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Original Research

Industrial CO_2 Emissions Efficiency and its Determinants in China: Analyzing Differences Across Regions and Industry Sectors

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Abstract

This paper utilizes industrial CO_2 emissions efficiency as a measure of the low-carbon transformation index and used industrial provincial panel data during 1997-2014 and industrial panel data during 2000-14 based on the modified Super-SBM model with undesirable outputs that measure carbon efficiency levels of different provinces and industrial sectors in China. Differences among sectors and provinces were calculated using the Dagum Gene coefficient and the subgroup decomposition method, and the determinants of carbon efficiency were explored by regression analysis. It turns out that industrial CO_2 emissions efficiency in China is generally low, and it has been steadily improving since 2003. Industrial carbon efficiency shows the unbalanced characteristics (high in eastern areas, low in western areas) and the value of the western regions was overtaken by the central region during the period of the 12th Five-Year Plan. From the perspective of industrial sectors, industrial CO_2 emissions efficiency of lightly polluted industries is significantly higher than that of moderately and heavily polluted industries. In addition, the carbon efficiency of technology-intensive industries and clean production industries as part of industries with light pollution is at an optimal level, while that of some resource-intensive industries and traditional manufacturing industries is relatively low. Both the regional and industrial sectors' Dagum Gini coefficients of industrial carbon efficiency exhibit the tendency of down first, and then up and stable on the whole. The regional disequilibrium problem mainly arises from the gap between the eastern and western regions, and the inter-industry gap is primarily manifested between heavily polluted and lightly polluted industries. The relationship between scale effect and industrial carbon efficiency presents a "U"-type curve. Ownership structure, technological innovation, government environment, and openness degree can all have a positive effect on industrial carbon efficiency, while endowment structure and energy

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consumption structure exert markedly negative effects. However, effects of these factors differ among different areas and different sectors.

Keywords: industrial CO_2 emissions efficiency, modified Super-SBM model with undesirable outputs, Dagum Gini coefficient and subgroup decomposition method

Introduction

Air pollution such as PM10 and CO_2, which in some cities reaches levels that threaten human health, is one of the biggest problems raised by modern life [1-2]. The highest CO_2 amount throughout the past 400,000 years was 320 ppm while it is currently around 385 ppm. Recent studies demonstrate that this increase is mainly caused by rapid urbanization and industrialization instead of the natural cycle of nature [3]. To pursue sustainable development, the "low carbonization" trend has taken shape and carbon emissions reduction has been an increasingly prominent issue facing every country in the world. In China, energy savings and emissions reduction have been the highlight of the national development strategy. To accelerate the green low-carbon development, the Chinese government made it clear in the 13th Five-Year Plan that by 2020 carbon dioxide (CO_2) emissions per unit of GDP will have fallen by 18% compared to 2015, and peaked at around 2030, and the peak should be reached as soon as possible. Industry is the leading part of China's economy as well as the biggest energy consumer and carbon emitter. At present, industrial energy consumption accounted for more than 70% of the total national energy consumption and industrial coal consumption, and carbon emissions from industrial fossil fuels, respectively, accounted for about 50% and 70%. Therefore, the key to achieving a low-carbon economy in China is to optimize the energy consumption structure and improve energy and carbon efficiencies of industry.

During early research an active effort focused on determining the CO_2 emissions efficiency measure index, which is usually measured by the ratio of total CO_2 emissions to a variable. For example, Kaya [4] first defined carbon productivity as the ratio of total carbon emissions to GDP in this period; Zhang et al. [5] believed a more scientific approach would be to measure CO_2 emissions efficiency using industrialized cumulative per capita emissions, per capita GDP emissions, and some new indexes. Obviously, the previous approach used the ratio of CO_2 emissions to a certain index to express carbon efficiency without considering the influence of energy structure and other factors that might replace them. In response, the index should be built in a more comprehensive and appropriate way [6]. Thus, data envelopment analysis (DEA) based on the total factor input-output started to be widely applied in the performance evaluation of carbon dioxide. Some researchers assess the level of carbon efficiency of different countries in the context of the whole world. For example, Zhou et.al. [7] drew upon the DEA model and the Malmquist index to measure the CO_2 emissions efficiencies of 18 countries with the highest CO_2 emissions and investigated relevant influencing factors. Iftikhar et al. [8] measured the carbon efficiencies of the world's 26 leading economies using the SBM method, and found that China, India, and Russia have the greatest potential to improve energy and carbon efficiencies. In addition to the analysis of carbon efficiency at the national level, in recent years some researchers have used the non-parametric DEA model to measure the carbon efficiency of China in different regions or industries. Zhou et al. [9] used the SBM model with undesirable outputs to investigate the efficiencies of industrial carbon emissions in different provinces of China. The industrial CO_2 emissions efficiency across the country showed an overall upward trend with the eastern coastal regions more concentrated than the central and western regions. From an industrial perspective, Wang et al. [10] used the DEA method and BML to further analyze the energy efficiency of carbon emissions of China's industrial sectors under carbon emissions constraints, and found that the level of energy efficiency of light industry is generally higher than that of heavy industry. Meng et al. [11] used the RAM-DEA model to estimate the low-carbon economic efficiency of Chinese industrial sectors and found that although most sectors are not completely efficient, efficiency improved greatly during the period.

Although there are research achievements in this field, most studies have focused on evaluating the level of efficiency and dynamic evolution, and only analyze China's carbon efficiency from a single dimension. However, there is a wide gap in resource structures, technical levels, energy structures, and other aspects across different regions and industries in China. In order to save energy and decrease CO_2 emissions of industry in China, the research effort should focus on the dynamic evolution as well as regional and industrial characteristics and differences. This paper also analyzed influence factors of carbon efficiency in terms of industry and region. According to the result, we also give some detailed policy recommendations in order to facilitate industrial low-carbon economic transformation.

Therefore, this paper attempts to extend the existing studies from the following three perspectives. First, the modified Super-SBM model with undesirable outputs was used to calculate industrial CO_2 emissions efficiency in China from two dimensions of region and industry; second, the Dagum Gini coefficient and subgroup decomposition method was used to analyze the non-equilibrium of regional and industrial carbon efficiencies; and third, the empirical analysis of influencing factors focused on the effect of various factors and heterogeneity in the full sample and sub samples.

Material and Methods

Modified Super-SBM Model with Undesirable Outputs

Existing research mainly uses a parametric or non-parametric approach to calculate efficiency based on the different frontier function estimation method [12]. Most researchers prefer to choose the data envelopment analysis (DEA) model because it doesn't need to assume the production frontier function form [13-14]. Studies have pointed out that the non-radial and non-oriented SBM model is better than the CCR-DEA and BCC-DEA models [15]. The SBM model has been widely used in the efficiency measurement first proposed by Tone [16]. To solve the problem that there are more than one of the most effective decision making units (DMUs), Tone [17] further proposed the Super-SBM model on the basis of the SBM model to sort those DMUs, the values of which are considering that the process of production will produce the undesirable outputs simultaneously, Tone [18] extends the traditional SBM model and constructs the SBM model with undesirable outputs. In order to solve the scheduling problem, some researchers have tried to construct a Super-SBM model with undesirable outputs by imitating Tone's idea [19-20]. However, there are errors in the defined index in their studies, so this paper uses a modified Super-SBM Model with undesirable Outputs introduced by Gómez-Calve et al. [21] to calculate CO_2 emissions efficiency.

