-45% by the year of 2020 based on the 2005

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level. In order to realize the above targets, a series policies, regulations and laws on energy utilization and environmental protection, as well as CO_2 emissions mitigation were proposed and implemented within the last ten years both at the national and provincial levels in China so as to support the Chinese government's efforts. According to official report issued in 2011, China's national energy intensity decreased by 19.1% during the 11th FYP period, indicating that the overall carbon emission reduction target was approximately achieved. However, during the first two years of the 12th FYP period (2011-2012), the national energy intensity just decreased by 2.02% and 3.62% respectively, both are lower than the annual reduction target (3.7%) for realizing the overall target of the 12th FYP. Thus the remainder national energy intensity reduction burden for Chinese government is still very heavy. Under such circumstance, it is worthwhile evaluating China's energy and emissions efficiency, measuring its energy saving and emissions reduction potential, and estimating its CO_2 emissions abatement costs, which may provide useful information for identifying the energy utilization and CO_2 emissions efficiency levels and efficiency promotion potentials of China, as well as provide policy making supports on emissions abatement cost estimating, carbon pricing in emissions trading system (which has been initially established in several pilot regions such as Beijing, Shanghai, Tianjin, and Chongqing etc.), and other related energy and environmental issues in China.

In this study, we aim to evaluate the industrial energy and CO_2 emissions efficiency of China's major cities. Because the industrial sector of China is the largest energy consumer and produces more than 70% of the CO_2 emissions, the energy and emissions efficiency evaluation for industrial sector in China are considered more important than other sectors. In addition, since the natural resources endowments, energy consumption structures, industrial structures, and economic growth modes of different Chinese regions are various, and different Chinese administrative regions have different energy saving and environmental protection policies and strategies, the industrial energy and emissions efficiency of China may vary significantly across different Chinese cities. Thus, it may essential and valuable to evaluate the energy and emissions efficiency of industrial sector in China at its major city level.

Energy and emissions efficiency evaluation is often in the form of efficiency indices, and Data Envelopment Analysis (DEA) is considered a successful method to evaluate the efficiency of various decision making unit (DMU). In the energy and emissions efficiency evaluation, many researchers have utilized DEA models [4]. And especially for the efficiency evaluation and shadow price estimating of China, quite a few studies have contributed to the literatures. For instance, Wei et al. studied the energy efficiency levels and changes of China's iron and steel sectors through DEA Malmquist index technique [5]. Wang et al. combined two undesirable output treatments with DEA window analysis model and evaluated the total-factor energy and emissions efficiency of China's 30 provinces [6]. Li and Hu measured the ecological-energy efficiency of China's 30 provinces by applying the slacks-based measure (SBM) DEA model [7]. Li analyzed the carbon emissions efficiency changes of Chinese provinces based on a distance function DEA method [8]. Recently, Wang et al. empirically investigated the provincial energy efficiency and energy productivity of China during the 11 FYP period [39]. In their study, the efficiency were measured by employing a non-radial directional distance function approach and three different production scenarios representing different constraints on energy conservation, carbon emission reduction, and economic growth were assigned so as to provide a more specific efficiency evaluation result. Yi et al. utilized a super-efficiency DEA model to measure the eco-efficiency of Chinese provincial capital cities by including environmental pollution as an undesirable output, and their efficiency results were further utilized as an indicator for the measure of urban sustainable development [44]. Jin and Lin estimated the environmental technical efficiency of China's provinces by using economic and pollution data and through DEA approach, and then a further examination on the role of technical efficiency and industrial pollution control instruments on pollution intensity in China was conducted in their study [45]. Wu et al. developed several static and dynamic energy efficiency indexes based on environmental DEA models and applied these indexes to measure the industrial energy efficiency of Chinese provinces [46]. In addition, Kaneko et al. estimated the shadow price of sulfur dioxide in China based on a direction distance function DEA method [9]. Ke et al. applied the direction distance function DEA method to study the shadow prices of industrial wastes in China [10].

However, few studies have focused on the CO_2 emissions abatement costs estimation of China. For example, Choi et al. applied a SBM DEA method to evaluate the energy and emissions efficiency and marginal abatement cost of energy related CO_2 emissions in China at the provincial level [11]. Lee and Zhang estimated the shadow prices of CO_2 emissions for 30 Chinese manufacturing industries through a distance function approach [12]. Since few studies have estimated the abatement cost of CO_2 emissions in China and, to our best knowledge, no study has focused on the CO_2 emissions abatement cost for industrial sector in Chinese cities, in this study, we employ a newly developed DEA approach [13] and following the method of [11] and [14] to first evaluate the regional energy and emissions efficiency of the industrial sector of Chinese major cities, and then measure the industrial energy saving and CO_2 emissions reduction potentials, as well as estimate the industrial CO_2 emissions abatement costs for different Chinese cities during the period of 2006-2010. The related policy implications are also proposed in this study based on the evaluation results.

The remainder of the paper is organized as follows. Section 2 explains the DEA based efficiency evaluation and shadow price estimating method utilized in this study. Section 3 introduces the data and variables. Section 4 to 6 respectively presents and discusses the results on energy and emissions efficiency evaluation, energy saving and emissions reduction potential measurement, and CO_2 emissions abatement cost estimation. Section 7 concludes this study.

2. Methodology

DEA methods have been widely utilized in energy and environmental efficiency evaluation studies since 1980s, and for modeling undesirable or bad outputs in these studies, DEA methods can be classified into two groups according to [4,15], which are those using the original undesirable outputs data and relying on the weak disposability assumption [16,17], and those based on data transformation or considering bad outputs as inputs [18,19]. The former treats undesirable outputs (e.g., pollutions, carbon emissions) as weakly disposable and null-joint outputs, while the latter treats undesirable outputs as freely disposable inputs. Here, the weak disposability assumption is a representation of the production process that both the desirable and undesirable outputs are included in the production efficiency evaluation simultaneously. If we utilize x, g, b to respectively represent the input, desirable output and undesirable output in a production process, then the reference technology of weak disposability is $T=\{(x,g,b)$: x can produce $(g,b)\}$ and it satisfies if $(x,g,b)\in T$ and $\theta\in[0,1]$ then $(\theta g,\theta b)\in T$. This definition indicates that any reduction on undesirable output will also cause a reduction on desirable output.

However, as discussed in [20,21] and [13], these commonly used techniques may lead to unacceptable implications of the tradeoffs among inputs, desirable outputs and undesirable outputs. For instance, the method proposed by [18] treats undesirable outputs as inputs which are strongly disposable. This approach dose not satisfies the jointness assumption on desirable and undesirable outputs, which is an intuitive and economically well-founded condition: any decrease in undesirable outputs must imply a decrease in desirable outputs simultaneously for efficient DMUs, i.e., undesirable outputs are not freely disposable that cannot be arbitrarily reduced without affecting the producing of desirable outputs. Therefore, this approach has been criticized by many studies (e.g., [21-24]).

In addition, by looking at the method proposed by [16] which relies on the weak disposability, the jointness of desirable and undesirable outputs is explicitly modeled. However, the shadow prices on undesirable outputs are unconstrained in this approach, which is not appropriate when measuring undesirable outputs in the economic sense: undesirable outputs, like pollutions, naturally should be considered as costs for decision makers that the non-positive shadow prices on undesirable outputs are unacceptable [25]. Because if the shadow prices of the undesirable outputs are negative, then the revenue obtained from both the desirable and the undesirable outputs will be positive and the undesirable outputs will be no longer "undesirable" from the economic point of view.

Using the output directional distance function is a sufficient way to ensure decreasing undesirable outputs and increasing desirable outputs at the same time, but is not sufficient enough to guarantee the appropriate shadow price on undesirable outputs [13]. Below is the weakly disposable undesirable outputs model proposed by [17]:

$$
\begin{aligned}
&\max \delta \\
&s.t.\ \ \sum\nolimits_{j=1}^{n}\lambda_j g_{rj} \ge g_{rj_0} + \delta d_r^g,\ r=1,...,s \\
&\qquad \sum\nolimits_{j=1}^{n}\lambda_j b_{fj} = b_{fj_0} - \delta d_f^b,\ f=1,...,h \\
&\qquad \sum\nolimits_{j=1}^{n}\lambda_j x_{ij} \le \theta x_{ij_0},\ i=1,...,m \qquad\qquad (1)\\
&\qquad \sum\nolimits_{j=1}^{n}\lambda_j = \theta \\
&\qquad \lambda_j \ge 0,\ j=1,...,n \\
&\qquad 0 \le \theta \le 1
\end{aligned}
$$

In Model (1), the inputs, desirable and undesirable outputs for DMU$_j$ (j=1,…,n) are respectively denoted by $x=(x_{1j},\ldots,x_{mj})$, $g=(g_{1j},\ldots,g_{sj})$, and $b=(b_{1j},\ldots,b_{hj})$. λ_j is intensity variables for connecting inputs and outputs by a convex combination. θ together with the fourth constraint are used to model the variable returns to scale (VRS) assumption. $d=(d_r^g, d_f^b)$ (r=1,..,s; f=1,…,h) is the direction vector, and δ is the efficiency measure of both desirable and undesirable outputs associated with a chosen direction. It should be noticed that the undesirable outputs related constraint of Model (1) is an equation constraint, which indicates the shadow prices on undesirable outputs are unconstraint (see the dual model of Model (1) in [13]). Recently, Leleu proposed a slightly different weakly disposable undesirable outputs model for VRS setting and non-negative shadow prices on the undesirable outputs [13]. This model is equivalent to Model (1) but with a different formulation as follows, which leads to a novel interpretation of the economic meaning of weak disposability and efficiency measurement.

