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Original Research

Dynamic and Spatial Character Analysis of Regional Marginal Abatement Costs of CO_2 Emissions from Energy Consumption: A Provincial Aspect

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Abstract

The Chinese government has made a commitment to achieve a 60-65% reduction of CO_2 emissions by 2030 compared with that in 2005. Most provinces are assigned differentiated reduction tasks due to different natural resources endowment, energy consumption structure, and economic developments. Marginal abatement cost (MAC) supplies cost information on regional pollutant reduction processes and should be an important evaluation indicator of policies. In this study, we build a quadratic parametric directional distance function (DDF) to estimate provincial MAC of CO_2 emissions in China during 2000-2015. Linear programming is used to solve the parameter estimation problem. Results are as follows:

1) LP method supplies efficient parameter estimation results and obtains 98.33% reliable MACs during the research period.

2) MAC keeps a growing trend for most provinces in 2000-2015. Especially when China enters the New Normal stage in 2012, this growing trend has been accelerated. These trends reveal that MAC gradually becomes a more important indicator to evaluate emission reduction measurements.

3) From a spatial distribution aspect, positive cluster feature has experienced such fluctuations as "apparent rise→significant decline→close to zero." In this stage, their spatial cluster is close to random distribution state.

Spatial heterogeneity turns to being enlarged, especially among provinces at higher MAC range. These evolutionary trends will have important influence on their carbon reduction measure implementing process. Eastern regions should turn more focus on low-carbon technology innovation to push their low-carbon transformation. For middle and western regions, they should promote their production efficiency

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and obtain more technology spillovers from eastern provinces in the future to stimulate their economic growth and low-carbon transformation.

Keywords: carbon dioxide emissions, marginal abatement cost, linear programming

Introduction

The Chinese government made a commitment to achieve a 60-65% reduction in carbon emission intensity by 2030 compared with that in 2005. Provinces in China are assigned differentiated reduction tasks during the 13th Five-Year Plan (2016-2020). Since 2012, China has entered a New Normal stage in economic development and central government has paid more attention to green development transformation. At the 19th CPC National Congress of China in 2017, President Xi Jin-ping pointed out that China's economy has stepped up from high-speed growth to high-quality growth stage, which means that more focus will be put on development quality improvement in the future. How to realize the carbon reduction target and green development shall gain more and more focus of the society. Under this background, exploring regional reduction potentials and optimizing their reduction path are important subjects for researchers and central government in China. Marginal abatement cost (MAC) of CO_2 emissions can supply much reduction information of the low-carbon transformation process and has been an important assessment indicator before implementing certain abatement measures.

On one hand, China has entered a new era and the principal contradiction for society has evolved. The contradiction is between unbalanced, inadequate development and people's ever-growing needs for a better life. The needs for good ecological environment nowadays contradict with unbalanced, inadequate environmental protection development among provinces. Provinces differ drastically in such terms as economic development, resource endowment, strategic positioning, and environmental protection fund inputs. Therefore, their low-carbon transformation process and emission reduction potentials vary significantly. On the other hand, there exist spatial spillover effects among adjacent provinces in green technology, talents, or investment aspects. Spatial clustering characteristics and dynamic trends should be under consideration. These will influence their carbon reduction policy implementation in order to optimize reduction paths in the future.

Abundant literature has been published in recent years regarding China's low-carbon transformation. Most researchers have studied carbon dioxide emission reduction effects by quantity or intensity indexes to assess low-carbon transformation performance (Han et al. 2017; Wu et el. 2016; Felix et al., 2017) [1-8]. Some conclusions are conducted from CO_2 emission efficiency index aspect [9-10]. As an important evaluation index, MAC can supply enough cost information of emission reduction policy implementation. Moreover, it also supplies economic development quality and reduction potential information. Under this background, MAC has attracted more and more focus from worldwide researchers. Maethee et al. (2014) evaluated the MAC of power industry NO_x emissions of the United States and analyzed its technical reduction potentials [11]. Tao (2017) analyzed the MAC of CO_2 emissions in Korea and simulated possible reduction effects in various scenarios [12]. [13-16] took the United States, India, Brazil, Armenia, and Georgia as samples and researched their MAC features. As the greatest CO_2 emitter in the world, China has made many efforts in reducing CO_2 emissions since 2000. Its emission intensity decreased drastically, by 42% in 2015, compared with that in 2005. However, emissions are still increasing and are close to 30 percent of the world. Many conclusions have been concluded in terms of MAC in China. From industrial aspects, Wu (2017) analyzed crop farming sector's MAC features to optimize the reduction path [17]. Liu (2017) assessed MACs of the cement, thermal power, coal, iron, and steel sectors' CO_2 emissions [18]. Yuan (2011) and Chen (2010) respectively studied the secondary industries' MAC trends [19-20]. Among regional MAC literature, [21-26] analyzed provincial MAC characteristics. Wei (2014) took 104 cities as research samples to evaluate MACs of CO_2 emissions [27]. In the 13th Five-Year Emission Reduction Plan released by the National Development and Reform Commission (NDRC) of China, five kinds of reduction targets are allocated for 31 provinces during 2016-2020: 20.5%, 19.5%, 18%, 17%, and 12%. Differentiated reduction targets are implemented for their various reduction potentials and emission characteristics. Exploring provincial MAC characteristics are of great significance to optimize their reduction paths and give full play to their cost-reduction potentials.