Consider a production system with L DMUs and each DMU has three factors: inputs, desirable outputs, and undesirable outputs (CO_2 in this paper). We define the three matrices X, Y^g, Y^b as follows:

$$X=[x_1,\ldots,x_L]\in \mathbb{R}_+^{m\times L},\ Y^g=[y_1^g,\ldots,y_L^g]\in \mathbb{R}_+^{s_1\times L} \text{ and } Y^b=[y_1^b,\ldots,y_L^b]\in \mathbb{R}_+^{s_2\times L}$$

Assume that $X > 0$, $Y^g > 0$, $Y^b > 0$. Then the production possibility set (T) can be defined as:

$$T=\left\{(x,y^g,y^b)\middle| x\geq\sum_{j=1}^{L}\lambda_j x_j, 0\leq y^g\leq\sum_{j=1}^{L}\lambda_j y_j^g, y^b\geq\sum_{j=1}^{L}\lambda_j y_j^b, l\leq e\lambda\leq u, \lambda\geq 0\right\} \tag{1}$$

$\lambda=(\lambda_1,\ldots,\lambda_L)'\in \mathbb{R}_+^L$ is the non-negative intensity vector and $e=(1,\ldots,1)\in \mathbb{R}_+^L$. Parameters l and u determine the return-to-scale assumption. The SBM model – including undesirable outputs for evaluating DMU(X_0, Y_0^g, Y_0^b) – is as follows:

$$\rho^*=\min_{(\lambda,s^-,s^g,s^b)}\left\{\frac{1-\frac{1}{m}\sum_{i=1}^{m}s_i^-/x_{i0}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\sum_{k=1}^{s_2}\frac{s_k^b}{y_{k0}^b}\right)}\right\}$$
$$\begin{aligned} s.t.\ & x_0=X\lambda+s^- \\ & y_0^g=Y^g\lambda-s^g \\ & y_0^b=Y^b\lambda+s^b \\ & s^-\geq 0, s^g\geq 0, s^b\geq 0, l\leq e\lambda\leq u, \lambda\geq 0 \end{aligned} \tag{2}$$

…where the vectors $s^-\in \mathbb{R}_+^m$, $s^b\in \mathbb{R}_+^{s_2}$ respectively correspond to excesses in inputs and bad outputs, and $s^g\in \mathbb{R}_+^{s_1}$ means shortages in good outputs. The objective value satisfies $0\leq\rho^*\leq 1$. $\rho^*=1$ ($s^-=s^b=s^b=0$) means DMU efficient, otherwise the evaluated DMU needs further improvement in the input and output. This fractional program can be solved by transforming it into an equivalent linear programming problem using the Charnes-Cooper transformation [22]:

$$\begin{aligned} [LP]\quad & \tau^*=\min_{(t,\Lambda,S^-,S^g,S^b)}\left\{t-\frac{1}{m}\sum_{i=1}^{m}S_i^-/x_{i0}\right\} \\ s.t.\quad & 1=t+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{S_r^g}{y_{r0}^g}+\sum_{k=1}^{s_2}\frac{S_k^b}{y_{k0}^b}\right) \\ & x_0t=X\Lambda+S^- \\ & y_0^g t=Y^g\Lambda-S^g \\ & y_0^b t=Y^b\Lambda+S^b \\ & S^-\geq 0, S^g\geq 0, S^b\geq 0, \Lambda\geq 0, t>0 \end{aligned} \tag{3}$$

…where $\Lambda=t\lambda, S^-=ts^-, S^g=ts^g, S^b=ts^b$. At this point the solution of the optimization problem is $\tau^*=\rho^*$ which is the industrial CO_2 emissions efficiency value calculated by the SBM model with undesirable outputs.

However, there is a common phenomenon that DMUs have "efficient status" denoted by 1. So it is of importance to discriminate these efficient DMUs. The improved Super-SBM model containing undesirable outputs used for evaluating the SBM-efficient DMUs is as follows. We define the $T\backslash(X_0, Y_0^g, Y_0^b)$ spanned by (X, Y^g, Y^b) excluding (X_0, Y_0^g, Y_0^b) as:

$$T\backslash(x_0,y_0^g,y_0^b)=\left\{(\bar{x},\bar{y}^g,\bar{y}^b)\middle|\bar{x}\geq\sum_{\substack{j=1\\j\neq 0}}^{L}\lambda_j x_j, 0\leq\bar{y}^g\leq\sum_{\substack{j=1\\j\neq 0}}^{L}\lambda_j y_j^g, \bar{y}^b\geq\sum_{\substack{j=1\\j\neq 0}}^{L}\lambda_j y_j^b, l\leq e\lambda\leq u, \lambda\geq 0\right\} \tag{4}$$

The second step is to define a subset $\overline{T}\backslash(x_0,y_0^g,y_0^b)$ of $T\backslash(x_0,y_0^g,y_0^b)$:

$$\overline{T}\backslash(x_0,y_0^g,y_0^b)=T\backslash(x_0,y_0^g,y_0^b)\cap\left\{\bar{x}\geq x_0, \bar{y}^g\leq y_0^g \text{ and } \bar{y}^b\geq y_0^b\right\} \tag{5}$$

The super efficiency value can be obtained by solving the following optimization problem:

$$\delta^* = \min_{\left(\lambda,\bar{x},\bar{y}^g,\bar{y}^b\right)} \left\{ \frac{\frac{1}{m+s_2}\left(\sum_{i=1}^{m} \frac{\bar{x}_i}{x_{i0}} + \sum_{k=1}^{s_2} \frac{\bar{y}_k^b}{y_{k0}^b} \right)}{\frac{1}{s_1}\left(\sum_{r=1}^{s_1} \frac{\bar{y}_r^g}{y_{r0}^g} \right)} \right\}$$

$$\begin{aligned} s.t.\quad & \bar{x} \ge \sum\nolimits_{j=1,\ne 0}^{L} \lambda_j x_j \\ & \bar{y}^g \le \sum\nolimits_{j=1,\ne 0}^{L} \lambda_j y_j^g \\ & \bar{y}^b \ge \sum\nolimits_{j=1,\ne 0}^{L} \lambda_j y_j^b \\ & \bar{x} \ge x_0, \bar{y}^g \le y_0^g, \bar{y}^b \ge y_0^b \\ & \bar{y}^g \ge 0, \bar{y}^b \ge 0, l \le e\lambda \le u, \lambda > 0 \end{aligned} \tag{6}$$

By introducing variable parameters $\phi \in \mathrm{v}^{m}$, $\psi \in \mathrm{v}^{s1}$ and $\gamma \in \mathrm{v}^{s2}$, and

$$\begin{aligned} \bar{x}_i &= x_{i0}(1+\phi_i) \qquad (i=1,...,m) \\ \bar{y}_r^g &= y_{r0}^g(1-\psi_r) \qquad (i=1,...,s_1) \\ \bar{y}_k^b &= y_{k0}^b(1+\gamma_k) \qquad (k=1,...,s_2) \end{aligned} \tag{7}$$

Then put parameters ϕ, ψ into Formula (6) and it can be equivalent to:

$$\delta^* = \min_{(\lambda,\phi,\psi,\gamma)} \left\{ \frac{1+\frac{1}{m+s_2}\left(\sum_{i=1}^{m} \phi_i + \sum_{k=1}^{s_2} \gamma_k \right)}{1-\frac{1}{s_1}\left(\sum_{r=1}^{s_1} \psi_r \right)} \right\} \tag{8}$$

$$\begin{aligned} s.t.\quad & \sum\nolimits_{j=1,\ne 0}^{L} x_{ij}\lambda_j - x_{i0}\phi_i \le x_{i0} \\ & \sum\nolimits_{j=1,\ne 0}^{L} y_{rj}^g\lambda_j + y_{r0}^g\psi_r \ge y_{r0}^g \\ & \sum\nolimits_{j=1,\ne 0}^{L} y_{kj}^b\lambda_j - y_{k0}^b\gamma_k \le y_{k0}^b \\ & \phi_i \ge 0(\forall_i), \psi_r \ge 0(\forall_i), \gamma_k \ge 0(\forall_i), \\ & \lambda_j \ge 0, l \le e\lambda \le u, \lambda > 0 \end{aligned}$$