$$
\begin{aligned}
&\max \delta \\
&s.t.\ \sum_{j=1}^{n} \lambda_j (g_{rj} - g_{rj_0}) \ge \sigma g_{rj_0} + \delta d_r^g, r = 1,\ldots,s \\
&\sum_{j=1}^{n} \lambda_j (b_{fj} - b_{fj_0}) \le \sigma b_{fj_0} - \delta d_f^b, f = 1,\ldots,h \\
&\sum_{j=1}^{n} \lambda_j (x_{ij} - x_{ij_0}) \le 0, i = 1,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j + \sigma = 1 \\
&\lambda_j \ge 0, j = 1,\ldots,n \\
&\sigma \ge 0
\end{aligned}
\tag{2}
$$

The definitions of x, g, b, λ, δ, and d are the same in Model (1), and σ together with the fourth constraint are used to model the VRS assumption. If the inequality sign in undesirable output related constraint is replace with equality sign then Model (2) is equivalent to Model (1). Similar to Model (1), it can be seen that Model (2) aims to increase desirable output, contract input and undesirable output as much as possible through a common adjustment δ, which indicates that Models (1) and (2) essentially provide the radial directional distance inefficiency measures. The dual model of Model (2) is as follow, which could lead to a meaningful economic interpretation on weakly disposable undesirable outputs:

$$
\begin{aligned}
&\min \phi \\
&s.t.\ \left(\sum_{r=1}^{s} p_r^g g_{rj} - \sum_{f=1}^{h} p_f^b b_{fj} - \sum_{i=1}^{m} p_i^x x_{ij}\right) - \\
&\left(\sum_{r=1}^{s} p_r^g g_{rj_0} - \sum_{f=1}^{h} p_f^b b_{fj_0} - \sum_{i=1}^{m} p_i^x x_{ij_0}\right) \le \phi, j = 1,\ldots,n \\
&\sum_{r=1}^{s} p_r^g d_r^g + \sum_{f=1}^{h} p_f^b d_f^b = 1 \\
&\sum_{r=1}^{s} p_r^g g_{rj_0} - \sum_{f=1}^{h} p_f^b b_{fj_0} + \phi \ge 0 \\
&p_r^g \ge 0, r = 1,\ldots,s \\
&p_f^b \ge 0, f = 1,\ldots,h \\
&p_i^x \ge 0, i = 1,\ldots,m
\end{aligned}
\tag{3}
$$

As explain in [13], in Model (3), the first n constraints calculate the profit differences between reference DMU$_j$ (j=1,…,n) and the currently under evaluating DMU$_{j0}$. ϕ is the upper bound of the above profit differences, which could be considered as the profit inefficiency measure of the evaluated DMU, and the optimization objective of Model (3) is to minimize the profit inefficiency of each DMU. The optimization in Model (3) is based on seeking the optimal shadow prices associated with inputs (x_{ij}, i=1,…,m), desirable outputs (g_{rj}, r=1,…,s), and undesirable outputs (b_{fj}, f=1,…,h), which are denoted by p_i^x (i=1,…,m), p_r^g (r=1,…,s), and p_f^b (f=1,…,h), respectively. The (n+1)th constraint is the normalization constraint to ensure the homogeneity (degree 1) of shadow prices on all inputs and outputs. The next constrain indicates that the efficient revenue from both the desirable and the undesirable outputs must be positive, together with the non-negative undesirable output shadow price constraint ($p_f^b \ge 0$), an economic content of Model (3) is founded: any producing activity can be conducted if and only if the revenue from the desirable outputs

($p_r^g g_{rj}$) compensates the cost of the undesirable outputs ($p_f^b b_{fj}$). Since Model (3) seeks to increase desirable outputs whilst decreasing undesirable outputs, an appropriate chosen of direction vector d=(d_r^g , d_f^b) (r=1,..,s; f=1,…,h) is necessary, which will also guarantee all the DMUs under evaluation can be projected to the appropriate section of the efficiency frontier that becomes unbounded for including non-negative undesirable output shadow price constraint. Thus, the constraint settings and direction vector choosing in Models (2) and (3) can be further considered as a tradeoff between the strong/weak disposability and non-negative/possible-negative undesirable output shadow price.

In Model (2), the DMU under evaluation is efficient in the utilizing of inputs and the producing of both desirable and undesirable outputs if the optimized objective δ^*=0 (and σ^*=1). If the DMU under evaluation is inefficient (δ^*>0), then its efficiency can be promoted through reducing the input excesses and fulfilling the desirable output shortages, as well as reducing the undesirable output excesses. Therefore, the specific efficiency of the input, desirable output and undesirable output, as well as the integrated energy-economic-emission efficiency for the under evaluating DMU can be respectively measured as:

Input efficiency=$1-\sigma^*$ (4)

$$\text{Desirable output efficiency} = \frac{g_{rj_0}}{g_{rj_0} + \delta^* d_r^g} \qquad (5)$$

$$\text{Undesirable output efficiency} = \frac{b_{fj_0} - \delta^* d_f^b}{b_{fj_0}} \qquad (6)$$

$$\text{Integrated efficiency} = \frac{1}{m+s+h}\left[m(1-\sigma^*) + \sum_{r=1}^{s} \frac{g_{rj_0}}{g_{rj_0} + \delta^* d_r^g} + \sum_{f=1}^{h} \frac{b_{fj_0} - \delta^* d_f^b}{b_{fj_0}} \right] \qquad (7)$$

In addition, the potential of input saving, desirable output extension, and undesirable output reduction of the under evaluating DMU can be respectively denoted by $\sigma^* x_i$, $\delta^* d_r^g$, and $\delta^* d_f^b$. Similar to [11] and [14], if the shadow price of a desirable output is assumed to be equal to its market price, then the relative shadow price of an undesirable output regarding to the above desirable output can be calculated as $p_f^b \big/ p_r^g$. Such calculation indicates that the shadow price of a specific undesirable output can be presented as the marginal rate of transformation between this undesirable output and a specific desirable output. In addition, the abatement costs of undesirable outputs can be denoted by their shadow prices as well.

3. Variables and Data

The models and the definitions proposed in Section 2 have been utilized to measure the energy and emissions efficiencies, the energy and emission reduction potentials, and the shadow prices denoted CO_2 emissions abatement costs of the industrial sector of Chinese major cities during 2006 and 2010. Consider the production process of industrial sector, we employ i) Capital: net value of fixed assets of industrial enterprises, ii) Labor: number of employed person of industrial enterprises, and iii) Energy: total energy consumption of industrial enterprises as input variables (x); value-added of industrial enterprises as desirable output variable (g); and i) total volume of industrial sulphur dioxide emissions (SO_2) and ii) total volume of industrial carbon dioxide emissions (CO_2) as undesirable outputs (b).

The capital, labor, energy, value-added, and SO_2 emissions data are collected from China statistical yearbook, China city statistical yearbook, China statistical yearbook on environment, China energy statistical yearbook, and previously studies, respectively [26-30]. And the CO_2 emissions data are estimated by applying the method and parameters suggested in [31-33] and based on the industrial fossil fuel consumption data of Chinese major cities. All the monetary variables, including fixed assets and value-added of industrial enterprises, have been converted into 2010 constant prices and transformed into US$ according to the yearly average exchange rates (Chinese currency RMB¥ to US$ are ¥7.945, ¥7.760, ¥7.045, ¥6.835, and ¥6.745 to $1, respectively, during 2006 and 2010). Energy consumption of industrial enterprises include all types of energy as coal, oil, gas, and electricity, and all of these energy have been converted into tonnes of coal equivalent (tce). Table 1 shows the descriptive statistics of input and output data.

[Insert Table 1 here]

4. China's regional industrial energy and emissions efficiency

4.1 China's eight economy-geography regions and their major cities

According to the economic development and geographical feature, China can be divided into eight economy-geography regions: the northeast area, the north coast area, the east coast area, the south coast area, the middle Yellow River area, the middle Yangtze River area, the southwest area and the northwest area (see Figure 1).

[Insert Figure 1 here]

Three industrial based cities (Shenyang, Changchun and Harbin) belong to the northeast area. The natural conditions and resources endowment of the provinces in this area are close to each other, and they have tightness economic interrelations among them. However, this area is faced with resource exhaustion problem, and need to upgrade and update its industrial structure for further development.

The north coast area includes two municipalities (China's national capital Beijing and Tianjin) and two provincial capitals (Shijiazhuang, Jinan) of China. This area is the strategic location of north China with huge economic aggregate, well-constructed infrastructure and convenient transportation system, advanced science and technology development, and well-developed education and culture condition.

The largest city of China (Shanghai) and two developed provinces' capitals (Nanjing and Hangzhou) located in the east coast area. This area started its modernization earlier than other Chinese regions and maintained tighter economic relations with foreign countries than other Chinese regions. It also holds both abundant physical capital and rich human capital.

The south coast area includes three coastal cities (Fuzhou, Guangzhou and Haikou). They are the earliest opening up cities since China started to implement the reform and opening-up policy in 1980s. The economic aggregate of this area also highly ranked in China, and the industrial sector of this area are developed completely.

Four central China cities (Xian, Taiyuan, Zhengzhou and Huhehot) located in the middle Yellow River area. This area is considered as resource-dependent area which is rich in resources of coal and natural gas. Thus, this area exports large volume of electricity to neighboring provinces each year. However, the opening to the outside world of this area is insufficient and it holds heavy burdens of industrial structure improvement and energy consumption structure adjustment.

The middle Yangtze River area has the best natural conditions for agricultural industry and sustains the highest population density in China. Wuhan and Changsha are the most important industry bases in this area, and Nanchang and Hefei are also known as large industrial cities in central China. Similar to the middle Yellow River area, this area also suffers insufficient opening to the outside world and faces high pressure of industrial transformation.

Five remote southwest cities (Kunming, Guiyang, Chengdu, Chongqing and Nanning) are located in the southwest mountainous area, which is still economic under development with under construction infrastructure and transportation system. This area is inhabited by ethnic minorities and the poverty level of this area is higher than the east and central areas of China. However, this area is rich in renewable energy resources as hydropower and biomass energy, and in the advanced situation for foreign trade with Southeast Asian countries.