Literature on MAC accounting methods is mainly on three frameworks: specialist investigation, energy economic system analysis, and production model of the supply side. The first framework is based on specialist investigation and it depends on their attitudes toward engineering schemes from a micro view [27]. The second method is based on 3E (energy-environment-economy) system frameworks such as CGE or CEEPA models [28-30]. Many hypotheses are given to build the model and cannot clearly reflect a policy transmission path. The third framework is based on production possibility set description with undesirable outputs. This method can clearly depict a transmission path from production properties under technical and economic constraints.

Upon the above comparisons, the production model of the supply side framework is selected to assess the provincial MACs in this study. [31-34] have studied the shadow price estimation process of pollutants under this framework. The environmental production model (EPM) is defined to describe this framework by many researchers. Parametric and non-parametric forms are both used to analyze MAC. Tu (2009), Liu (2011), and Wu (2017) etc. used non-parametric EPM to estimate MACs [17, 26, 35]. The parametric model has good differential properties and many literatures are conducted to evaluate MACs under this framework [20-22, 27]. Directional distance function (DDF) was proposed by Färe et al. in 2005 to depict EPM as it tries to handle the undesirable outputs by a directional vector $g = (g_y, -g_b)$ [38]. Which form is the best function for DDF? Fukuyamaa and Weber (2008) have argued that quadratic function form is the best choice for its flexible function form and it is often regarded as the approximate second-order solution of an unknown function form [36]. Upon the above conclusions, parameter estimation of the quadratic DDF is the key step to analyzing provincial MAC characteristics during the research period in China.

Current concerns of MAC characteristics are mainly on their dynamic tendency and regional differences research in China. Chen (2016) evaluated provincial differences with the Theil Index [21]. Wei used variation coefficient to analyze MAC differences among cities [25]. When regional differences are considered, regions are usually regarded as independent individuals and their spatial autocorrelations are without consideration. Based upon Tobler (1979), there exist spatial autocorrelations among adjacent regions [37]. Are there spatial spillovers in terms of MAC among adjacent provinces in China? Does spatial autocorrelation phenomenon have a significant effect on their transformation? Answers shall be given in this study.

The literature review above leads to the following conclusions: (1) Directional distance function has been used widely to estimate MAC in a region or country. It has become the standard method. However, current studies only try to estimate regional MAC information and reveal their dynamic changing trends. Less concern is paid on this spatial distribution character analysis of MACs among provinces in China. (2) The research period during current conclusions are often divided according to the Five-Year Periods, such as 2001-2005, 2006-2010, and 2011-2015, because governmental central policies in China are carried out according to these classifications. In this study, we selected one typical year, 2012, as the critical year to divide the research period: 2000-2012 and 2013-2015. The reason is that China's economy entered into the New Normal Stage and the government put more effort into economic structure optimization and low-carbon transformation policies. Thus changing trends and spatial characteristics during 2013-2015 can supply the current low-carbon transformation information of 30 provinces in China.

Upon above analysis, this study contributes to the literature in the following ways: (1) we supply a new aspect to explore provincial reduction potentials and to assess their low-carbon transformation process. The LP method is used to estimate all parameters of DDF and to obtain MAC information during 2000-2015 in China. (2) Moran Index, Moran Scatter Diagram (MSD), and Kernel density function are utilized to analyze their dynamic trends and spatial distribution characteristics among provinces in terms of MAC. These conclusions shall bring more information while implementing emission reduction measures for China.

The remainder of this paper is organized as follows: the second part is a provincial MAC estimation model and character measuring method that also describes data collection sources and index processing methods. The third part gives parameter estimation results and then analyzes detailed dynamic and spatial characteristics among provinces. The final part is the main conclusions and policy implications for China to transform into a low-carbon economy in the future.

Material and Methods

In this section the environmental production model (EPM) is selected to depict the regional production process with desirable and undesirable outputs (Färe et al., 2005) [38]. It is an input output process with multiple inputs and multiple outputs. With this framework, MAC is estimated with its shadow price of undesirable outputs: carbon dioxide emissions. Based on estimation results and kernel density function, Moran index and Moran scatter diagram are used to analyze their dynamic trends and spatial distribution characteristics among provinces.

MAC Estimation Model

EPM is used in this study to obtain provincial MAC during the research period in China. It is proposed by Färe et al. (2005) to depict the environmental production technology of an entity by input-output relations when undesirable outputs are considered [38]. Undesirable outputs are pollutants and they are regarded as the by-products of desirable outputs. Possible production sets $P(x)$ are expressed as follows in Eq. (1), where x is input vector, and (x, b) demonstrates desirable and undesirable output vector which are jointly produced. y represents desirable output and b represents undesirable output. Considering production features, $P(x)$ should satisfy the following properties: (1) Convex, bounded, and closed sets. (2) Desirable outputs are disposable and undesirable outputs are weakly disposable. (3) Two kinds of outputs are jointly produced.

$$P(x) = \{(x, y, b) : x \quad can \quad produce \quad (y, b)\} \tag{1}$$

A direction distance function (DDF) is utilized to describe the environmental production technology.