Similarly, the above fractional program can be solved by transforming it into an equivalent linear programming problem using the Charnes-Cooper transformation:

$$\begin{aligned} [LP] \quad & \delta^* = \min_{(\Lambda,\Phi,\Psi,\Gamma)} \left\{ t + \frac{1}{m+s_2}\left(\sum_{i=1}^{m} \Phi_i + \sum_{k=1}^{s_2} \Gamma_k \right) \right\} \\ s.t.\quad & 1 = t - \frac{1}{s_1}\left(\sum_{r=1}^{s_1} \Psi_r \right) \\ & \sum\nolimits_{j=1,\ne 0}^{L} x_{ij}\Lambda_j - x_{i0}\Phi_i - x_{i0}t \le 0, (i=1,\ldots,m) \\ & \sum\nolimits_{j=1,\ne 0}^{L} y_{rj}^g\Lambda_j + y_{r0}^g\Psi_r - y_{r0}^g t \ge 0, (r=1,\ldots,s_1) \\ & \sum\nolimits_{j=1,\ne 0}^{L} y_{kj}^b\Lambda_j - y_{k0}^b\Gamma_k - y_{k0}^b t \le 0, (k=1,\ldots,s_2) \\ & \Phi_i \ge 0(\forall_i), \Psi \ge 0(\forall_r), \Gamma \ge 0(\forall_k), \\ & \Lambda_j \ge 0, lt \le e\Lambda \le ut, \Lambda \ge 0, t > 0 \end{aligned} \tag{9}$$

…where $\Lambda = t\lambda, \Phi = t\phi, \Psi = t\psi, \Gamma = t\gamma$.

The solution of the optimization problem is δ^*, which is the industrial CO_2 emissions efficiency value calculated by the Super-SBM model with undesirable outputs. This method has the following characteristics: first, it belongs to a DEA model with undesirable outputs; second, it is solved by a super-slack-based measure model; third, it further ranks the efficiency to discriminate between these efficient DMUs.

We need to set constant returns to scale (CRS) or variable returns to scale (VRS) assumption when applying the DEA model. CRS assumption may lower the calculation results. According to the study, when the results of CRS and VRS are different, the results of VRS should be prioritized [23]. As a result, VRS assumption was selected in our research. During existing literature there are mainly four methods including contemporaneous DEA, sequence DEA, window DEA, and global DEA to construct the frontier function, and this paper uses global DEA to measure efficiency.

Difference Analysis Based on Dagum Gene Coefficient and Subgroup Decomposition Method

As a rule, researchers usually utilize coefficient of variation, the Theil index, and the gene coefficient to measure differences. Although the coefficient of variation can indicate overall differences, it should not be decomposed to reflect the inner structure and reveal the origin of differences. And the Theil index is widely used in measuring differences in various groups and reflecting the contribution of each difference to the overall gap by index decomposition. Nevertheless, the Theil index requires each sample group to follow normal distribution in measurement, and each group should be independent and have the same variance. But Dagum [24-25] pointed out that the Theil index still has a great flaw as it does not consider the distribution of the sub-sample in each group and only considers the differences. Gene coefficient is a traditional method for analyzing the differences between each group, but it will be limited in research because it is unable to indicate the contribution of each difference. However, the gene coefficient decomposition method proposed by Dagum not only breaks the limitation in the traditional one but also solves the flaws in Theil index decomposition.

Based on the gene coefficient decomposition method (G), Dagum divided the gap into three parts: 1) contribution of intergroup net value gap (G_w), 2) contribution of intragroup gap (G_{nb}), and 3) contribution of intensity of transvariation (G_t) ($G = G_w + G_{nb} + G_t$). According to the definition of gene coefficient by Dagum, G is calculated as follows:

$$G = \frac{\sum_{i=1}^{n}\sum_{r=1}^{n}\left|y_i - y_r\right|}{2\bar{y}n^2} = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{2\bar{y}n^2} \tag{10}$$

In the equation, k is the divided group number (for example, we divided the whole country into the eastern, central, western, and $k = 3$); n is the total number, with n_j and n_h representing the individual number group j (or h) contained; y_{ji} and y_{hr} represent the industrial carbon efficiencies of group j (or h) or individual i (or r); and y is the average efficiency of the total sample. First of all, the regions are ranked on the basis of the average level before decomposing the gene coefficient as follows (11):

$$\overline{y_h} \leq \cdots \leq \overline{y_j} \leq \cdots \leq \overline{y_k} \tag{11}$$

Second, we decompose the gene coefficient into three parts: $G = G_w+G_{nb}+ G_t$. In the article the equation (12) is the intergroup gene coefficient G_{jj}, and equation (13) is the intragroup gene coefficient G_{jh}; Equation (14) is the intergroup contribution of gap (G_w); Equation (15) is the intragroup contribution of gap (G_{nb}); and Equation (16) represents the contribution of intensity of transvariation (G_t).

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{ji} - y_{jr}\right|}{2\overline{y_j}n_j^2} \tag{12}$$

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{(\overline{y_j}+\overline{y_h})n_j n_h} \tag{13}$$

$$G_w = \sum_{j=1}^{k} G_{jj}P_jS_j \tag{14}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(P_jS_h + P_hS_j)D_{jh} \tag{15}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(P_jS_h + P_hS_j)(1-D_{jh}) \tag{16}$$

Thereunto $P_{j(h)} = n_{j(h)}/n$, $S_{j(h)} = n_{j(h)}\overline{y_{j(h)}}/n\overline{y}$, $j(h) = 1, 2, ..., k$; S_j and S_h separately represent the proportion that the sum of industrial carbon efficiency in group j (or h), accounting for the sum of the total carbon efficiency value and satisfying $\sum_{j(h)=1}^{k} P_{j(h)} = \sum_{j(h)=1}^{k} S_{j(h)} = 1$, $\sum_{j=1}^{k}\sum_{h=1}^{k} P_jS_h = \sum_{h=1}^{k}\sum_{j=1}^{k} P_hS_j = 1$. Because D_{jh} is the absolute ratio of industrial carbon efficiency between groups j and h, we obtain the definition as follows (17):

$$D_{jh} = \frac{d_{jh} - P_{jh}}{d_{jh} + P_{jh}} \tag{17}$$

Thereunto d_{jh} is the difference of industrial carbon efficiency between groups j and h, which is the expectation of the sum of the whole samples that satisfy y_{ji}-y_{hr}>0 in group j and group h; P_{jh} is the expectation of the sum of the whole samples that satisfy y_{ji}-y_{hr}<0 in groups j and h, and we obtain the equations as (18) and (19):

$$d_{jh} = \int_0^{\infty} dF_j(y)\int_0^{y}(y-x)dF_h(x) \tag{18}$$

$$p_{jh} = \int_0^{\infty} dF_h(y)\int_0^{y}(y-x)dF_j(x) \tag{19}$$

In the above equation, F_j (F_h) separately represents the cumulative distribution function of group j (h).