Cities in the northwest area (Lanzhou, Xining, Ningxia and Urumqi) are all inland cities with very harsh natural conditions, especially lack of water. This area covers a vast territory with a sparse population and a small market.

Nowadays, it has become China's largest energy production base for its resources endowment of oil and natural gas. This area also links the Central Asia energy-rich countries with China for further energy cooperation.

Through Model (2) and the efficiency definitions (4)-(7), the integrated efficiency (total factor efficiency), input efficiency (energy utilization efficiency), desirable output efficiency (production efficiency) and undesirable output efficiency (CO_2 emissions efficiency) of the industrial sector of 30 Chinese major cities can be measured, and the related industrial energy saving and CO_2 emissions reduction potentials of each city can be estimated. For data absence, cities in Tibet and Taiwan, and HongKong and Macao are not included in our study. The evaluation results are reported in Table 2.

4.2 Total factor efficiency

Regarding the total factor energy and emissions efficiency of industrial sector of Chinese major cities during 2006 and 2010, Table 2 indicates that the north coast area enjoys the highest 5-year average efficiency score of 0.948, followed by the south coast area with the average score of 0.939 and the east coast area with the average score of 0.935. To the contrary, the northwest area suffers the lowest 5-year average efficiency score of 0.549, and the southwest area also evidences a comparatively low average score of 0.701. On average, the total factor efficiency variance is 0.399, and the industrial sector of Chinese cities in the coast area performs best, but that of the cities in the west area worst. The efficiencies of the cities along the middle reaches of the two big rivers (Middle Yangtze and Yellow River area) and the northeast are ranked in the middle.

[Insert Table 2 and Figure 2 here]

Figure 2 illustrates the 5-year average total factor efficiency of industrial sector of 30 Chinese major cities. It can be seen that the efficiency score of Tianjin is highest (0.988), followed by Haikou, Shanghai, Guangzhou, and Shenyang, whose efficiency scores are all above 0.95. These cities (except Haikou) are all economically well-developed cities in China and thus evidence better total factor efficiency. Although Haikou is not an economically developed region, it economy mainly relies on agriculture and tourism, thus its energy consumption and CO_2 emissions are comparatively low, which may also lead to a high total factor efficiency. Including the above 5 cities, there are up to 14 Chinese cities have high total factor efficiency scores which are all above 0.90, and the average efficiency score of them are 0.945. This indicates that during 2006 and 2010, about half of Chinese major cities could have approximately a 5% total factor efficiency increase potential on average in their industrial sector, if these cities operate on the joint frontier of energy utilization, CO_2 emissions, and production technology. On the contrary, there are ten cities suffer low total factor efficiency scores which are all below 0.80, and the average efficiency score of them are 0.604. It means that the industrial sector of these cities could accomplish on average an approximately 40% total factor efficiency increase, if they operate on the production frontier. Among these ten cities, Xining evidences the lowest total factor efficiency (0.448), followed by Guiyang, Yinchuan, Lanzhou, and Nanning, whose efficiency cores are all below 0.60. All these cities are located in the north and south west regions, which are considered the most economically undeveloped areas of China. The non-parametric one-tailed Kruskal-Wallis test is utilized to exam the regional efficiency difference, and the results show that there is statistically significant (at 1% significance level) total factor efficiency difference between the 5 best performed cities (Tianjin, Haikou, Shanghai, Guangzhou, and Shenyang) and the 5 worst performed cities (Xining, Guiyang, Yinchuan, Lanzhou, and Nanning), which indicates that up to 2010, there is still obvious unbalanced and inequitable growth in the nationwide development of China from the perspective of regional industrial total factor energy and emissions efficiency.

[Insert Figure 3 here]

Figure 3 illustrates the efficiency changes of total factor efficiency and the decomposed energy utilization, CO_2 emissions, and production efficiency. It can be seen that, although there are still large efficiency gaps among Chinese cities, the average total factor efficiency of Chinese 30 major cities kept on increasing from 0.737 in 2006 to 0.875 in 2010. In addition, the coefficient of variation (CV) of the total factor efficiencies of these cities decreased from 0.23 in 2006 to 0.18 in 2010, which indicates that the problem of inequitable nationwide development has started to mitigate.

In addition, it can be seen from Figure 3 that, for the industrial sector of major Chinese cities, the average energy utilization efficiency is lower than the average CO_2 emissions efficiency in almost all years during the study period, which indicates that, at the current stage, promoting the performance of energy utilization may lead to a more evident effect in increasing the total factor energy and emissions efficiency of the industrial sector of Chinese major cities.

4.3 Energy utilization efficiency and CO_2 emissions efficiency

According to the efficiency definitions proposed in Section 2, the integrated total factor energy and emissions efficiency can be decomposed into the energy utilization efficiency, CO_2 emissions efficiency, and production efficiency. As illustrated in Figure 3, all of the above decomposed efficiency scores increased from 2006 to 2010, in which the energy utilization efficiency continuously increased for every year during this period. The scores of CO_2 emissions efficiency and production efficiency increased from 2006 to 2007, temporally and slightly decreased in the starting year of 2008's world financial crisis, and then back to the increasing tunnel since 2009. In addition, during the same period, the CVs of both energy utilization efficiency and CO_2 emissions efficiency decreased (from 0.35 to 0.26 for the former, and from 0.23 to 0.15 for the latter), which indicate that, not only form the integrated total factor efficiency perspective but from the decomposed energy and emissions efficiency, the gaps among different Chinese regions has begun to shrink. The decreasing of the regional efficiency differences will play an important role in the nationwide equitable development of China in the future.

Figure 4 shows the average energy utilization and CO_2 emissions efficiency scores of Chinese 30 major cities (grouped in eight economy-geography regions) during 2006-2010. Regarding to the energy utilization efficiency, there are 11 cities performed efficient with unity scores for their industrial sector, in which, 7 cities (e.g., Tianjin and Shanghai) are located in the coast area but only one city (Chongqing) is from the west area. The average energy utilization efficiency scores for all these 30 cities during 2006-2010 varies from 0.199 (Xining) to 1 (Shenyang and Guangzhou etc.), with a mean value of 0.810, which indicates that, if the industrial sector of all these cities operate on the energy utilization frontier, there could be, on average, approximately a 19% efficiency increase and energy saving space for the industrial sector of Chinese major cities.

Regarding to the CO_2 emissions efficiency, there is no city performed efficient in its industrial sector. The highest average efficiency score comes from Haikou and the lowest from Lanzhou, ranging from 0.411 to 0.994. There are also 11 cities have high CO_2 emissions efficiency scores above 0.90 for their industrial sector, in which 5 are the coast area cities and another 5 cities are in the middle reaches areas of Yellow and Yangtze River. The mean value of the CO_2 emissions efficiency scores of all these 30 cities during 2006-2010 is 0.832, indicating that, these 30 cities could, on average, increase their CO_2 emissions efficiency and reduce their CO_2 emissions by approximately 17% in the industrial sector, if these cities all operate on the frontier of CO_2 emissions.

[Insert Figure 4 here]

Figure 5 illustrates the boxplots of the energy utilization efficiency scores of the cities in the eight economy-geography regions of China. It shows that the medians of efficiency scores of four regions are highest (unity scores): the north, east and south coast areas, as well as the middle Yangtze River area. They are higher than the medians of efficiency scores of the middle Yellow River area (0.930), which are followed by the northeast area (0.809) and the southwest area (0.513). The median of efficiency scores of the northwest area (0.375) is the lowest. For the variances of efficiency scores, that of the southwest area is the largest, followed by the middle Yangtze River area and the northwest area. The variances of efficiency scores of the northeast area, the middle Yellow River area, and the south and north coast area are comparatively small. In general, the regional industrial energy utilization efficiency scores of the cities in the coast areas are higher and more concentrated than those of the north area and the river reaches area. However, the regional industrial energy utilization efficiency scores of the cities in the west area are both the lowest and the most divergent in

China. These results indicate that the burdens of promoting industrial energy utilization efficiency and mitigating region-wide growth inequality for the west area cities are much heavier than those on the shoulders of coast area cities in China's further development.

[Insert Figure 5 here]

With regard to the CO_2 emissions efficiency, Figure 6 illustrates a different feature. There is no region have unity median efficiency score, and the median CO_2 emissions efficiency score gap among the eight regions is narrower than that of the energy utilization efficiency score gap, which ranges from 0.712 (northwest area) to 0.951 (south coast area). In addition, the median CO_2 emissions efficiency scores of the north coast and middle Yangtze River areas are comparatively high (above 0.90), but those of the northeast, southwest, and middle Yellow River areas are all below 0.85. It also can be found in Figure 6 that the variance of CO_2 emissions efficiency scores of the northwest area is the largest, followed by those of the middle Yellow River area, the southwest area, and the northeast area. The variances of the remaining four regions are comparatively small. The above results indicate that, including the west area cities, the cities in the middle Yellow River area also shoulder heavy burdens of CO_2 emissions efficiency promotion. Furthermore, the efforts to balance the current inequitable region-wide development in the northeast area also should be paid much more attention.

[Insert Figure 6 here]

According to the 5-year average scores of regional industrial energy utilization efficiency and CO_2 emissions efficiency, we categorize 30 Chinese major cities into four groups through High/Low energy/emissions efficiency cluster (divided by the efficiency medians) as reported in Table 3. It is notable that almost all north coast cities belong to the Double-High efficiency group (with only one exception of Jinan), and all northwest cities belong to the Double-Low efficiency group. In the middle Yellow River area, two cities (Huhehot and Zhengzhou) belong to the Double-High efficiency group; however, the remaining two cities (Xian and Taiyuan) belong to the Double-Low efficiency group. All the cities in the east and south coast areas belong to the High energy efficiency group, in which Shanghai, Haikou and Guangzhou are also in the High emissions efficiency group. In the southwest area, the comparatively economy well-developed cities (Chengdu and Chongqing) belong to the High energy efficiency group, but the other three underdeveloped cities (Nanning, Kunming and Guiyang) still remain in Double-Low efficiency group. The cities in the middle Yangtze River area belong to the Low-High (or High-Low) efficiency group, and none of them could perform best in both energy utilization and CO_2 emissions. The High energy efficiency but Low emissions efficiency indicates that the structure of industrial energy consumption is high carbon intensity, i.e. the percentage of coal consumption in total energy consumption of the industrial sector in those High-Low grouped cities are comparatively higher than that of the Double-High grouped cities. On the contrary, the Low energy efficiency but High emissions efficiency means that the performances of energy consumption and industrial production of those cities are ill, although they may emit comparatively less CO_2 from their industrial sector because they consume less high carbon intensity energy.