This DDF depicts the gap degree between the production technologies of a decision-making unit (DMU) with the optimal production technology (production frontier). When distance D is zero, it implies that the DMU has the optimal technology and it is exactly on the production frontier. When D rises, it means the production efficiency of this DMU is lower and the gap degree with the frontier is being enlarged. The gap degree D is depicted as followed in Eq. (2).

$$D(x,y,b:g)=max\left\{\beta:\left(y+\beta g_y,b-\beta g_b\right)\in P(x)\right\} \tag{2}$$

In Eq. (2), $g = (g_y,-g_b)$ is defined as the directional vector to reflect production adjustment quantity in terms of per output. g_y reflects the desirable adjustment quantity per unit and g_b is the undesirable adjustment quantity. β is the production expansion ratio of desirable and reduction multiplier of undesirable outputs of DMU. Under production hypotheses, DDF also satisfies such properties as nonnegative, monotonic decreasing function of y, monotonic increasing function of b and of x, and translation properties. Eq. (2) is taken from the derivatives of both sides and results are as follows in Eq. (3):

$$\frac{\partial y}{\partial b}=-\frac{\partial D(x,y,b:g)/\partial b}{\partial D(x,y,b:g)/\partial y} \tag{3}$$

Marginal abatement cost of undesirable output is as follows in Eq. (4). P_b is the price of undesirable output and P_b is the price of desirable output.

$$P_b=\frac{\partial y}{\partial b}\cdot P_y=-\frac{\partial D(x,y,b:g)/\partial b}{\partial D(x,y,b:g)/\partial y}\cdot P_y \tag{4}$$

Three kinds of inputs are considered: capital (K), labors (L), and energy (E). Desirable output is regional domestic production scale and undesirable output is CO_2 emissions. Under quadratic function form, D_{kt} is as follows in Eq. (5), where t represents the period and k represents the province:

$$\begin{aligned}D_{kt}(x,y,b:g)=&\alpha_0+\alpha_1\cdot K_{kt}+\alpha_2\cdot L_{kt}+\alpha_3\cdot E_{kt}+\alpha_4\cdot y_{kt}+\alpha_5\cdot b_{kt}+0.5\alpha_6\cdot K_{kt}^2\\&+0.5\alpha_7\cdot L_{kt}^2+0.5\alpha_8\cdot E_{kt}^2+0.5\alpha_9\cdot y_{kt}^2+0.5\alpha_{10}\cdot b_{kt}^2+\alpha_{11}\cdot K_{kt}L_{kt}\\&+\alpha_{12}\cdot K_{kt}E_{kt}+\alpha_{13}\cdot L_{kt}E_{kt}+\alpha_{14}\cdot K_{kt}b_{kt}+\alpha_{15}\cdot L_{kt}b_{kt}+\alpha_{16}\cdot E_{kt}b_{kt}\\&+\alpha_{17}\cdot K_{kt}y_{kt}+\alpha_{18}\cdot L_{kt}y_{kt}+\alpha_{19}\cdot E_{kt}y_{kt}+\alpha_{20}\cdot y_{kt}b_{kt}\end{aligned} \tag{5}$$

For all DMUs, optimal estimators for parameters in Eq. (5) should minimize the average deviation degree from the production frontiers and it is to minimize the sum of deviations for all DMUs. It is expressed as Eq. (6). All hypotheses such as nonnegative, monotonic decreasing function of y, monotonic increasing function of b and of x, and translation properties become the constraints of this objective function in Eq. (6). They are shown as H_1-H_5. Based on Färe et al. (2005), Fukyyama et al. (2008), and Chen S.Y. (2010) [20, 36, 38], directional vector g takes (1,–1). As regional domestic output is a monetary unit and its price is taken $P_y = 1$.

$$Min\ Q=\sum_t\sum_k\left[D(x_{kt},y_{kt},b_{kt}:g)-0\right] \tag{6}$$

– H_1: Nonnegative property: $D_{kt}\geq 0$ for all k and t

– H_2: Monotonic increasing with respect to inputs: $\frac{\partial D_{kt}}{\partial K_{kt}}\geq 0$; $\frac{\partial D_{kt}}{\partial L_{kt}}\geq 0$ and $\frac{\partial D_{kt}}{\partial E_{kt}}\geq 0$ forall k and t

– H_3: Monotonic increasing with respect to undesirable outputs: $\frac{\partial D_{kt}}{\partial b_{kt}}\geq 0$ for all k and t

– H_4: Monotonic decreasing with respect to undesirable outputs: $\frac{\partial D_{kt}}{\partial y_{kt}}\leq 0$ for all k and t

– H_5: Translation property: $a_4-a_5=-1$; $a_9=a_{10}=a_{20}$; $a_{14}=a_{17}$; $a_{15}=a_{18}$; $a_{16}=a_{19}$

DynamicTrends of Provincial MACs

As a widely used nonparametric test method, kernel density estimation is often used to estimate an unknown density function [39]. It supplies distribution characteristics directly from the training data and decreases estimation errors resulting from beforehand function form assumptions [40]. In this section, kernel density function is estimated in terms of MAC among provinces to reflect their dynamic trends. For variable z (z_1, z_2,..., z_n), kernel density function is estimated as Eq. (7), where h represents the bandwidth and K(·) represents the Epanechnikov core function:

$$f(z)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{z-z_i}{h}\right) \tag{7}$$