Multiple Factor Regression Model

We utilize regression Equation (20) to examine the relationship between industrial carbon efficiency and its determinants:

$$\begin{aligned} CE_{it} &= \alpha + \beta_1 scale_{it} + \beta_2 scale_{it}^2 + \beta_3 kl + \beta_4 os + \beta_5 ms + \\ &+ \beta_6 es + \beta_7 R\&D + \beta_8 regulation + \beta_9 trade + u_i + v_t + \varepsilon_{it} \end{aligned} \tag{20}$$

… where "i" indicates unit (region or industry) and "t" indicates time (year). We use industrial CO_2 efficiency (CE) as a dependent variable, while *scale, kl, os, ms, es, R&D, regulation,* and *trade* are explanatory variables; u and v represent fixed individual effect and fixed time effect, respectively; and ε is the random error term. The panel data have features of "large N and small T," so there is no need to test the unit root and cointegration. As for the ordinary panel model, the fixed effect (FE) and random effect (RE) models are in place. From the perspective of economic theories, RE is rarely used. However, a proper model needs to be examined and chosen through the Hausman test. Upon testing, both the fixed individual and time-effect models were chosen. Due to limited space we have omitted the testing process.

Variables and Data Sources

Variables and Data Sources for Modified Super-SBM Model with Undesirable Output

In order to investigate the low-carbon effect of China's industry systematically and comprehensively, we constructed a cross-section dimension of panel data from two angles (provinces and industry sectors). We selected 30 provinces in mainland China (except for Tibet due to the absence of relevant energy data) from 1997 to 2014 as well as 35 Chinese industry sectors from 2000 to 2014. All the multi-inputs and multi-outputs data could be available from the China Statistical Yearbook (1998-2015), the China Industrial Statistical Yearbook

(1998-2015), the China Energy Statistical Yearbook (1998-2015), the China Labor Statistical Yearbook (1998-2015), and the economic census. Referring to domestic and international research, this paper chose the input and output indicators as follows. We have already dealt with some variables adjusted from a nominal value to exclude the effects of general price changes during the period of sample observation.

As for the input indicators, capital and labor are typically the two basic elements in studies on efficiency [26]. We choose net value of fixed assets adjusted by price indices of investment in fixed assets and annual average employees as indicators for capital and labor, respectively, based on previous studies [27]. Since the average employees of industry sectors data was missing in 2012, it is estimated by referencing the approach of Cheng's research [28]. In addition, due to the fact that energy consumption is the main source of undesirable output, especially greenhouse gas (CO_2), the industrial energy consumption converted to tons of standard coal equivalent is considered as the third input.

As for the desirable output indicator, there are industrial added value and total gross output value – two methods based on current literature. Most researchers have chosen the former approach [29], while some researchers also have used the total output value of industry as a composite output [30]. we consider that energy consumption in the process of industrial production has the characteristics of industrial intermediate inputs and in view of the integrity of the data, the total industrial output value is finally selected as the proxy variable for desirable output. The producer price index (PPI) is used to adjust the price index.

As for the undesirable output indicators, the statistics of CO_2 are still lacking in China's existing data. According to studies of mainstream literature, we use the method guided by the Intergovernmental Panel on Climate Change (IPCC) [31] to estimate the CO_2 emission data of different provinces and industry sectors in China, focusing on three kinds of fossil fuels: coal, crude oil, and natural gas.

Variables and Data Sources for Regression Model

Based on current literatures on productivity and ecological efficiency, considering the reality in China and the limitation of data availability, this research utilizes eight indexes such as the scale factor (*scale*) and its square term (scale^2), endowment structure (*kl*), ownership structure (*os*), marketing structure (*ms*), energy-consumption structure (*es*), technological innovation (*R&D*), government environmental regulation (*regulation*), and openness degree (*trade*) (Table 1). Also, this paper selects provincial panel data from 1997 to 2014 and industrial panel data in from 2001 to 2014 as cited by the China Statistical Yearbook, the China Industrial Statistical Yearbook, the China Statistical Yearbook on Science and Technology, the China Energy Statistical Yearbook, and the China Statistical Yearbook on the Environment. By analyzing the correlation coefficients of all the explanatory variables, it turns out that the absolute values of the correlation coefficients are below 0.8 while the variance inflation factor (VIF) is less than 10. Therefore, this suggests that there is no multicollinearity between explanatory variables.

Results and Discussion

Industrial CO_2 Emissions Efficiency

This paper uses MATLAB programming to calculate the results of the regional industrial carbon efficiency value of 1997-2014 and the industry sector's carbon efficiency value of 2000-14.

Regional Industrial Carbon Efficiency

At the national level, China's overall level of industrial CO_2 emissions efficiency stays low, but began to rise steadily from 2003 (Table 2, Fig. 1). The calculation results show that the average levels of industrial CO_2 emissions efficiency were 0.198, 0.236, 0.315, and 0.452 during the

Table 1. Definitions of variables and price deflators.

Variables	Unit	Definitions of variables	Price deflator
Scale	10 thousands/ per unit	Ratio of gross output value to enterprises on a national scale	PPI
kl	10 thousands/ per person	Ratio of net fixed assets value to employees on a national scale	PPI
os	%	Ratio of state-owned and state-controlled enterprises' output value to gross output value	/
ms	%	Ratio of large and medium enterprises' output value to gross output value	/
es	%	Ratio of coal consumption to energy consumption	/
R&D	%	Ratio of large and medium enterprises' technological activities employees to whole employees	/
Regulation	Yuan/ton	Logarithm of ratio of charges for pollution discharge fees to pollution emissions (SO_2 and COD)	CPI
Trade	%	Ratio of total import and export trade to GDP	/

9th (1997-2000), 10th (2001-05), 11th (2006-10), and 12th (2011-14) five-year plans. During 1997-2002 the level of carbon efficiency remained unchanged. But since the beginning of 2003, through the impact of the Scientific Outlook on Development Policy, industrial carbon efficiency has gradually increased. Based on the technical effect and structural effect of energy conversion in recent years in China, the efficiency of carbon emissions in the 12th Five-Year-Plan period was significantly higher than that in the previous five-year period.

From the perspective of regional space, the industrial carbon emission efficiencies in the eastern region is higher than those in the central and western regions, and the high-efficiency areas are mainly concentrated in the three major economic circles (the Circum-Bohai Sea, the Yangtze River Delta, and the Pearl River Delta) in eastern coastal areas. Due to natural conditions and historical reasons, prior to the 11th Five-Year-Plan period, Hebei and Liaoning provinces formed an industrial pattern with iron and steel, coal, chemical, and other pollution-intensive industries as leading industries. However, after the 12th Five-Year-Plan period, Hebei and Liaoning played the role of "service" and "rise" in Beijing-Tianjin-Hebei collaborative development. So when the efficiencies of carbon emissions were significantly enhanced in the eastern region, the marginal effect of Hebei and Liaoning were below average, but are still on the rise. The eastern provinces have a multiplier effect on the development of low-carbon industries. The CO_2 emissions efficiencies in the central area and the western

Table 2. Average industrial CO_2 emissions efficiency in Chinese provinces during the five-year plan period.