[Insert Table 3 here]

4.4 CO_2 emissions efficiency and economic development

Several existing researches on Environmental (or Carbon) Kuznets Curve (EKC or CKC) in China at the regional level has proposed that there exists an inverted-U-shaped relationship between the level of pollutants (e.g., SO_2, NO_x, waste water, and solid waste) or CO_2 emissions and the level of economic development or income [34,35]. That is, environmental pressure increases up to a certain level as economic grows and income goes up; after that certain level, the environmental pressure decreases [36]. The EKC reveals how environmental qualities change as the fortunes of a country or a region change.

In this study, we further investigate the existence of EKC relationship between the regional industrial CO_2 emissions efficiency and the regional economic development and income growth, which are respectively represented by the industrial value added per capita (IVAPC) and regional GDP per capita (GDPPC) of 30 Chinese major cities. Industrial CO_2 emissions efficiency scores are calculated through Model (2) and definition (6), and the data on IVAPC and GDPPC are obtained through our calculation and from China city statistical yearbook [29]. The monetary data have been converted into 2010 constant prices (US$). Following [36] and [37], we propose the following EKC regression model:

$$CO_2E_i = c_i + \beta_1 IVAPC_i + \beta_2 IVAPC_i^2 + \beta_3 IVAPC_i^3 + \varepsilon_i \qquad (8)$$

where CO_2E is the industrial CO_2 emissions efficiency score, subscript i denotes a city, c is the constant, β are the coefficients of the explanatory variables, ε is a random error term.

The regression results from panel least squares cross-section fixed effect method indicate that none of the coefficients of the variables are significant different from zero. Therefore, although a positive coefficient for *IVAPC*, a negative coefficient for its quadratic term, and a positive coefficient for its cubic term are identified, the Environmental Kuznets Curve hypothesis cannot be confirmed between the CO_2 emissions efficiency and the level of industrial value added per capita in the industrial sector of Chinese major cities.

Furthermore, we propose the following EKC regression model which is used to investigate the relationship between the regional industrial CO_2 emissions efficiency and the regional income:

$$CO_2E_i = c_i + \beta_1 GDPPC_i + \beta_2 GDPPC_i^2 + \beta_3 GDPPC_i^3 + \boldsymbol{\eta}\mathbf{z}_i + \varepsilon_i \qquad (9)$$

where CO_2E is the industrial CO_2 emissions efficiency score, subscript i denotes a city, c is the constant, β are the coefficients of the explanatory variables, $\mathbf{z}$ represents the vector of other variables may have influence on the industrial CO_2 emissions efficiency, $\boldsymbol{\eta}$ is the coefficient vector of the other explanatory variables, ε is a random error term. Since the regression here can also be seen as based on time series data, a further extended formal time series empirical analysis on identifying the influencing factor of CO_2 emissions efficiency can be conducted as in the researches of Zhou et al., Wang et al., and Zhu et al. [38-40].

[Insert Figure 7 and Table 4 here]

The panel least squares cross-section fixed effect method is utilized for regression and the result shown in Figure 7 indicates an N-shaped relation between CO_2 emissions efficiency and GDP per capita. As reported in the second column of Table 4, a positive coefficient for *GDPPC* associated with a negative coefficient for its quadratic term and a positive coefficient for its cubic term implies an efficiency increase at the early stage of income growth, which is followed by a stage of efficiency decrease or decelerated efficiency increase, then a further efficiency increase accrues once a certain level of income is reached. As shown in Table 5, all coefficients estimated are significant different from zero with the significance levels of 5%. The R^2 and adjusted R^2 values are high enough, and the D-W value is close to 2 indicating that the residuals have the characteristics of independence. This result confirms the existence of Environmental (Carbon) Kuznets Curve between the CO_2 emissions efficiency and the level of GDP per capita in the industrial sector of Chinese major cities.

According to the characteristics of a cubic equation, the inflection point of the N-shaped EKC can be obtained at the point of *GDPPC*=12052 US$. However, there is no any turning point on this EKC curve, since it is a monotonically increasing curve. This result indicates that the industrial CO_2 emissions efficiency increases with the rising of income in Chinese major cities. In addition, when the *GDPPC* is less than 12052 US$, the efficiency increase will decelerate with the increasing of *GDPPC*, and when the *GDPPC* exceeds 12052 US$, the efficiency increase will accelerate with the increasing of *GDPPC*.

The third column of Table 4 reports another panel least squares fixed effect method based regression, in which a new variable of industrial energy consumption per capita (*ENEPC*) is added. The regression result also reveals an N-shaped relation between CO_2 emissions efficiency and GDP per capita. Similarly, there is no turning point on this EKC curve, and the inflection point can be observed at *GDPPC*=12341 US$.

Based on the results of the above two regressions, we could come to the conclusion that the Environmental (Carbon) Kuznets Curve in the industrial sector of Chinese major cities exist between the level of industrial CO_2 emissions efficiency and the level of GDP per capita, and the efficiency increases with the rising of GDP per capita, especially, when GDP per capita reaches the range of [12052, 12341] US$, the efficiency increase will accelerate.

We consider the possible reason for the N-shaped relation between CO_2 emissions efficiency and GDP per capita as follows. In the early stage of economic development during the latest one or two decades, the energy utilization efficiency in industrial sector significantly increased, which leads to a faster increase in the value-added of industrial enterprises than the increase of industrial energy consumption and related CO_2 emissions. However, during the following period of economic fluctuations and real estate investment booming, a great number of energy intensive industrial projects were approved and established, which leads to a fast recovering of industrial economy but also a tremendous increase in energy consumption and CO_2 emissions in industry. Thus, the promotion process of CO_2 emissions efficiency may be slowed down or even temporally interrupted. Then, when a certain level of income has been achieved and the government has noticed the unsustainability of economic growth based on the uncontrolled energy consumption, stricter environmental regulations and CO_2 emissions control targets were implemented, or even been given priority to in the developed regions, thus the energy consumption based CO_2 emissions efficiency got back to the tunnel of sustained increase.

5. China's regional industrial energy saving and emissions reduction potential

5.1 Energy saving potential

According to the definitions of efficiency measurements proposed in Section 2, the potential of input reduction, desirable output extension, as well as undesirable output reduction can be calculate by utilizing the optimal solutions of Model (2). Figure 9 and 10 respectively illustrate the industrial energy saving potentials and targets of Chinese major cities in eight economy-geography regions during 2006-2010.

[Insert Figure 8 here]

As shown in Figure 8, the total industrial energy saving potential of all 30 Chinese cities is accumulated to 57.89 million tonne of coal equivalent (tce) in 2006, which slightly increased to 59.62 million tce in 2007. After that, it continuously decreased from 55.93 million tce (in 2008) to 41.65 million tce (in 2010). The industrial energy saving potential of cities in the northwest area is the largest, which accounts for approximate 39% of the total energy saving potential of all Chinese major cities during this period. The percentages of the cities in the southwest and northeast areas are about 29% and 14%, which are ranked second and third, respectively, among all eight Chinese regions. The industrial energy saving potentials of the above three regions accounts for more than 80% of that of all Chinese major cities during 2006-2010. In addition, there is no energy saving potential for the industrial sector of the east coast area cities during the same period, because they all exhibit the best energy utilization efficiency compared with other Chinese cities during this period. The percentages of the cities in the remaining two coast areas are also very low (range from 1% to 3%), and the percentages of the cities along the middle river reaches just take about 6% to 8% as well. These results indicate that the cities in the west area will play the most critical role in China's industrial energy saving efforts in the future.

[Insert Figure 9 here]

Figure 9 further illustrates that, although the industrial energy saving potentials of the north and east coast area cities are comparatively low, these regions should also pay much attention on their energy efficiency promotions and energy savings, because their current total industrial energy consumptions and industrial energy saving targets are much higher than other Chinese cities during 2006-2010, thus their industrial energy utilization efficiencies and industrial energy saving efforts will directly and obviously affect the situation of the entire China.

5.2 Emissions reduction potential

Figure 10 and 11 respectively show the industrial CO_2 emissions reduction potentials and targets of Chinese major cities in eight economy-geography regions during 2006-2010. Different form the feature of industrial energy saving potential, Figure 10 firstly illustrates that the total industrial CO_2 emissions reduction potentials of all 30 Chinese major cities significantly decreased from 305.41 million tonnes of CO_2 (tCO_2) in 2006 to 143.48 million tCO_2 in 2010. The most evident decrease happens in the cities of the north coast area (-75%), follow by those of the cities in the middle Yangtze River area (-72%) and the northeast area (-70%). Secondly, it can be seen that the cities in the middle Yellow River area hold the largest 5-year accumulated industrial CO_2 emissions reduction potential (310.11 million tCO_2), which accounts for 30% of the total accumulated industrial CO_2 emissions reduction potential of all Chinese cities. The accumulated industrial CO_2 emissions reduction potentials of cities in the northwest, southwest and east coast areas are all above 100 million tonnes, which also take more than 10% of the total industrial CO_2 emissions reduction potential. Furthermore, the industrial CO_2 emissions reduction potentials of the remaining four regions are below 95 million tonnes tCO_2, and their percentages vary from 4% to 9%. These results indicate that the heaviest burden of industrial CO_2 emissions reduction is laid on the shoulder of the cities in the middle Yellow river area, and the burdens of the cities in the South coast and Middle Yangtze River area are much lighter. In addition, the remaining cities in the northwest, southwest, east and north coast, and northeast areas will shoulder approximately the same and medium industrial CO_2 emissions reduction burdens.