Spatial Cluster Character Measurement

Spatial cluster character is to reveal the spatial autocorrelation degree among all provinces. Global spatial autocorrelation degree can be evaluated by Moran Index (Moran I). Its formula is shown as Eq. (8). In Eq. (8), i and j represent two regions among the n regions, and w_{ij} depicts spatial adjacency relations of the two and all w_{ij} form spatial weight matrix W. For variable z, $\overline{z}$, and s^2 are its mean and variance values. *Moran I* varies at the range of [-1, 1]. When it is greater than zero, it reveals positive spatial autocorrelation character. If it is less than zero, it shows negative spatial autocorrelations globally. When it is close to zero, it means weak spatial autocorrelation. When its absolute value becomes more, there is more spatial cluster phenomenon globally.

$$Moran\ I = \frac{1}{s^2} \cdot \frac{\sum_{i,j=1}^{n} w_{ij}(z_i - \overline{z})(z_j - \overline{z})}{\sum_{i,j=1}^{n} w_{ij}} \tag{8}$$

Spatial Heterogeneity Evaluation Method

Moran scatter diagram (MSD) is widely used to reflect spatial heterogeneity characteristics. As Moran I cannot reflect detailed cluster regions, MSD can solve this problem through a scatter diagram in a Cartesian coordinate system. In MSD, the horizontal axis represents variable x and vertical axis represents its spatial lag value. Four quadrants reveal four types of spatial relations: H-H, L-H, L-L, and H-L. From this aspect, we can conclude their spatial heterogeneity characteristics and evolutionary trends. When a province is in H-H type, it means these provinces and their neighbors all have higher variable values. When it is in H-L type, it has higher variable values while its neighbors are lower values. When provinces are in H-H or L-L types, they have positive spatial character. When they are in H-L or L-H types, they show negative spatial characteristics.

Data Sources and Processing Description

Marginal abatement costs of all provinces in this study are estimated based on "three inputs and two outputs." Data are collected from the China Statistical Yearbook, the China Energy Statistical Yearbook, and the Provincial Statistical Yearbook. There are 34 provincial administrative regions in China. Due to lack of data for Hong Kong, Macau, Taiwan, and Tibet, the remaining 30 provinces are included in this study for exploring their dynamic trend and spatial distribution characteristics. The observation period is from 2000 to 2015. Since 2012, the Chinese central government has been devoted to economic structure optimization and accelerating its low-carbon transformation. Under this background, the research period is divided into two sub-stages: 2000-2012 and 2013-2015. All variables used are processed as follows:

Capital inputs (K). There is no capital stock data released by the Chinese government. In the study, provincial capital inputs are estimated with the approach proposed by Zhang (2004) [41]. The formula is as Eq. (9). K_t and K_{t-1} represent capital stock at periods t and t–1, respectively. I_t is a fixed assets investment scale at year t, and δ is depreciation rate. According to Zhang (2004), δ is equal to 9.6% and the primary capital stock K_0 in 2000 uses his estimation results [41]. To avoid the price fluctuation of years, I_t should be adjusted according to constant price in 2000.

$$K_t = K_{t-1} \cdot (1-\delta) + I_t \tag{9}$$

Labor inputs (L). Average employee scale of a year is used here to reveal provincial labor input scale. $\hat{L}_t$ represents its employee scale at the end of year t, and L is mean value of the two adjacent years. The formula is as follows in Eq. (10):

$$L_t = (\hat{L}_t + L_{t-1}) / 2 \tag{10}$$

Energy inputs (E). In this study, energy inputs of a province are represented by its total energy consumption. Eight energy types are included in this study: coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel oil, and natural gas. Total energy consumption is the sum of the eight energy types. For its physical quantity, they are converted into standard coal equivalent. Conversion factors of the eight energy types are 0.7143 kg/kg, 0.9714 kg/kg, 1.4286 kg/kg, 1.4286 kg/kg, 1.4714 kg/kg, 1.4714 kg/kg, 1.4714 kg/kg, and 1.33kg/m^3.

Desirable outputs (y). Gross domestic product of each province is selected to reveal its economic scale as desirable outputs. To avoid price fluctuations, nominal gross products data are adjusted to the real gross domestic product scale at a constant price (price base year = 2000). Data are from the China Statistical Yearbook (2001-2016).

Undesirable outputs (b). Based on provincial data availability in China, this study chose energy-related carbon dioxide emissions (CO_2) as the undesirable output scale indicator. They are calculated based on the formula given by IPCC (2006) [42] and the formula follows. In Eq. (11), j represents the energy type and λ is their emission coefficient of eight energy types: 2.7716 kg/kg, 3.1350 kg/kg, 2.1476 kg/kg, 2.2678 kg/kg, 2.0306 kg/kg, 2.0951 kg/kg, 2.0951 kg/kg, and 1.6438 kg/kg:

$$b = \sum_{j=1}^{8} E_j \cdot \lambda_j \tag{11}$$

Descriptive statistics of the data on inputs and outputs are presented in Table 1.