Region	Province	The 9th five-year period	The 10th five-year period	The 11th five-year period	The 12th five-year period
East	Beijing	0.1860	0.3103	0.4840	0.8516
	Tianjin	0.2050	0.3185	0.5488	0.8247
	Hebei	0.1108	0.1429	0.2148	0.2869
	Liaoning	0.0914	0.1287	0.2140	0.3146
	Shanghai	0.2144	0.3258	0.5570	0.8076
	Jiangsu	0.1855	0.2962	0.5015	0.8573
	Zhejiang	0.1844	0.2686	0.4069	0.5897
	Fujian	0.2047	0.2647	0.3936	0.6623
	Shandong	0.1430	0.2060	0.3453	0.5526
	Guangdong	0.2002	0.3168	0.5159	0.8082
	Hainan	1.1792	0.9491	0.9024	0.9866
Central	Shanxi	0.0958	0.1042	0.1233	0.1557
	Jilin	0.1332	0.1791	0.2649	0.4166
	Heilongjiang	0.1027	0.1094	0.1193	0.1448
	Anhui	0.1378	0.1750	0.2715	0.4557
	Jiangxi	0.1715	0.2074	0.2773	0.4065
	Henan	0.1195	0.1511	0.2429	0.3736
	Hubei	0.1395	0.1568	0.2232	0.4091
	Hunan	0.1315	0.1684	0.2452	0.3870
West	Inner Mongolia	0.1488	0.1511	0.2139	0.2933
	Guangxi	0.1640	0.1802	0.2065	0.3009
	Chongqing	0.1925	0.2776	0.3550	0.6061
	Sichuan	0.1085	0.1469	0.2547	0.3614
	Guizhou	0.1817	0.1742	0.1810	0.2337
	Yunnan	0.1748	0.2059	0.2321	0.2729
	Shaanxi	0.1469	0.1645	0.1976	0.2461
	Gansu	0.1756	0.1793	0.1932	0.2261
	Qinghai	0.2164	0.3282	0.3269	0.3237
	Ningxia	0.3305	0.3026	0.2850	0.2601
	Xinjiang	0.1656	0.1761	0.1485	0.1310
National Average		0.1980	0.2355	0.3149	0.4515

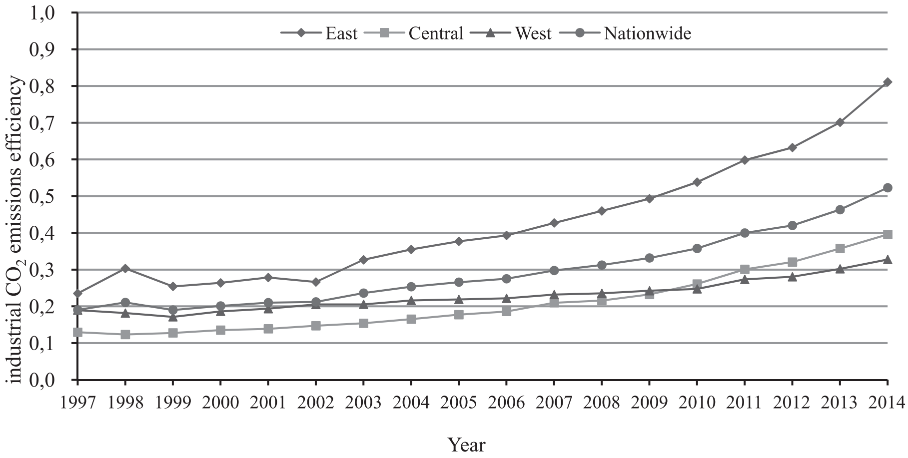

Fig. 1. Industrial CO_2 emissions efficiency tendency of different areas over time.

provinces gradually increase with China's economic development, but the growth rates are still lower than that of the eastern region and differences between them were expanding. This is rooted in the development mode of high pollution and emissions in the central and western regions. It is noteworthy that before the 11th Five-Year-Plan period, the CO_2 emissions efficiency of the western region is higher than the central region because the economic development in the western provinces is relatively backward and with low destruction of ecology and the environment. However, with the promotion of China's western development strategy and the advancement of a well-off society, the CO_2 emissions efficiencies in the western region have not been effectively improved due to the unreasonable energy structure and extensive economic development mode. Thus, the efficiency value in the western area gradually lagged behind other regions in China in the 12th Five-Year-Plan period.

Calculation Results of Industrial Carbon Efficiency in Industrial Sectors

We chose industrial effluent, discharge gas, solid waste, chemical oxygen demand (COD), ammonia nitrogen, sulfur dioxide (SO_2), chimneys, and dust as the indexes for various industrial pollutants to measure pollutant emissions intensity. China's industrial sectors are divided into heavily, moderately, and lightly polluted industries according to the method proposed by Zhao [32]. Data are cited from the China Statistical Yearbook on the Environment.

The results indicate that CO_2 emissions efficiencies of various industries show an upward trend in 2000-14 in China, but obvious heterogenicity still exists (Table 3, Fig. 2). Carbon efficiency in the lightly polluted sectors is observably higher than that in the moderately and heavily polluted sectors. Furthermore, there is a dynamic variation in the comparison of CO_2 emissions efficiency between moderately and heavily polluted sectors. The moderately polluted industries are mainly composed of the traditional manufacturing industries, which were devastated by the financial crisis. And the integrated level of carbon efficiencies in moderately polluted industries were toppled by the heavily polluted industries since 2008 due to the sluggish export trade. And the profit and efficiency decrease in manufacturing enterprises as a result of the sharp drop in external demand. Across different industries, manufacture of Tobacco boasts the highest level (0.753), while the coal mining and washing industry has the lowest value (0.098). In addition, due to the lower energy efficiency, higher economic output and less pollution emissions, the carbon efficiencies of technology-intensive industry (including the manufacture of communication devices, computers, and other electronic equipment and the manufacture of instruments, cultural and official mechanics, etc.) and cleaner production industry (such as cultural, educational, and sports goods manufacturing, gas production and supply, etc.) is palpably higher than that of other industries. Also, some resource-intensive industries (like oil and natural gas mining) and traditional manufacturing (such as papermaking and paper products, manufacturing of non-metal products, the textile industry, etc.) have lower levels of efficiency because of their high energy consumption and CO_2 emissions.

Dagum Gene Coefficient and Decomposition of Carbon Efficiency

Dagum Gene Coefficient and Decomposition on Regional Industrial Carbon Efficiency

According to the above method, our study estimated the gene coefficient of regional industrial carbon efficiency in 1997-2014 and decomposed it based on the eastern, central, and western regions. It indicates that the average Dagum gene coefficient value during the period of sample observation is 0.275, and shows the "falling before rising" tendency (Table 4). The imbalance of carbon efficiencies among regions arises from the inter-regional differences. This indicates that the difference between the eastern

Table 3. Average CO_2 emissions efficiencies of industrial sectors in China, 2000-14.

Heavily polluted industries		Moderately polluted industries		Lightly polluted industries	
Coal mining and washing	0.0979	Oil and natural gas mining	0.1152	Tobacco manufacturing	0.7528
Ferrous metal mining	0.3443	Non-metal mining	0.2156	Textile clothes, shoes, hats manufacturing	0.1944
Non-ferrous metal mining	0.2507	Food manufacturing	0.2151	Furniture manufacturing	0.5542
Agricultural products processing	0.4165	Beverage manufacturing	0.1936	Press and intermediary replication	0.2870
Textile industry	0.1726	Leather, fur, feather manufacturing	0.2568	Cultural, educational, and sports goods manufacturing	0.4936
Papermaking and paper products	0.1300	Wood processing, and wood, bamboo, cane, palm, and straw manufacturing	0.2361	Manufacture of ordinary machinery	0.2609
Oil processing, coking and nuclear fuels processing	0.4995	Manufacture of medicine	0.2081	Manufacture of electric machines	0.3884
Manufacture of chemical materials and products	0.2746	Manufacture of chemical fibers	0.1935	Manufacture of communication devices, computers, and other electronic equipment	0.5186
Manufacturing of non-metal products	0.1418	Manufacture of chemical rubber and plastics	0.1984	Manufacture of instruments, cultural and official mechanics	0.6589
Smelting and rolling process of ferrous metal	0.3756	Manufacture of metal products	0.2432		
Smelting and rolling process of non-ferrous metal	0.3731	Manufacture of special equipment	0.2593		
Production and supply of electricity, power	0.2067	Manufacture of transportation and equipment	0.4003		
Water production and supply	0.2707	Gas production and supply	0.5331		
Average	0.2734	Average	0.2514	Average	0.4565

and central regions is much more obvious prior to the 11th Five-Year-Plan period while the difference between the east and the west is more outstanding during the 11th Five-Year-Plan period. However, the gap between the central and the west is relatively small. In terms of the intra-regional differences, the fluctuation decreases in the eastern region while the tendency increases slowly among the central and western regions. But in general the level of the three major regions tends to be balanced.