[Insert Figure 10 here]

Figure 11 further shows that, including the cities in the middle Yellow River area, those in the north and east coast areas also could play an important role in China's CO_2 emissions reduction effort, because all of these regions are the largest industrial CO_2 emissions contributors in China during 2006-2010. Thus, the effect of industrial CO_2 emissions mitigation of these three regions could significantly influence the overall effect of China.

[Insert Figure 11 here]

6. China's regional industrial CO_2 emissions abatement cost

In addition to the efficiency evaluation, we further estimate the industrial CO_2 emissions abatement costs of 30 Chinese major cities through Model (3). The relative shadow prices of CO_2 for each Chinese region regarding to the regional industrial value-added are reported in Table 6. As indicated in [11], since the shadow price of CO_2 emissions can be seen as the opportunity abatement cost of CO_2 emissions in terms of industrial value-added, the shadow price represents the marginal abatement cost of CO_2 emissions from industrial sector in different Chinese major cities.

[Insert Table 6 here]

It can be seen from Table 6 that, the arithmetic average shadow price (normal average abatement cost) is 56.61 US$ per tCO_2, and the weighted arithmetic average shadow price (emissions volume adjusted average abatement cost) is 45.81 US$ per tCO_2 for the industrial sector of Chinese major cities during 2006-2010. This price is higher than the current market price of carbon emission trading in the EU, which is 8.12€ per tCO_2 on average in 2012, and that of the previous studies [11], which is 7.2 US$ per tCO_2 during 2001-2010. But it is lower than the shadow price calculated in [41], which is about 73.1 US$ per tCO_2 in 2007. The principle of environmental economics indicates that the marginal abatement cost of CO_2 emissions are negatively related with the total amount of CO_2 emissions, i.e., the amount of CO_2 emissions is higher for a region, its marginal abatement cost is lower. Since we just evaluate the CO_2 emissions from industrial sector at the city level instead of the total CO_2 emissions from the combustion of fossil fuel at the provincial or national level of China, the amount of CO_2 emissions calculated in this study is lower than that in [11], thus the comparatively higher shadow price of CO_2 emissions found in this study is reasonable. In addition, the high shadow price calculated in [41] may derive from the method they applied, that the directional distance function method requires extending the desirable outputs and contracting the undesirable outputs simultaneously.

According to the weighted arithmetic average shadow prices reported in Table 6, the CO_2 emissions abatement cost of industrial sector of Chinese major cities fluctuated with a range from 36.89 to 59.34 during 2006-2010. The highest 5-year average price appears in the east coast area with 170.70 US$, and the lowest price appears in the middle Yellow River area with 6.32 US$. Except the above two regions, the industrial CO_2 emissions abatement costs in the west area are higher than those in the coast area and the river reaches area.

[Insert Figure 12 here]

Figure 12 illustrates the average shadow prices of industrial CO_2 emissions for Chinese 30 cities and the relationship between the industrial CO_2 emissions abatement costs and industrial CO_2 emissions efficiency scores of these cities. It can be found that, in general, there is a positive relationship between the above two variables, indicating that the city with higher industrial CO_2 emissions efficiency will also sustain higher CO_2 emissions abatement cost. Among the industrial sector of 30 Chinese major cities, Hangzhou evidences the highest CO_2 emissions abatement cost, while Haikou has the lowest CO_2 emissions abatement cost. In addition, the CO_2 emissions abatement costs of Hangzhou, Shanghai, Chengdu, Nanchang and Xining are ranked top five among 30 Chinese major cities which are all above 45 US$ per tCO_2, and the CO_2 emissions abatement costs of Yinchuan, Taiyuan, Harbin and Huhehot are all below 5 US$ per tCO_2 and ranked bottom among 30 Chinese major cities.

The large gaps on industrial CO_2 emissions abatement costs between different Chinese regions provide the necessity and possibility for establishing a regional emissions trading system, and through which, an efficient and cost saving CO_2 emissions reduction scheme can be realized at the national level. If such a trading system is brought in Chinese market between different cities, the market price of CO_2 emissions can be set between 6 US$ and 170 US$, according to the average CO_2 abatement costs during 2006-2010.

[Insert Figures 13 and 14 here]

We further illustrate the relationship between CO_2 shadow price and CO_2 emissions efficiency for all 150 observations in Figure 13, in which we could see that the observations can be obviously divided into three groups according to the wide ranged shadow prices. The first group includes the observations whose shadow prices are below 30 US$, and the second group includes the observations whose shadow prices are between 30 US$ and 200 US$. There is a comparatively significant positive relationship between CO_2 emissions abatement cost and CO_2 emissions efficiency in the first group, as seen in the first scatterplot in Figure 14. Furthermore, the third group evidences the highest shadow prices which are above 200 US$. However the relationship between the above two variables in the second and third groups are not significant (see the second and third scatterplots in Figure 14). This result indicates that the hypothesis proposed above that the regions with higher CO_2 emissions efficiency will also evidence higher CO_2 emissions abatement costs is only applicable to the regions with comparatively lower CO_2 shadow prices (below 30 US$ and with an average of 8.8 US$ during 2006-2010 in this study). Thus, to set two different market prices of CO_2 emissions respectively for the cities in the first group (low shadow price group) and the cities in the second and third group (high shadow price group) may lead to a more efficient and cost saving CO_2 emissions trading market in China.

7. Conclusions

Evaluating the industrial energy and emissions efficiency, measuring the industrial energy saving and emissions reduction potential, and estimating the industrial CO_2 emissions abatement cost for Chinese major cities are necessary for identifying the energy utilization and CO_2 emissions performance and efficiency promotion potentials at the regional level, as well as providing policy making supports on emissions abatement cost estimating and other related energy and environmental issues in China. In this study, we apply a newly developed DEA based method to evaluate the regional energy and emissions efficiencies and the energy saving and emissions reduction potentials of the industrial sector of 30 Chinese major cities during 2006-2010. In addition, the shadow prices of industrial CO_2 emissions, i.e., the marginal abatement costs of CO_2 emissions of the industrial sector for these 30 Chinese cities during 2006-2010 are estimated.

The evaluation results show that: (i) Regarding the total factor energy and emissions efficiency, the industrial sector of Chinese cities in the coast area perform best, but that of the cities in the west area perform worst, the cities in the river reaches area and the northeast area are ranked in the middle.

(ii) The average total factor efficiency of Tianjin is highest, and that of Xining is lowest. There is statistically significant efficiency difference between the cost area cities and the west area cities.

(iii) Economically well-developed cities evidence better total factor efficiency, and economically underdeveloped cities suffer worse total factor efficiency. Although, there is still obviously unbalanced and inequitable growth in the nationwide industrial development of China, the problem of inequitable nationwide development has started to mitigate since 2006.

(iv) Regarding the energy utilization efficiency, CO_2 emissions efficiency, and production efficiency, all of them increased during 2006-2010, and the efficiency gaps among different Chinese cities decreased during the same period.

(v) There are 11 cities performed efficient (with unity efficiency scores) in energy utilization, but there is no cities performed efficiency in CO_2 emissions. On average, these 30 Chinese major cities could respectively have an approximately 19% energy utilization efficiency increase space and 17% CO_2 emissions efficiency increase space during 2006-2010, if the industrial sector of these cities operate on the production frontier.

(vi) At the current stage, promoting the energy utilization efficiency will play a more important role in increasing the total factor efficiency of the industrial sector of Chinese cities, and the burdens of promoting energy utilization efficiency so as to mitigate the region-wide growth inequality for the west area cities are much heavier than those on the shoulders of coast area cities.

(vii) The Environmental (Carbon) Kuznets Curve exists in the industrial sector of Chinese major cities between the level of CO_2 emissions efficiency and the level of income, that is the CO_2 emissions efficiency increases at the early stage of income growth, then the increase slows down until a certain level of income is reached, and after that a further accelerated efficiency increase accrues. According to the N-shaped EKC, the inflection point for the industrial emissions efficiency of China (at the city level) is located in the range of 12052 to 12341 US$ of GDP per capita.

(viii) For all 30 Chinese major cities, the total industrial energy saving potential is 41 million tce and the total industrial CO_2 emissions reduction potential is 143 million tCO_2 in 2010. And during the period of 2006-2010, the cities in the northwest area evidence the largest energy saving potential and the cities in the middle Yellow River area hold the largest CO_2 emissions reduction potential.

(ix) The average CO_2 shadow price, i.e., average emissions abatement cost, for the industrial sector of Chinese major cities is 45 US$ during 2006-2010. For the cities whose CO_2 shadow prices are below 30 US$, there exists a positive relationship between the level of CO_2 shadow price and the level of CO_2 emissions efficiency, that is the region with higher CO_2 emissions efficiency will also suffer higher CO_2 emissions abatement cost.

(x) The highest average CO_2 emissions abatement cost (170 US$) appears in the east coast cities and the lowest average CO_2 emissions abatement cost (6 US$) appears in the middle Yellow River area cities. The large gaps on industrial CO_2 emissions abatement costs between different Chinese regions provide a necessity and possibility for establishing a regional carbon emissions trading system so as to achieve an efficient and cost saving carbon emissions reduction scheme in China.

Finally, it should be noticed that the results on DEA based efficiency evaluation, shadow price denoted CO_2 emissions abatement cost, theoretically optimized energy saving and emissions reduction potentials, as well as the shape of Carbon Kuznets Curve and its inflection point identified from the empirical study are all depended on the sample Chinese cities included and their input and output data set, and relied on the efficiency evaluation models we chose. Further research may extend this study in at least four ways: (i) Combining the idea of newly developed non-radial directional distance function with the non-negative shadow pricing Models (2) and (3), so as to overcome the possible overestimating of efficiency levels from the radial directional distance efficiency measures [42]. (ii) Covering a greater number of industrial cities in China and lengthening the time period for evaluation [2] so as to provide a more reliable estimation on the relationship between the environmental pressure and the level of economic development. (iii) A formal time series analysis [39] or panel data analysis of identifying the influencing factors of industrial energy and emissions efficiency should be conducted and more relevant variables should be included for testing, so as to give a more stable and robust empirical results. (iv) The Malmquist or Luenberger productivity analysis [43] can be involved in the study for detecting the energy and emissions productivity change and the causes of productivity change (i.e., efficiency change and technical change) for the industrial sector of each Chinese city.