Results and Discussion

In this section, MACs are estimates of 30 provinces in China during 2000-2015. Based on the results, dynamic trends and spatial distribution characteristics are analyzed based on research methods in Section 2.

Table 1. Descriptive statistics of input data, output data.

Variables		Units	Obs	Mean	Std. dev.	Max	Min
Inputs	Capital	10^8 Yuan	480	21378	21462	126441	739
	Labor	10^4 persons	480	2467	1650	6620	274
	Energy	10^4 Tons	480	10514	7540	38899	480
Outputs	GDP	10^8 Yuan	480	8575	8476	47420	264
	CO_2	10^4 Tons	480	30551	24054	137579	546

MAC Estimation Results and Effective Test

According to Section 2.1, all parameters in Eq. (5) are estimated in order to obtain provincial MAC information during the research period. According to the estimation method in Section 2.1, estimators of 20 parameters in Eq. (5) are the LP solutions under H_1-H_5 constraints in Eq. (6). In order to obtain solutions convergence in LP, all input and output variables should be standardized at first. Based on Table 1, primary values are divided by their means and standardized variables are identified with suffix ~.MINOS solver in GAMS software, which is used to solve this LP problem for parameter estimations. With data collected in Section 2.5, the optimal parameter estimations are obtained and shown in Table 2.

With the parameter estimation results, 480 distance values are obtained. The efficiency test of this model is carried out with the five constraints (H_1-H_5) of linear programming model in Eq. (6). Results show that there are eight values that violate these constraints. Of them, six values violate non-negative hypothesis (H_1), one violates the third hypothesis (H_3), and one violates the second hypothesis (H_2). The other 472 values satisfy all hypotheses. On the above analysis, the efficiency ratio of this model is 98.33% and estimation results can be used to obtain regional MAC information for 30 provinces of the research period.

From Table 2, five parametric estimates of $\widetilde{E}$, $\widetilde{E}^2$, $\widetilde{K}\widetilde{E}$, $\widetilde{L}\widetilde{E}$, and $\widetilde{E}\widetilde{b}$ are zero. Parameters of the two variables $\widetilde{E}$ and $\widetilde{E}^2$ reveal the direct influence on distance value. The other three variables' parameters indicate indirect effects on distance value whether by capital, labor, or both outputs. Zero reveals that energy input factor has a weak influence on distance values. Furthermore, it has no effect on provincial MAC during this period. Fundamental changes don't happen in Chinese energy consumption structure and coal still occupies more than 60 percent in 2015. This may be the explanation for the zero effects on MACs during 2000-2015. The other two inputs and two outputs variables have significant effects on distance values and MACs during the period. They may influence MACs directly by themselves or indirectly by cross effects. Above all, their potential directions to reduce MACs can be obtained through these significant factors or through energy consumption structure optimization. With Eqs. (3) and (4), MACs are obtained among 30 provinces during 2000-2015. The point interpolation method is used to handle the eight invalid values.

Many estimation results have been concluded of provincial MACs in China and there exist many differences among them. [22] studied MACs of CO_2 among 30 provinces during 2006-2014 and selected 2006 as the base period. Thus, MACs are obtained as fixed price levels of 2006. In this study, 2000 is selected as the base year and MACs of 30 provinces are obtained under this price level. [23] estimated CO_2 marginal abatement costs among 30 provinces during 2000-2012. In this

Table 2. Estimation results for the 20 parameters in DDF (standardized variables).

Parameter	Estimation	Parameter	Estimation	Parameter	Estimation
α_0	0.046	α_7	-0.072	α_{14}	0.163
α_1	0.864	α_8	0	α_{15}	0.118
α_2	0.064	α_9	-0.118	α_{16}	0
α_3	0	α_{10}	-0.118	α_{17}	0.163
α_4	-0.835	α_{11}	-0.104	α_{18}	0.118
α_5	0.165	α_{12}	0	α_{19}	0
α_6	-0.311	α_{13}	0	α_{20}	-0.118

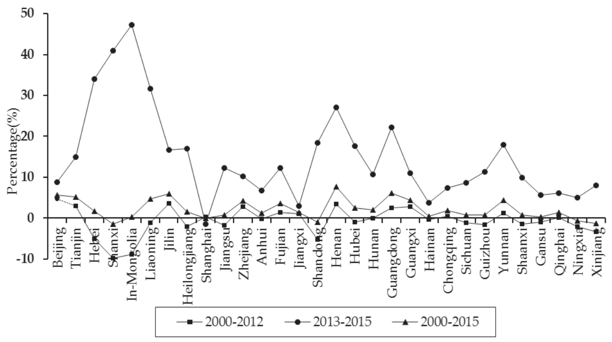

Fig. 1. Annual MAC growth ratios during 2000-2015 for 30 provinces in China.