Dagum Gene Coefficient and Decomposition on Carbon Efficiency of China's Industrial Sectors

The present study further estimated the gene coefficient of carbon efficiency of China's industrial sectors in 2001-14, and decomposed it based on the three groups: heavily, moderately, and lightly polluted industry. This indicates that the average Dagum gene coefficient of carbon efficiency in our industrial sectors is 0.111, and keeps stable in 2000-14 except in 2008 (Table 5). Besides, inter-group differences prove that the difference between heavily polluted and moderately polluted industries is larger, while the H-M difference is relatively small. As to the intra-group differences, the level of heavily polluted industries group is the highest and fluctuates greatly. On the contrary, the level of the moderately polluted industries group is the smallest and the variability of moderately and slightly polluted industries shows a convergent tendency.

Analysis of Factors Influencing CO_2 Emissions Efficiency

To ensure the accuracy of variable index selection, variables are gradually put forward in the regression equation. Estimation results presented in Table 6 show that the variable coefficients are almost the same in model (1-8), which indicates the stability of estimation results. Take model (8) as an example, where enterprise scale is generally related to carbon efficiency showing U-shape. This result corresponds with the environmental Kuznets curve (EKC) hypothesis that scale expansion in the primary stage mostly depends on high energy consumption and high pollution, which decreases the carbon efficiency level. After the inflection point at 7.723 of scale, a win-win outcome can be achieved. When the industrial enterprise scale reaches a certain level, carbon efficiency will be improved markedly. However, its effect is limited in terms of small coefficient value and this means the level of positive scale effect should be improved. Endowment structure (*kl*) has a significant

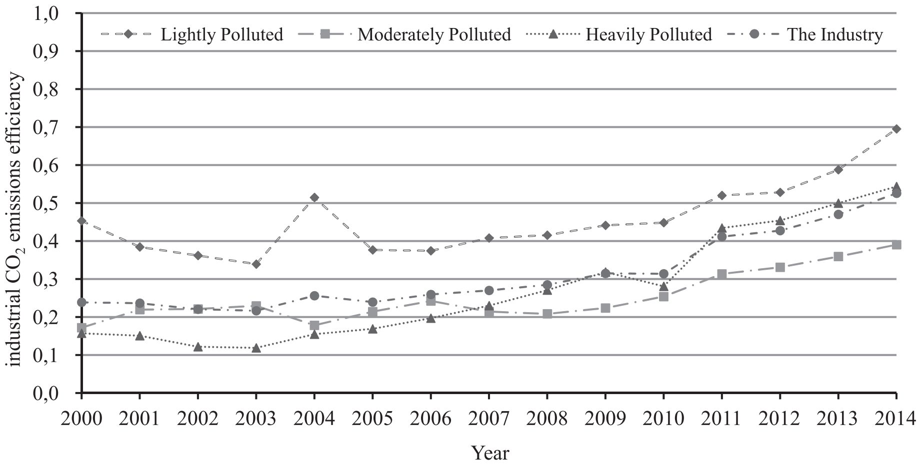

Fig. 2. Industrial CO_2 emissions efficiency tendencies of different industries, 2000-14.

but negative coefficient at the 1%significance level. The rise of *kl* means the exchange of economic structure from labor-intensive industries to capital-intensive industries, which are mostly pollution-intensive industries, leading to the decline of carbon efficiency. This result is in good agreement with the study by Li et al. [33]. Ownership structure (*os*) has a statistically significant and positive effect, which means areas with more state-owned enterprises are more willing to undertake social responsibility, and government can carry out environmental protection and resource conservation systems in a more efficient way. Marketing structure (*ms*) coefficient is negative, but the conclusion is unstable. Energy-consumption structure (*es*) has a negative effect on carbon efficiency significantly, which indicates that it is in urgent need of changing the consumed composition

Table 4. Dagum gene coefficient and decomposition on regional industrial carbon efficiency in China.

Year	G (General)	Intra-regional differences			Inter-regional differences			Contribution date (%)		
		East (E)	Central (C)	West (W)	E-C	E-C	C-W	Intra-region	Inter-region	Intensity of transvariation
1997	0.2774	0.3651	0.1142	0.1860	0.3278	0.2999	0.2126	32.84	42.24	24.92
1998	0.3447	0.4723	0.0964	0.1381	0.4472	0.3745	0.2041	32.32	54.55	13.13
1999	0.2624	0.3482	0.0893	0.1121	0.3584	0.2851	0.1669	30.67	55.74	13.59
2000	0.2602	0.3280	0.0987	0.1395	0.3506	0.2804	0.1783	30.72	53.46	15.82
2001	0.2690	0.3252	0.1065	0.1540	0.3637	0.2889	0.1878	30.50	53.84	15.66
2002	0.2341	0.2408	0.1203	0.1655	0.3205	0.2456	0.1939	29.09	51.40	19.51
2003	0.2700	0.2913	0.1206	0.1533	0.3823	0.2959	0.1785	28.78	60.00	11.22
2004	0.2659	0.2681	0.1221	0.1578	0.3803	0.2950	0.1762	27.93	62.64	9.43
2005	0.2626	0.2576	0.1217	0.1477	0.3748	0.3041	0.1594	27.14	64.29	8.57
2006	0.2544	0.2226	0.1269	0.1387	0.3696	0.3065	0.1539	25.12	66.87	8.01
2007	0.2520	0.2003	0.1419	0.1376	0.3574	0.3173	0.1557	23.88	66.21	9.91
2008	0.2651	0.2068	0.1271	0.1374	0.3781	0.3435	0.1514	23.04	67.55	9.41
2009	0.2737	0.2084	0.1587	0.1479	0.3749	0.3564	0.1655	23.42	66.25	10.33
2010	0.2825	0.2040	0.1540	0.1627	0.3656	0.3834	0.1803	22.79	66.79	10.42
2011	0.2826	0.1868	0.1619	0.1782	0.3542	0.3879	0.2025	22.16	66.73	11.11
2012	0.2842	0.1739	0.1700	0.1771	0.3501	0.3973	0.2163	21.22	68.39	10.40
2013	0.2930	0.1721	0.1663	0.1841	0.3536	0.4121	0.2417	20.58	68.28	11.14
2014	0.3174	0.1894	0.1716	0.2096	0.3803	0.4429	0.2633	20.05	68.36	11.59

Table 5. Dagum gene coefficient and decomposition on carbon efficiency of China's industrial sectors.