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Table 1 Descriptive statistics of inputs and outputs for industrial sector of Chinese 30 major cities (2006-2010)

Input and output	Net value of fixed assets of industrial enterprises (billion US$)	Number of employed person of industrial enterprises (thousand persons)	Total energy consumption of industrial enterprises (million tce)	Value-added of industrial enterprises (billion US$)	Total volume of industrial sulphur dioxide emissions (thousand tonnes SO_2)	Total volume of industrial carbon dioxide emissions (million tonnes CO_2)
Mean	19.44	604.55	16.90	16.48	112.84	39.62
Max	119.66	2956.30	58.56	90.44	711.54	116.23
Min	1.30	44.10	0.05	0.98	0.09	0.09
Std. dev.	21.04	592.86	12.08	16.20	114.91	28.02

Table 2 China's regional total factor energy and emissions efficiency of industrial sector

Efficiency	Area	2006		2007		2008		2009		2010		5-year average	
		score	rank	score	rank	score	rank	score	rank	score	rank	score	rank
Total factor efficiency	Northeast area	0.7458	5	0.8107	5	0.7920	6	0.8802	5	0.9274	5	0.8312	6
	North coast area	0.8930	1	0.9333	3	0.9576	1	0.9703	1	0.9841	1	0.9477	1
	East coast area	0.8902	2	0.9409	2	0.9371	3	0.9505	4	0.9577	4	0.9353	3
	South coast area	0.8677	3	0.9505	1	0.9537	2	0.9539	3	0.9695	3	0.9391	2
	Middle Yellow River area	0.7484	4	0.8635	4	0.8552	5	0.8390	6	0.8643	6	0.8341	5
	Middle Yangtze River area	0.7271	6	0.7669	6	0.8849	4	0.9597	2	0.9697	2	0.8617	4
	Southwest area	0.6396	7	0.6911	7	0.7035	7	0.7213	7	0.7501	7	0.7011	7
	Northwest area	0.4829	8	0.4888	8	0.5027	8	0.6002	8	0.6694	8	0.5488	8
	All China's major cities	0.7371	-	0.7924	-	0.8123	-	0.8479	-	0.8755	-	0.8130	-
Energy utilization efficiency	Northeast area	0.7809	5	0.7904	5	0.8164	6	0.8631	6	0.9170	6	0.8336	5
	North coast area	0.9578	2	0.9532	4	0.9812	3	0.9898	3	1.0000	2.5	0.9764	3
	East coast area	1.0000	1	1.0000	1.5	1.0000	1.5	1.0000	1.5	1.0000	2.5	1.0000	1
	South coast area	0.8908	3	1.0000	1.5	1.0000	1.5	1.0000	1.5	1.0000	2.5	0.9782	2
	Middle Yellow River area	0.8263	4	0.9544	3	0.9311	4	0.9076	5	0.9400	5	0.9119	4
	Middle Yangtze River area	0.6452	6	0.6388	6	0.8689	5	0.9737	4	1.0000	2.5	0.8253	6
	Southwest area	0.6310	7	0.6335	7	0.6597	7	0.6578	7	0.6958	7	0.6555	7
	Northwest area	0.4326	8	0.3644	8	0.3802	8	0.4483	8	0.5332	8	0.4318	8
	All China's major cities	0.7539	-	0.7727	-	0.8131	-	0.8385	-	0.8708	-	0.8098	-
CO_2 emissions efficiency	Northeast area	0.7349	5	0.8515	5	0.7925	6	0.9081	5	0.9469	4	0.8468	5
	North coast area	0.8509	2	0.9290	1	0.9460	1	0.9606	1	0.9739	1	0.9321	1
	East coast area	0.8058	4	0.9021	4	0.8937	4	0.9178	4	0.9306	5	0.8900	4
	South coast area	0.8662	1	0.9172	2	0.9225	2	0.9192	3	0.9480	3	0.9146	2
	Middle Yellow River area	0.6807	6	0.7866	6	0.7954	5	0.7817	7	0.8029	8	0.7694	6
	Middle Yangtze River area	0.8339	3	0.9102	3	0.9151	3	0.9566	2	0.9503	2	0.9132	3
	Southwest area	0.6654	7	0.7654	7	0.7684	7	0.8054	6	0.8238	6	0.7657	7
	Northwest area	0.5325	8	0.6257	8	0.6386	8	0.7679	8	0.8200	7	0.6769	8
	All China's major cities	0.7380	-	0.8282	-	0.8283	-	0.8710	-	0.8928	-	0.8316	-
Production efficiency	Northeast area	0.6625	5	0.7900	5	0.7178	6	0.8758	4	0.9195	3	0.7931	5
	North coast area	0.7827	2	0.8823	1	0.9103	1	0.9314	1	0.9568	1	0.8927	1
	East coast area	0.7297	4	0.8414	4	0.8353	4	0.8677	5	0.8851	5	0.8318	4
	South coast area	0.8014	1	0.8688	2	0.8774	2	0.8850	3	0.9208	2	0.8707	2
	Middle Yellow River area	0.6500	6	0.7446	6	0.7469	5	0.7481	6	0.7602	8	0.7299	6
	Middle Yangtze River area	0.7591	3	0.8649	3	0.8727	3	0.9242	2	0.9175	4	0.8677	3
	Southwest area	0.6133	7	0.7150	7	0.7053	7	0.7437	7	0.7655	7	0.7086	7
	Northwest area	0.5344	8	0.5885	8	0.5984	8	0.7205	8	0.7770	6	0.6438	8
	All China's major cities	0.6851	-	0.7799	-	0.7777	-	0.8300	-	0.8550	-	0.7855	-

Table 3 Cluster regional energy utilization and CO_2 emissions efficiency of industrial sector of 30 Chinese major cities (2006-2010)

Efficiency cluster of industrial sector of major cities	High energy utilization efficiency				Low energy utilization efficiency			
High CO_2 emissions efficiency	Shenyang Huhehot Zhengzhou	Tianjin Shijiazhuang Beijing	Shanghai Chengdu	Haikou Guangzhou	Changchun	Jinan Hefei Changsha Nanchang		
Low CO_2 emissions efficiency	Fuzhou	Wuhan	Nanjing Hangzhou Chongqing		Harbin Xian Taiyuan		Nanning Kunming Guiyang	Urumqi Yinchuan Xining Lanzhou
Legend	Northeast area	North coast area	East coast area	South coast area	Middle Yellow River area	Middle Yangtze River area	Southwest area	Northwest area

Table 4 Coefficient estimation of Environmental (Carbon) Kuznets Curve

Variables	Regression 1	Regression 2
c	0.4868***	0.4128***
	(16.957)	(11.046)
	[0.000]	[0.000]
GDPPC	0.1076***	0.0953***
	(9.322)	(7.777)
	[0.000]	[0.000]
$GDPPC^2$	-0.0085***	-0.0071***
	(-6.456)	(-4.701)
	[0.000]	[0.000]
$GDPPC^3$	0.0002***	0.0002***
	(5.363)	(3.727)
	[0.000]	[0.0003]
ENEPC	-	0.0374***
		(3.234)
		[0.0016]
R^2	0.995	0.997
Adj - R^2	0.994	0.996
F	782.174	1029.623
	[0.000]	[0.000]
D-W	1.852	1.894

Note: The values in the parentheses and square brackets are t-Statistic and p-value, respectively. ** and *** indicate the significance levels of 5% and 1%, respectively. D-W is the Durbin-Watson statistic.

Table 5 China's regional CO_2 emissions abatement cost of industrial sector

		Area	2006	2007	2008	2009	2010	mean
Shadow price denoted CO_2 emissions abatement cost ($\$_{2010}$)	Arithmetic average shadow price	Northeast area	17.24	6.20	8.27	10.34	12.24	10.86
		North coast area	10.96	12.77	15.85	18.20	26.50	16.86
		East coast area	171.57	178.74	372.34	203.36	240.34	233.27
		South coast area	51.97	7.35	9.07	29.20	12.21	21.96
		Middle Yellow River area	6.66	4.39	5.37	6.07	17.40	7.97
		Middle Yangtze River area	34.37	4.62	81.00	43.06	84.70	49.55
		Southwest area	36.91	12.76	43.12	136.00	171.97	80.15
		Northwest area	22.16	30.28	35.87	36.21	36.93	32.29
		All China's major cities	43.98	32.14	71.36	60.30	75.28	56.61
	Weighted arithmetic average shadow price	Northeast area	10.91	6.22	8.50	10.82	12.70	9.99
		North coast area	11.49	13.38	16.69	19.40	23.51	16.96
		East coast area	164.72	168.80	287.51	115.09	124.61	170.70
		South coast area	36.36	13.62	16.07	53.42	20.42	27.68
		Middle Yellow River area	6.06	4.36	5.34	5.69	10.12	6.32
		Middle Yangtze River area	17.68	6.34	29.67	20.66	43.16	23.60
		Southwest area	27.39	13.66	27.23	88.88	97.23	54.48
		Northwest area	22.54	32.48	36.88	35.12	34.33	32.83
		All China's major cities	40.86	36.89	59.34	43.48	47.84	45.81