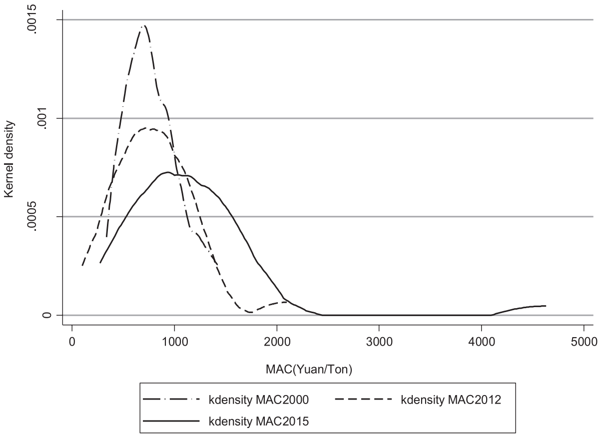

Fig. 2. Kernel density curve of MAC among 30 provinces in 2000, 2012, and 2015.

study, seven energy types were selected to estimate CO_2 emissions, and emissions from cement production are considered for provinces in its study. With comparison, the main differences are from three sources. The first one is research period differences and they selected different base periods as the MACs of provinces. The second source comes from carbon dioxide emission estimation methods. Three energy types (coal, oil, and natural gas) are selected in many researchers and many studies selected more detailed energy types. The other source of MAC estimation results is from parametric and non-parametric EPM processes. Chen (2010) studied these two kinds of estimation results and found significant differences [20].

Since 2012, the Chinese economy has been transformed into the New Normal stage and put more effort into accelerating its low carbon transformation process. Thus the research period in this study is divided into two sub-stages: before 2012 and after 2012. Fig. 1 reveals provincial MAC growth rate fluctuations during 2000-2012, 2013-2015, and 2000-2015. From Fig. 1 we can conclude that almost all provinces are growing in terms of MAC, except some provinces such as Shanxi, Ningxia, and Xinjiang. Compared with the two curves of two sub-stages, the average growth rates in 2013-2015 are significantly higher than those in 2000-2012 for most provinces. Only MAC in Shanghai apparently did not grow during the two stages. Such provinces as Shanxi, Hebei, Liaoning, Inner Mongolia, Shangdong, Henan, and Guangdong grow at the most speeds. For instance, Liaoning has grown annually from -1.11% in 2000-2012 to 31.64% in 2013-2015 in terms of MAC.

Dynamic Trends Among 30 Provinces

Based on equations in Section 2, Fig. 2 describes marginal abatement cost distribution states in three selected years across 30 provinces. From Fig. 2, the kernel density curve of MAC is always a right-skewed distribution, which indicates more provinces located at the right side. Compared with three curves in Fig. 2, it moves downward and right. From 2000 to 2012, this right tendency is not apparent while the downward trend is significant. It reveals that marginal abatement costs did not increase over this time as the variance turns more than before. From 2012 to 2015, the right and downward shift are both significant. This means that mean value increases more apparently and fewer provinces are located near the average value. The right shift reveals that expectation value of MAC is increasing and the downward shift shows the variation keeps a rising trend. The right side of the curve becomes fatter and it means more provinces at the high cost range. For instance, the probability value is rising apparently, where MAC is higher than 1500 Yuan/Ton. These provinces such as Henan, Guangxi, Yunnan, and Zhejiang should be put in first place to arrange their low carbon path arrangement. Exploring the main influential factors is the main direction for these provinces to stimulate their reduction potentials and optimize reduction costs.

Spatial Clusters Characteristics Analysis

Based on Equation (8), Moran I values among 30 provinces are obtained during the research period. They are shown in Table 3. *Moran I* varies greatly and it appears in such trends as "apparent rise → great

Table 3. Moran's I values and their statistical significance test results ($\alpha = 0.05$).

Year	Moran	Z-value	P-value	Sig.	Year	Moran	Z-value	P-value	Sig.
2000	0.2773	2.5568	0.0130	Yes	2008	0.3523	3.1772	0.0050	Yes
2001	0.2730	2.7074	0.0060	Yes	2009	0.2920	2.7746	0.0050	Yes
2002	0.2844	2.8023	0.0090	Yes	2010	0.2273	2.2626	0.0190	Yes
2003	0.2912	2.8306	0.0060	Yes	2011	0.2231	2.1842	0.0270	Yes
2004	0.3559	3.6836	0.0010	Yes	2012	0.1394	1.4892	0.0700	Yes
2005	0.3862	3.5491	0.0010	Yes	2013	0.0849	1.1338	0.1350	No
2006	0.4119	3.7298	0.0010	Yes	2014	0.0449	0.8749	0.2060	No
2007	0.3630	3.2662	0.0040	Yes	2015	0.0110	0.5281	0.2850	No

Table 4. Specific provinces included in the four quadrants in MSD

Year	H-H Type	L-H Type	L-L Type	H-L Type
2000	Anhui, Hunan, Guangxi, Guangdong, Yunan, Shandong, Hubei, Jiangxi, Zhejiang, Shaanxi, Henan, Jiangsu	Shanxi, Guizhou, Shanghai, Chongqing, Hainan, Qinghai, Fujian	Gansu, Ningxia, Mongolia, Xinjiang, Heilongjiang, Liaoning, Tianjin, Hebei, Beijing, Jilin	Sichuan
2012	Anhui, Hunan, Guangxi, Guangdong, Yunnan, Zhejiang, Jiangxi, Fujian, Chongqing, Jiangsu	Shanxi, Guizhou, Shanghai, Shandong, Hubei, Hainan, Shaanxi	Gansu, Ningxia, Mongolia, Xinjiang, Heilongjiang, Liaoning, Tianjin, Hebei, Qinghai	Sichuan, Henan, Beijing, Jilin
2015	Anhui, Hunan, Guangxi, Guangdong, Yunnan, Fujian, Hubei	Shanxi, Guizhou, Shanghai, Shandong, Jiangxi, Shaanxi, Hebei	Gansu, Ningxia, Inner Mongolia, Xinjiang, Heilongjiang, Liaoning, Tianjin, Hainan, Qinghai, Chongqing	Sichuan, Henan, Beijing, Jilin, Zhejiang, Jiangsu

decline → almost close to zero.” In 2000, *Moran I* value is 0.2773 and it grows to 0.4119 in 2006 with 48.5 percent growth totally. From 2007 to 2015, it declines sharply from 0.3630 to 0.0110. It declines more than 50 percent annually.