Year	G (General)	Intra-group differences			Inter-group differences			Contribution rate (%)		
		Heavily polluted (h)	Moderately polluted (m)	Lightly polluted (l)	H-M	H-L	M-L	Intra-group	Inter-group	Intensity of transvariation
2000	0.1300	0.5462	0.2645	0.4311	0.4663	0.6388	0.5177	25.79	47.49	26.73
2001	0.1300	0.5087	0.3801	0.3397	0.4887	0.5812	0.4598	27.46	42.45	30.09
2002	0.1107	0.3807	0.3600	0.2937	0.4354	0.5426	0.4309	25.95	53.21	20.84
2003	0.0988	0.3131	0.3405	0.2446	0.4030	0.5037	0.3923	25.44	55.69	18.87
2004	0.1015	0.3031	0.1774	0.4455	0.2642	0.5726	0.5160	23.87	64.07	12.06
2005	0.0883	0.2703	0.2697	0.2755	0.2919	0.4235	0.3756	26.47	52.11	21.41
2006	0.0982	0.2639	0.3317	0.2916	0.3211	0.3706	0.3902	28.91	40.60	30.49
2007	0.0813	0.2504	0.2068	0.2923	0.2451	0.3455	0.3604	27.63	47.41	24.97
2008	0.2835	0.2780	0.1622	0.2508	0.2585	0.3122	0.3566	57.86	30.23	11.91
2009	0.0921	0.3623	0.1970	0.2397	0.3158	0.3519	0.3591	28.71	45.16	26.13
2010	0.0743	0.2883	0.1747	0.2032	0.2491	0.3148	0.3176	27.46	45.11	27.43
2011	0.0849	0.3599	0.1688	0.1770	0.3230	0.3146	0.2933	29.05	37.03	33.92
2012	0.0901	0.3716	0.1891	0.1882	0.3398	0.3196	0.2814	29.98	33.41	36.60
2013	0.0950	0.3582	0.2151	0.2397	0.3475	0.3215	0.3108	30.32	33.66	36.02
2014	0.0990	0.3543	0.2480	0.2635	0.3619	0.3296	0.3594	29.75	36.98	33.28

of the energy taking coal as main, encouraging the use of new energy. Technological innovation (*R&D*) has a positive and insignificant coefficient on carbon efficiency. Efficiency will rise by around 1.190% if R&D increases by 1% as theoretically expected. Government environmental regulation (*regulation*) is a significant positive determinant of carbon efficiency at the 5% significance level and carbon efficiency can be increased by a market-based incentive tool such as charges for disposing pollutants. There is a positive and statistically significant correlation between openness degree (trade) and carbon efficiency. The reason is that capital, technology, and advanced managing experiences are introduced into China with the adoption of open policies. Besides, as the worldwide environmental protection wave is on the rise, the environmental factor strengthens the influence on international trade ceaselessly. Moreover, a green trade barrier forces industrial enterprises in our country to transform and promote themselves to optimize carbon efficiency.

Judging from the analytical results, there are distinct differences in carbon efficiencies among sectors and provinces, so our research effort is ongoing as to whether there is any heterogeneity in determinants' effects by sub-sample regression. It is noted that the variable (*regulation*) defined as operating cost of wastewater and waste gas pollution control in the industrial sector because of the lack of discharge data in industrial sectors [34], and the variable of openness degree (*trade*) is excluded for the lack of import and export trade data in industrial sectors. Estimation results are shown in Table 7. Results in different regions are similar to whole sample regression, but some variables have different effects in different areas. First, the positive effect of *os* on carbon efficiency is concentrated in the eastern areas, coefficients are opposite in the central and western areas, and negative effect is more distinct – particularly in the central areas. Combining the estimated results of *regulation* shows that regulation works best in the eastern areas and worst in the central areas, in which case the eastern area is the top-level design leader to promote the environmental protection system. As required by relevant departments, state-owned enterprises set an excellent example on energy-saving and emission-reduction, while western areas with a fragile environment need an environmental protection system at a higher level so that strengthening regulation restriction can protect the environmental bearing capacity. However, limited in technology and talents, western provinces that account for the majority of the state-owned economy will still be balanced between the traditional method of development and environmental production, so the variable of *os* is negative indistinctively. The failure of regulation and negative effect of *os* are shown in central areas where traditional manufacturing industry and the raw materials processing industry are leading industry, indicating that large state-owned enterprises in central provinces with particular political and economic positions built a stable interest relationship with local government and law-enforcement departments for environmental protection. This phenomenon will

Table 6. Regression result of the whole sample>

Explanatory Variables	Explained variable: industrial CO_2 efficiency (CE) based on global DEA method							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Scale	-1.2201***	-0.8970***	-0.7023***	-0.6950***	-0.6919***	-0.5881***	-0.5981***	-0.5437***
	(0.1440)	(0.1300)	(0.1292)	(0.1293)	(0.1282)	(0.1344)	(0.1338)	(0.1356)
$Scale^2$	0.0680***	0.0531***	0.0428***	0.0428***	0.0428***	0.0372***	0.0378***	0.0352***
	(0.0079)	(0.0071)	(0.0071)	(0.0071)	(0.0070)	(0.0073)	(0.0073)	(0.0074)
kl		-0.2672***	-0.2718***	-0.2763***	-0.2808***	-0.2911***	-0.2988***	-0.2997***
		(0.0226)	(0.0218)	(0.0221)	(0.0220)	(0.0223)	(0.0224)	(0.0223)
os			0.2910***	0.3340***	0.3513***	0.3456***	0.3809***	0.3944***
			(0.0470)	(0.0598)	(0.0596)	(0.0594)	(0.0609)	(0.0610)
ms				-0.0777	-0.1011	-0.0942	-0.1046	-0.1193*
				(0.0671)	(0.0671)	(0.0668)	(0.0666)	(0.0667)
es					-0.0980***	-0.0899***	-0.0811**	-0.0804**
					(0.0327)	(0.0327)	(0.0328)	(0.0326)
R&D						1.0050**	0.9761**	1.1895***
						(0.4084)	(0.4066)	(0.4166)
Regulation							0.0235**	0.0234**
							(0.0099)	(0.0098)
Trade								0.0754**
								(0.0344)
constants	5.4182***	4.3206***	3.3146***	3.2880***	3.3288***	2.8454***	2.7570***	2.4771***
	(0.6289)	(0.5627)	(0.5662)	(0.5665)	(0.5620)	(0.5926)	(0.5910)	(0.6024)
Fixed time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Individual effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(within) R^2	0.5890	0.6805	0.7038	0.7046	0.7099	0.7135	0.7168	0.7196
F Statistics	37.03***	52.18***	55.32***	52.90***	51.82***	50.43***	49.10***	47.77***
Group	30	30	30	30	30	30	30	30
Observations	540	540	540	540	540	540	540	540

Notes: * indicates significance at the 10% level; ** indicates significance at 5% the level; *** indicates significance at the 1% level. The value in parentheses is standard error.

make less pollution cost for large state-owned enterprises but also public resource and capital occupied by them. As a result, the higher the degree of administrative resource allocation, the lower the efficiency. Second, the negative effect of *es* on carbon efficiency is more palpable in the central and western areas because industrial development in the central and western areas, contrary to the eastern areas, still depends on traditional energy resources. And the application of new energy needs further enhancement. The comparative advantage of technological innovation (*R&D*) in the east is higher than that in the center and west, which is in agreement with reality. Lastly, the positive effect of *trade* is remarkable only in western areas, which turns out that the western economy with the weakest foundation optimizes its mode of production in a larger space in the process of integration with the international market. Therefore, efficiency will rise by around 0.428 units when trade increases by one point.

From the perspective of results of industry sectors, determinates have various influences. First, it can be seen that the variable of *scale* is the most effective in heavily polluted industries and least obvious in moderately polluted industries. Combined with the variable of *os*, with larger and medium-sized enterprises being concentrated in moderately polluted industries, the higher the carbon efficiency became. This means that we need to expand scale to make full use of scale economy in moderately polluted industries. Second, the variable coefficient of *os* is significantly negative in lightly polluted industries, which is different from what was analyzed before, possibly because there are many cleaning industries with high and new technology included in lightly polluted industries. This economy with the combination of different types of ownership joining in fair competition is favorable to arouse vitality of technical innovation, particularly in scientific and technological medium and small-sized

Table 7. The regression result of sub-sample.