Figure 1 Major cities in eight economy-geography regions of China

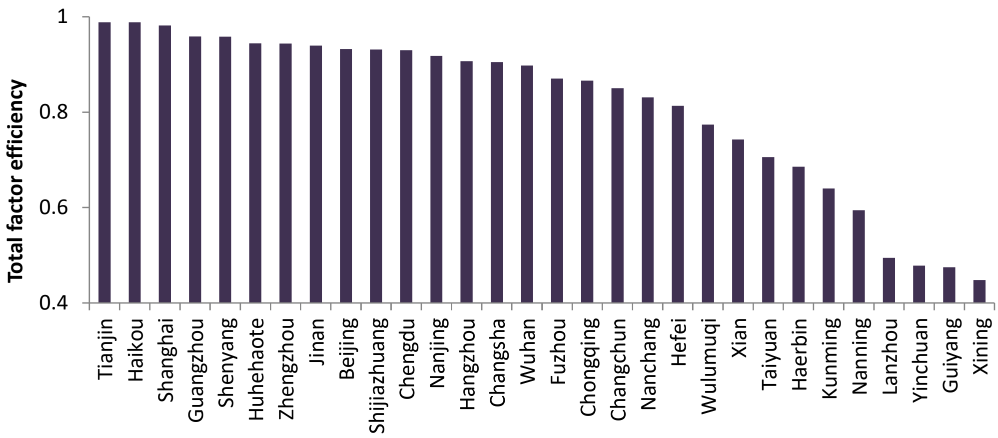

Figure 2 China's regional industrial total factor energy and emissions efficiency (5-year average)

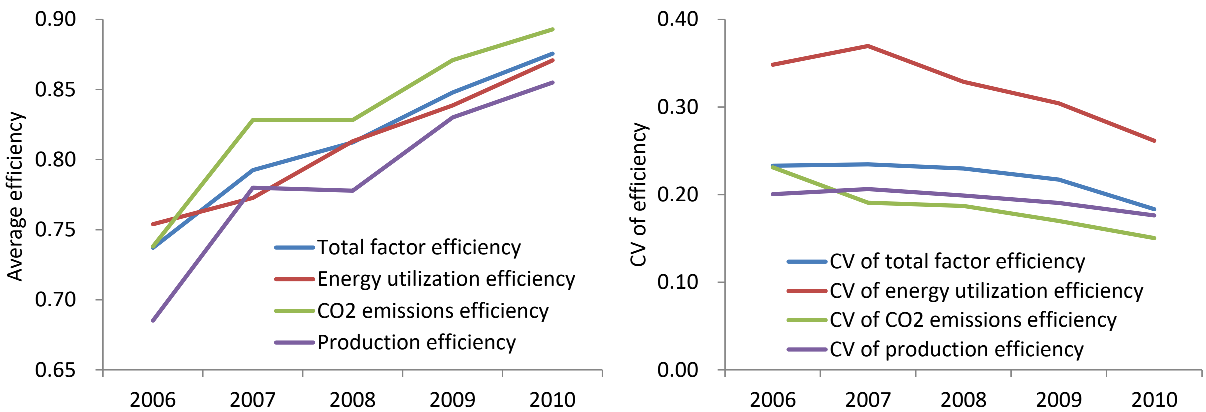

Figure 3 China's regional industrial total factor energy and emissions efficiency changes (2006-2010)

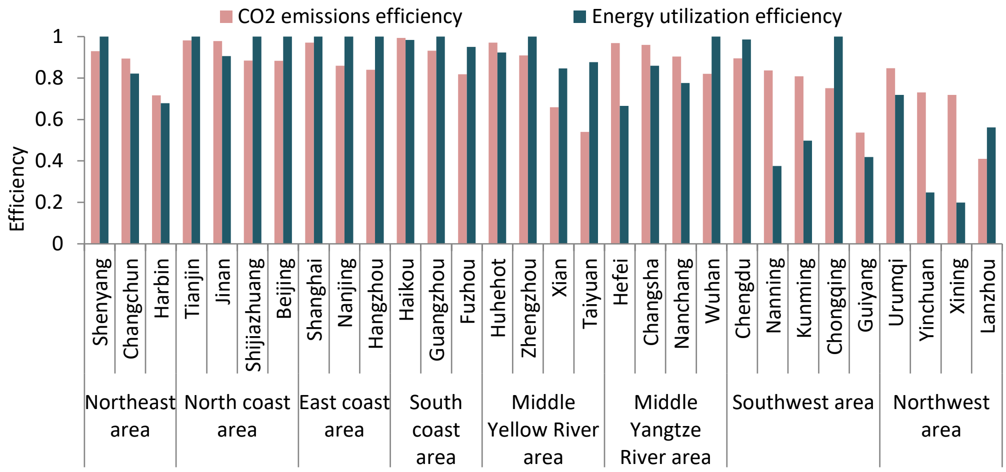

Figure 4 China's regional industrial CO_2 emissions efficiency and energy utilization efficiency (5-year average)

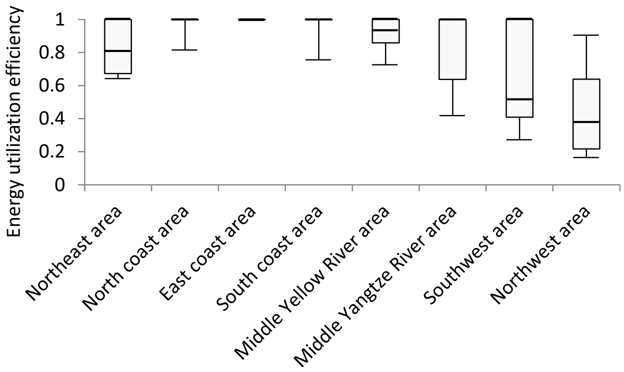

Figure 5 Boxplots of China's regional industrial energy utilization efficiency

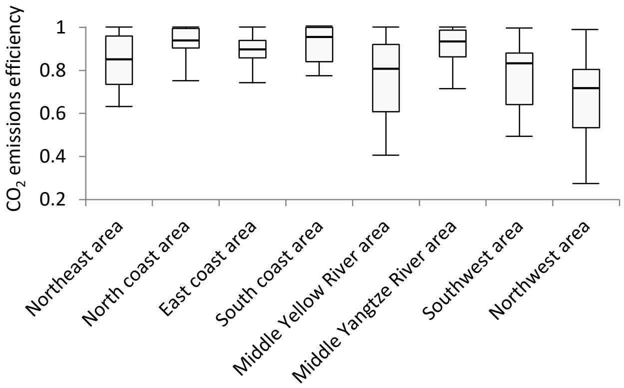

Figure 6 Boxplots of China's regional industrial CO_2 emissions efficiency

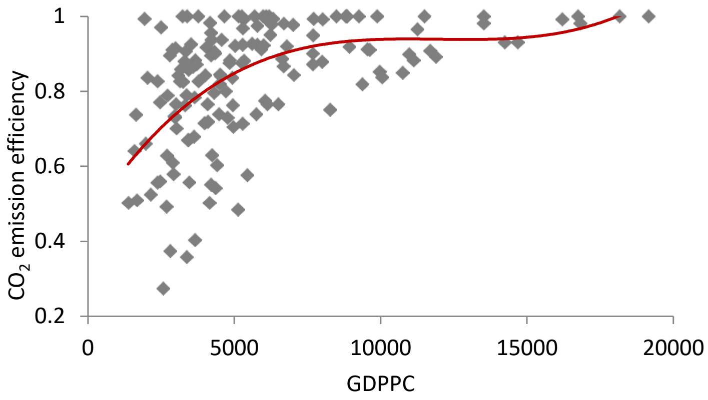

Figure 7 Relationship between industrial CO_2 emissions efficiency and GDP per capita

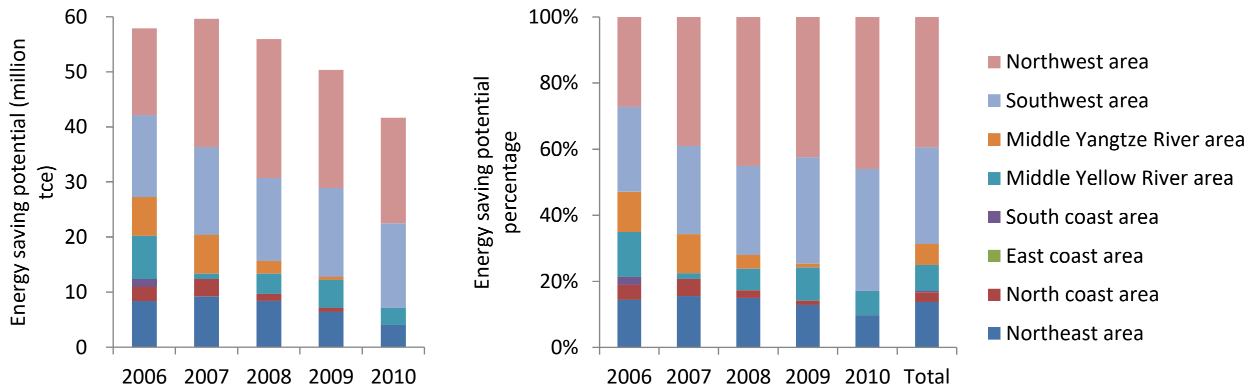

Figure 8 Regional industrial energy saving potential and it percentage for Chinese cities in eight regions