Moran I is greater than zero during the period and it means a positive spatial cluster character globally. When provinces with higher MACs are adjacent to provinces with higher MACs, they are divided into “H-H” kind. Provinces with lower MACs are adjacent with such provinces with lower MACs and they belong to the “L-L” kind. These two kinds both show positively spatial cluster character. When *Moran I* rises, it means more provinces are of these two kinds (“H-H” and “L-L”). When it comes to decreases, it means fewer provinces are of the kinds and more provinces turns to “H-L” or “L-H” kinds.

According to the significance test results in Table 3, *Moran I* is a significant indicator during 2000-2012 and becomes insignificant during 2013-2015. During 2000-2006, “H-H” and ”L-L” cluster characteristics are intensified greatly. In 2006-2013, positively spatial character is weakened while it is still significant. When China comes into the New Normal stage (after 2012), it declines almost to zero. This means positive spatial character is being offset by a negative spatial cluster trend. More provinces are of “H-L” or “L-H” types. Spatial cluster character gradually turns to spatial heterogeneity character in terms of MAC.

Spatial Heterogeneity Characteristics Analysis

Moran scatter diagram (MSD) is obtained in terms of MAC to reveal provincial heterogeneity character. Fig. 3 shows the MSDs of the three typical years. From Fig. 3a), there are 12 provinces in the first quadrant in 2000 and 10 in the third. The positive spatial clusters occupy more than 70% of the total in 2000. The H-H type is the most province clustering types among the four. There are seven provinces in the second quadrant and 1 in the fourth. In 2012 the four types of provinces are 10, 7, 9, and 4, respectively (Fig. 3b). In Fig. 3c) there are 7, 7, 10, and 6 provinces of the four types in 2015. Provinces in “H-H” types are continuously decreasing while provinces in “H-L” types keep rising during the research period. There is apparent change in the distribution shape of MSD from 2000, 2012 to 2015. Province distribution is close to random distribution state among the 30 provinces in 2015. However, which provinces have happened great changes in terms of MAC? Table 4 may supply enough information for us.

Table 4 gives detailed information of provinces in each type in 2000, 2012, and 2015. In “H-H” type, there is an apparent declining trend in dynamic evolution aspect. Five provinces such as Anhui, Hunan, Guangxi, Guangdong, and Yunnan don’t change and they are always of the first quadrant. Such provinces as Jiangxi, Shaanxi, and Shandong have turned from “H-H” into “L-H” types. Some provinces such as Zhejiang, Henan, and Jiangsu have turned into “H-L” types. In western China, many provinces such as Gansu, Ningxia, Mongolia, Xinjiang, and Qinghai are in the “L-L” type. Provinces Beijing, Tianjin, and Hebei are all in the third quadrant in 2000. In 2012, Hebei turned into “L-H”type and Beijing into “H-L” type. MAC of Beijing is with higher MAC values and lower growth rate in the current stage. Hebei province is with lower MAC level and higher growth rate. During their low carbon transformation process, regional cooperative for Beijing, Tianjin, and Hebei may bring out more opportunities for them in terms of MAC to promote carbon reduction effects in the future.

Western provinces in the third quadrants have the same characteristics in MAC aspect. They have lower MAC values and lower growing rate in this stage. As with most underdeveloped provinces, how to realize their economic growth and low carbon transformation are both important subjects. With “One Belt, One Road” policies being implemented, these spatial cluster provinces may unite together to realize green economic development.

For other regions, a regional cooperative pattern is being formed to take use of their advantages in MAC aspect. For example, Shanghai, Jiangsu, and Zhejiang form the Yangtze River Economic Zone. They have great inter-provincial economic spillovers whether