Explanatory Variables	Explained variable: industrial CO_2 efficiency (CE) based on global DEA method					
	Regional Groups			Sector Groups		
	East	Central	West	heavy	moderate	light
Scale	-0.8381***	-0.6059***	-0.4134***	-1.6935***	-0.1024	-0.3733*
	(0.2715)	(0.1670)	(0.1381)	(0.2473)	(0.1793)	(0.2003)
Scale²	0.0438***	0.0384***	0.0292***	0.1033***	0.0015	0.0342***
	(0.0144)	(0.0092)	(0.0078)	(0.0130)	(0.0098)	(0.0100)
kl	-0.0809*	-0.2246***	-0.1152***	-0.6550***	-0.1150*	-0.2907***
	(0.0549)	(0.0354)	(0.0256)	(0.1151)	(0.0951)	(0.0826)
os	0.8942***	-0.1349*	-0.0580	-0.1082	0.1905	-1.3110***
	(0.1144)	(0.0794)	(0.0589)	(0.3684)	(0.2826)	(0.4696)
ms	0.0852	-0.0165	-0.0545	-0.8605**	0.4479*	-0.0676
	(0.1194)	(0.0666)	(0.0728)	(0.4020)	(0.2373)	(0.3365)
es	-0.1645	-0.1494***	-0.0674***	-0.1547**	-0.3107***	0.3637
	(0.1213)	(0.0461)	(0.0198)	(0.0675)	(0.0954)	(0.2251)
R&D	1.6670*	1.2294**	0.8209**	5.5745***	2.2555***	1.1094*
	(0.9799)	(0.6022)	(0.3757)	(1.4753)	(0.6174)	(0.6159)
Regulation	0.0466**	-0.0162	0.0163**	0.0073	0.0561**	0.0388*
	(0.0226)	(0.0106)	(0.0079)	(0.0194)	(0.0247)	(0.0213)
Trade	0.0477	0.0177	0.4276***			
	(0.0532)	(0.1647)	(0.0677)			
Constants	3.6566***	3.0006***	1.8701***	9.0513***	0.1872	1.4646
	(1.2375)	(0.7386)	(0.5896)	(1.2087)	(0.9468)	(1.0401)
Fixed time effect	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
(within) R²	0.8388	0.2395	0.7479	0.6967	0.3751	0.6840
F Statistics	32.21***	39.98***	18.37***	16.19**	4.23***	9.90***
Group	11	8	11	13	13	9
observations	198	144	198	182	182	126

Notes: *indicates significance at the 10% level; **indicates significance at 5% the level; ***indicates significance at the 1% level. The value in parentheses is standard error.

enterprises. Hence a bigger proportion of the state-owned economy will decrease carbon efficiency. Third, the negative effect of the variable *es* is concentrated in heavily and moderately polluted industries. The requirement for traditional energy is low in lightly polluted industries, so the adjustment of energy consumption structure is less effective on industry. The marginal contributions of technological innovation (*R&D*) are in heavily, moderately, and lightly polluted industries by descending order. Lastly, the positive effect of the variable *regulation* is insignificant in heavily polluted industries and are the highest sensitive in moderately polluted industries for the reason that the environmental standard and pollution cost is relatively low for heavily polluted industries. So, government should reinforce environmental control in promoting energy-saving and emission-reduction of heavily-polluting industries.

Conclusions

In this paper, CO_2 emissions efficiency was used to measure low-carbon transformation. Provincial panel-data from 1997 to 2014 and industrial sector panel-data from 2001 to 2014 were selected, and carbon efficiencies were measured based on modificatory Super-SBM model with undesirable output. Differences among sectors and provinces were calculated using the Dagum gene coefficient and subgroup decomposition method. We further analyzed the main determinants by regression analysis on the basis of the above results.

First, from the national perspective, industrial carbon efficiency in our country is generally low, which exhibits a gradually upward trend from 2003. The results of different areas show that carbon efficiency in the eastern areas is palpably higher than the central areas and the western areas, and the western areas are outstripped by the central areas and have lagged behind since the 12th Five-year Plan. The results of different sectors indicate that the carbon efficiency of lightly polluted industries is significantly higher than that of moderately and heavily polluted industries. Technology-intensive industries and cleaning production industries of lightly polluted industries maintain an optimal level, while some resource-intensive industries and traditional manufacturing industries with high energy consumption and a large amount of carbon emissions have lower efficiency. Second, the Dagum gene coefficient of carbon efficiency in industrial areas during the period of sample observation first drops and then rises. The value keeps stable, excluding the coefficient in 2008. Industrial carbon efficiency shows the unbalanced characteristics (high in eastern areas and low in western areas) mainly because of the gap between regions, and the intra-regional differences in three areas are small. Different sectors also have different carbon efficiencies. The carbon efficiency in heavily polluted industries differs greatly from lightly polluted industries. The intra-group difference is the highest in heavily polluted industries and ranges most widely. There is a trend of convergence for moderately and lightly polluted industries. Third, in the determinants regression analysis, the relationship between scale effect and industrial carbon efficiency presents a U-type curve. Ownership structure, technological innovation, government environment, and openness degree can have a positive effect on industrial carbon efficiency, while endowment structure and energy-consumption structure exert a markedly negative effect. However, the effects of these factors differ among different areas and different sectors.

According to the conclusions of the research, the following recommendations are provided. Primarily, goals and policies should be laid out for carbon emission reduction by discretion and adopting to local conditions because of the diversity of carbon efficiency in different areas. In detail, the level of low-carbon economic development in the eastern coastal areas in China can be increased so as to lead the development of western and central areas, particularly by supporting technology and capital and reducing the differences among areas. In addition, it is the U-shape relationship between the scale of industrial enterprises and carbon emission efficiency in China that urges industrial enterprises to strengthen scale advantages to improve the efficiency of energy-saving and emission-reduction by market and government. In terms of market, an environment of both efficiency and fairness should be built, and merging and recombining should be carried out effectively, laggard industries with high energy consumption, severe pollution, and high emissions should be phased out, manufacturing industry with high equipment should be developed rapidly, scale economy should be achieved, and scale diseconomy should be eliminated. In terms of government, the capacity to control the emissions of greenhouse gases should be enhanced, and a series of policies and capital support to realize industrial enterprise development as well as carbon emission reduction should be implemented. Moreover, the innovation and application of low-carbon technology plays a crucial role in the improvement of efficiency of carbon emissions, such as low energy-consuming technologies, clean biotechnologies, and bioremediation technologies. With regard to low energy-consuming technologies, the capability of independent research and development should be gradually increased with the introduction, digestion, and absorption of foreign advanced technologies of low energy consumption, which can reform the traditional heavy industries, such as iron and steel, automobiles, and cement, to improve the efficient utilization of fossil energy. With respect to clean biotechnologies, the enterprise research and development institutions intensify the international technical cooperation to give impetus to the exploitation of renewable energy, including hydro, wind, and solar energy – especially for the utilization of bioenergy. For instance, the application of liquid bio-fuel production technology, biomass gasification technology, and biomass production processing technology contribute to managing organic wastes to bioenergy. With regard to bioremediation technologies, the government should increase financial investment and policy support to encourage the corporate R&D institutes to push forward this research and applications in the biomass industry with the guidance of "sozology." For example, the adoption of biomining in the mining industry has a positive effect in some developed countries. Actually, it is predicted that bioremediation technologies will be beneficial for these industries with lower efficiencies of carbon emissions. Furthermore, the government should promote the capacity to handle control emissions of greenhouse gases and realize industrial enterprise development as well as carbon emission reduction through a series of policies and capital support. Moreover, it is promising to build a green trade system and form a structure of trade focused on technology-intensive products from pollution-intensive products, and make green trade come true.

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