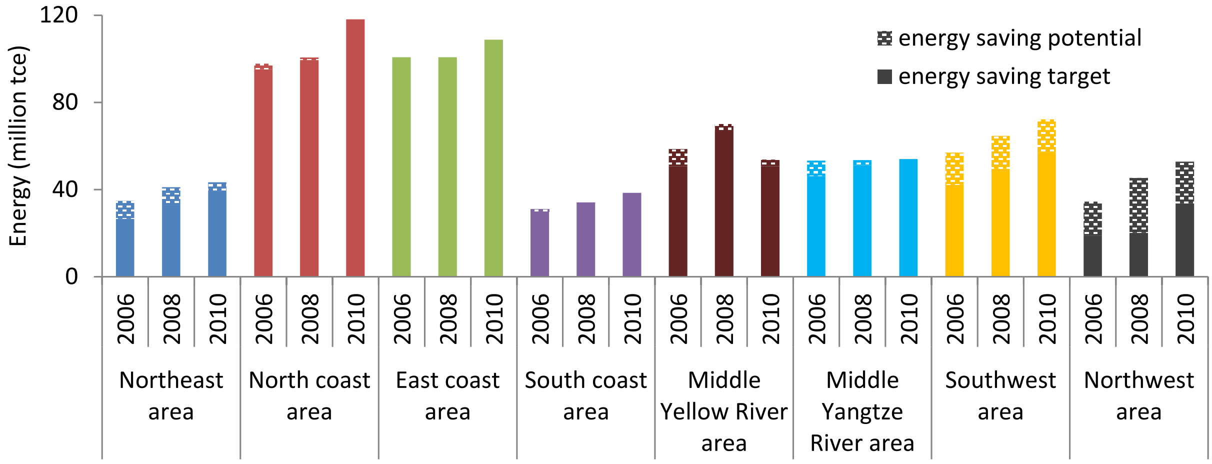

Figure 9 Industrial energy saving potentials and targets for different regions in select years

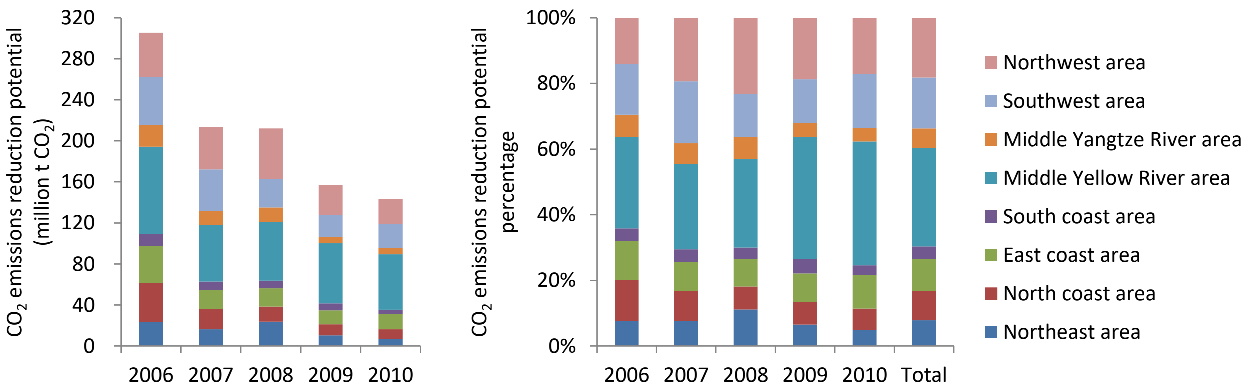

Figure 10 Regional industrial CO_2 emissions reduction potential and it percentage for Chinese cities in eight regions

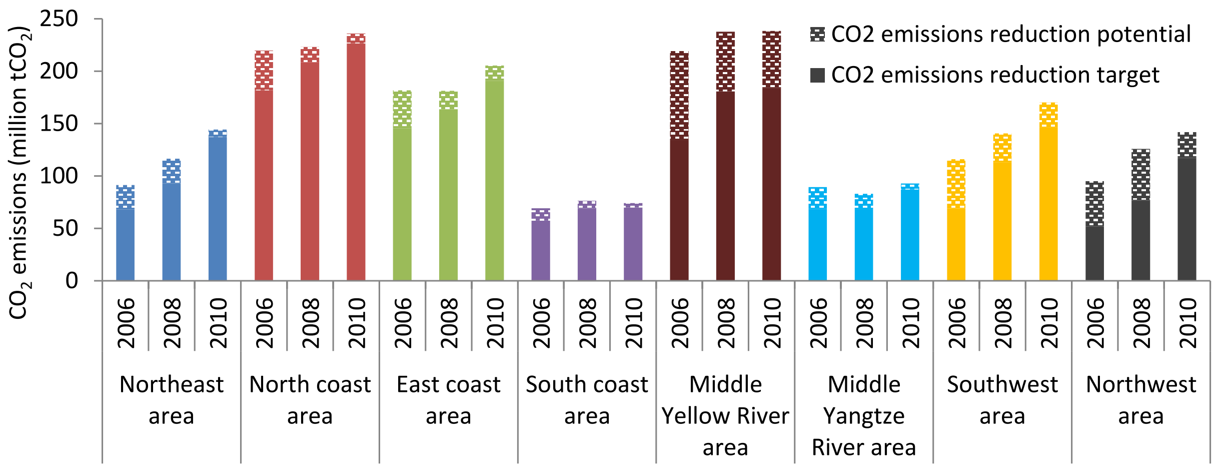

Figure 11Industrial CO_2 emissions reduction potentials and targets for different regions in select years

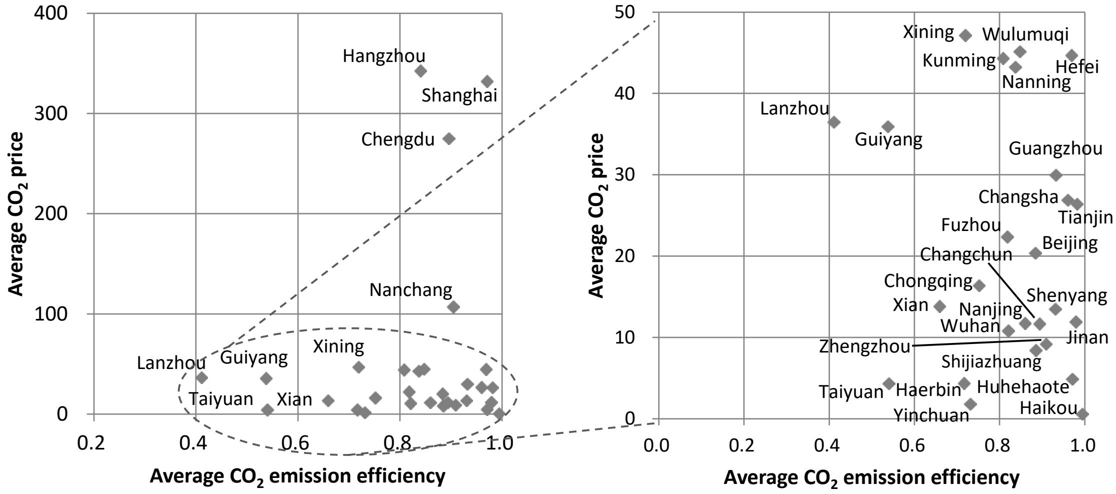

Figure 12 Relationship between average CO_2 shadow price ($\$_{2010}$) and average CO_2 emissions efficiency

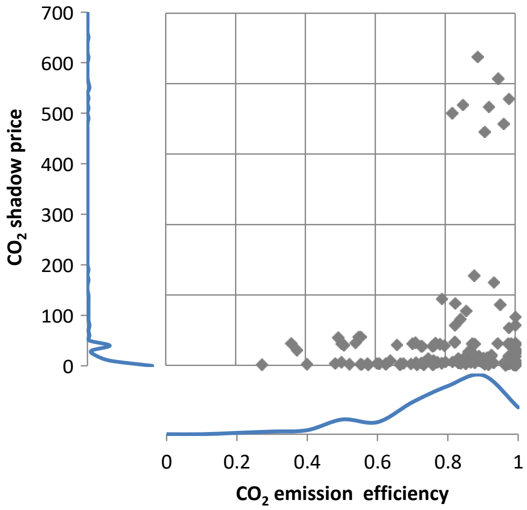

Figure 13 Relationship between CO_2 shadow price ($\$_{2010}$) and CO_2 emissions efficiency for all observations

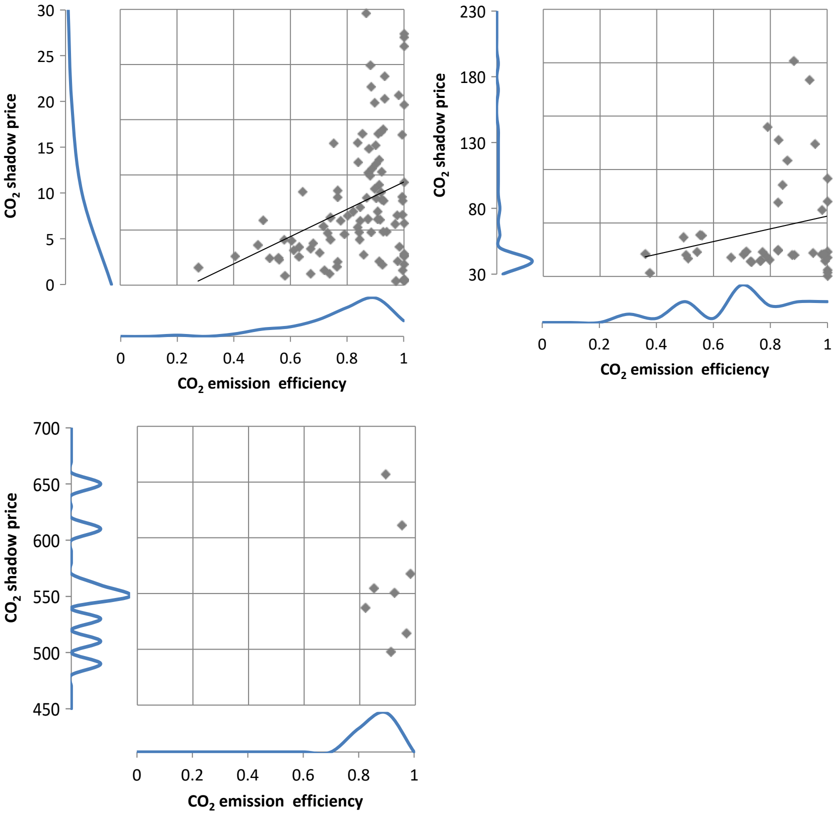

Figure 14 Relationship between CO_2 shadow price ($\$_{2010}$) and CO_2 emissions efficiency for three different price groups