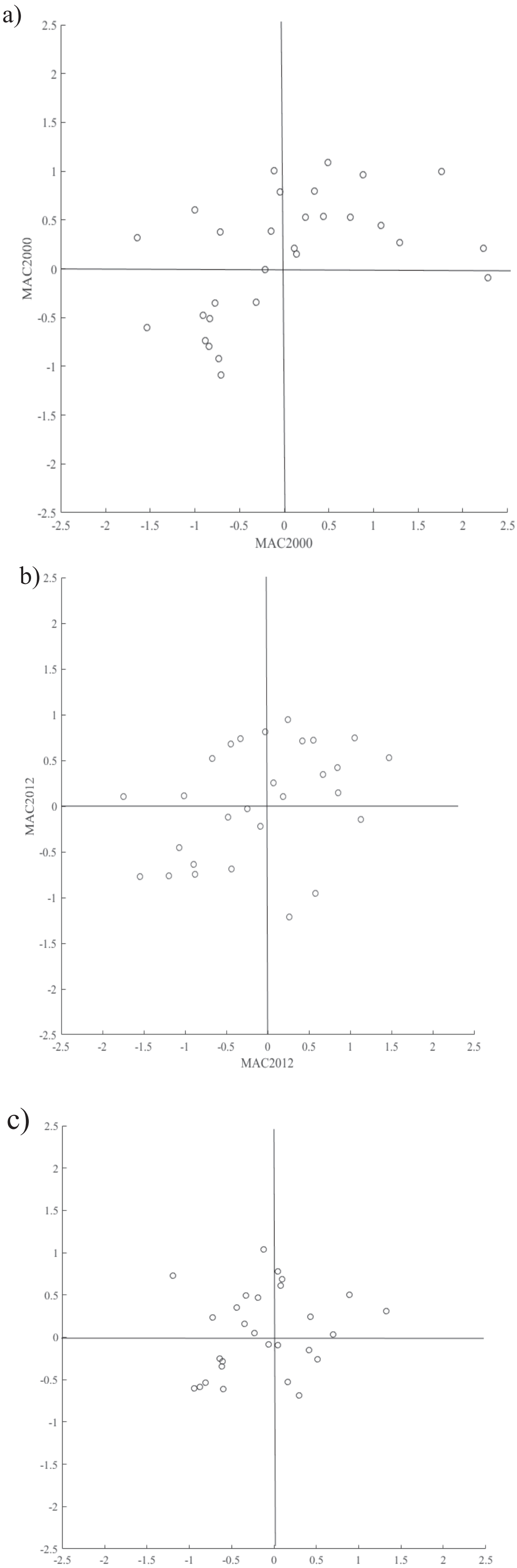

Fig. 3. MSD of MAC among 30 provinces in 2000, 2012, and 2015.

in funds, talents, or technology. However, the three provinces show differentiated MAC evolution trails during the period. Shanghai is of L-H type for its lower MAC and lower growth rate. Jiangsu and Zhejiang are of “H-L” type. Based on parameter estimate results, how to realize cooperatively to give their advantages to the full in reducing MACs is a good subject for them during their economic cooperatives in the future.

Conclusions and Policy Implications

In this paper, we estimate provincial MAC of carbon dioxide emissions in China during 2000-2015 under the parametric environmental production model framework. Dynamic trends and spatial character are analyzed in order to supply detailed information to optimize their low carbon transformation path. Some conclusions and policy implications are obtained as follows.

Main Conclusions

1) Linear programming method is suitable for estimating all parameters of EPM and they supply efficient MAC results. Of the 480 results, 472 values satisfy all five constraints, and efficiency ratio is up to 98.33%. Energy input factor has no direct or indirect effect on MACs. Capital, labor, economic scale, and carbon emissions have direct effects and cross-effects on distance values and MACs. Based on such transmission paths, reduction potentials in terms of MAC should be explored to accelerate their carbon transformation process in the future.
2) MAC keeps a rising trend while spatial heterogeneity at the higher MAC range is increasing. During the research period, positive spatial clusters have experienced such fluctuations as “apparent rise →drastically drop→ close to zero.” Provinces of “H-H” type keep decreasing while provinces of “H-L” type are rising in this stage. Such provinces as Jiangxi, Shaanxi, and Shandong have turned from “H-H” type into “L-H” type. Some provinces such as Zhejiang, Henan, and Jiangsu have turned into “H-L” types. In the western region in China, many provinces such as Gansu, Ningxia, Mongolia, Xinjiang, and Qinghai are in the “L-L” type. Interregional cooperation is being formed for some provinces such as the Beijing-Tianjin-Hebei Zone, the Yangtze River Economic Zone, and some provinces of western regions in the future to accelerate the low-carbon transformation process.

Policy Implications

Under the above conclusions, some policy implications are proposed as follows:

1) With growing marginal abatement cost, how to promote MAC to decline is an important subject for 30 provinces. Exploring the reduction potentials

through improving production efficiency or emission-reduction technology progress are the main directions to reduce MACs in the future. For such provinces as Beijing, Shanghai, Zhejiang, and Jiangsu, their economy develops most efficiently among 30 provinces and their reduction potentials are to stimulate technology innovation, especially emission-reduction technology progress. For western regions, their economic developments are at the lowest level among provinces. With lowest production efficiency and lowest technology endowment, they have the most reduction potentials from production efficiency and technology spillovers from outside regions.

2) Spatial character and its trends supplies important information when low-carbon transformation paths are optimized. The spatial heterogeneity trend becomes dominant in the MAC aspect. MACs in most eastern regions are more than those in middle and western regions. Spatial coordination among provinces during reducing emissions may reduce reduction costs for the central government. The regional cooperative pattern is being formed to make use of their advantages in MAC aspect. For example, Shanghai, Jiangsu, and Zhejiang form the Yangtze River Economic Zone. They have great inter-provincial economic spillover whether in funds, talent, or technology. MAC variation may promote their cooperation mode formation. MAC information may supply a sufficient basis when inter-regional ecological compensation pricing mechanism negation is considered.

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Conflict of Interest

The authors declare no conflict of interest.

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