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RESEARCH ARTICLE

Spatio-temporal evolution characteristics and influencing factors of carbon emission reduction potential in China

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Abstract
This study first attempts to use the parameterized quadratic directional distance function (DDF) approach to calculate China's provincial carbon abatement cost and carbon reduction potential (CRP) under different scenarios from 2000 to 2017. Afterward, considering three different scenarios, we analyze the spatio-temporal characteristics and the dynamic evolution pattern of CRP. We also employ spatial Durbin model (SDM) to investigate the influencing factors of CRP. The results are obtained as follows: (1) CRP across the three scenarios varies considerably across provinces and different-located groups. CRP higher areas are mainly located in the economically developed eastern coastal regions, while most provinces with low CRP are concentrated in the western region. (2) Provinces with a similar CRP showed a significant geographic agglomeration, and the agglomeration effect was strengthened first and then weakened. Simultaneously, the local spatial distribution of moderation carbon reduction potential (MCRP), fairness carbon reduction potential (FCRP), and efficiency carbon reduction potential (ECRP) shows a slight spatial polarization feature. (3) Through the SDM analysis and spillover effect decomposition, we find that improvement of regional CRP not only depends on economic development, industrial structure adjustment, and energy efficiency elevation, but also involves energy structure optimization, low-carbon innovation, and population. The low-carbon innovation provides critical support for local CRP under the efficiency scenario but restrains the local CRP under the fairness scenario. Therefore, the central government should emphasize local conditions and the ex-ante scenario assessment, strengthen regional interactive governance, optimize energy efficiency, and promote the application of clean energy to enhance CRP.

Keywords Carbon emission reduction potential · Carbon abatement cost · Directional distance function · Policymaker preference · Spatio-temporal evolution · Spatial Durbin model

Introduction

Economic development has always been closely related to natural resource consumption (Song et al. 2019). Extensive resource utilization has brought about serious ecological damage and environmental consequences. Over the past 40 years, China has experienced rapid economic growth and the speedy growth of energy demand, but the contradiction between resource environmental constraints and economic development has become increasingly prominent (Wei et al. 2020; Zhang et al. 2020b). Faced with the severe challenge of environmental sustainability, the Chinese government has taken many measures to promote green low-carbon development. For example, China has pledged to reduce CO_2 emissions per unit GDP by 60–65% in 2030 compared with 2005 levels at the 2015 Paris climate conference (Chen et al. 2019). Furthermore, the government reiterated that China would increase its nationally determined contribution, strive to reach the carbon peak by 2030, and achieve "carbon neutrality" by 2060 at the 75th UN General Assembly. Innovation-driven and green, zero-carbon-oriented industrial changes have become the vane of China's modern economic system. However, China has a vast territory, and there are significant interregional differences in resource endowments, industrial structures, and economic development, which will inevitably lead to differences in the spatial distribution of carbon reduction potential (CRP) in the process of green low-carbon development (Guo et al. 2011; Wang et al. 2019; Liu et al.

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2020). Understanding regional heterogeneity in air pollution management is critical to field-oriented governance (Choi et al. 2020). Therefore, to provide a theoretical basis for achieving high-efficiency carbon emission reduction in China, it is imperative to accurately grasp the evolutionary characteristics of CRP and its driving factors.

In fact, exploiting carbon emission reduction potential and exploring new green low-carbon development paths are common concerns worldwide. A low CRP would construct a significant barrier to environmental sustainability in developed and developing countries. Considerable existing studies have analyzed the carbon reduction potential on energy efficiency improvement in individual or a small number of regions, which is mainly in a single nation (Zuberi and Patel 2017), the region with high energy demand (Wei et al. 2015) and heavy industrialization (Liu et al. 2020; Huang and Wu 2021), or the specific industrial sector characterized by high carbon emissions (An et al. 2018; Chen and Chen 2019; Xia et al. 2020). Those studies all found that enormous energy-efficiency potential can be increased through technology improvement and encourage policy implementation. Among all of them, several studies revealed that it is better to implement differentiated emission reduction policies in different areas according to the local energy resource endowment and facilitate regional cooperation (Zhang et al. 2016; Chen et al. 2021). In the current study, there is still a knowledge gap about how to make effective emission reduction policies and increase regional carbon emission potential from the perspective of policymakers. Thus, analyzing the spatial-temporal evolution of CRP at the provincial level is critical to help policymakers formulate reasonable mitigation policies for carbon emissions by considering regional situations. However, little literature has shed light upon the spatial-temporal evolution features and the key driving factors of CRP in a developing country. With the improvement of status in the world economy and fossil energy field (Wei et al. 2020), China's CRP spatio-temporal evolution characteristics and influencing factors are a vital epitome for other developing countries. Under such a circumstance, it is critical to estimate the provincial CRP and explore energy efficiency improvement path in China.

This paper attempts to use the parameterized quadratic function of the directional distance function (DDF) approach to estimate the carbon abatement costs and evaluate the provincial CRP through setting three different scenarios. This paper contributes to current literature in 3 ways. First, this study innovatively evaluates the provincial CRP from the perspective of policymakers' preferences. Few studies have examined the carbon emission reduction potential in China from the perspective of policymakers' preferences against this background up to now. Moreover, differing from the existing literature about the carbon emission reduction potential (Wei et al. 2012; An et al. 2018), the purpose of this paper is to analyze each province's CRP and help the government make appropriate regional environmental policies aimed at increasing carbon emission reduction potential, rather than how to allocate CO_2 abatement responsibility among provinces or how much CO_2 should be reduced. Second, we analyze the spatial-temporal evolution characteristics and the dynamic evolution pattern of CRP and clarify the heterogeneous characteristics of CRP under three different scenarios. Third, we employ the spatial econometric model to investigate the CRP's influencing factors in China, while spatial econometric models are rarely used to study the influencing factors of CRP. The previous study generally assumed that inter-jurisdiction regions were cross-section independent so that spatial interaction effects were ignored (Wang et al. 2019). In addition, LeSage (2008) argued that a local province's characteristics might depend on its neighbors; econometric models without considering the spatial dependence of variables often lead to inaccurate results. Therefore, our research evaluates the changes in Chinese provinces' CRP and the effects of related factors on CRP more accurately since 2000, which can provide more reference for policymakers to stimulate the potential of regional low-carbon transformation.

The rest of the paper is structured as follows. "Literature review" presents the related literature. "Methodology and data" describes the CRP measurement approach, the DDF, spatial economic models, variable selection, and data sources. "Spatio-temporal evolution characteristics of carbon reduction potential" presents the spatio-temporal characteristics and the dynamic evolution pattern of CRP under different scenarios. The empirical results are reported in "Empirical results" section. "Conclusions and policy implications" summarizes and provides the corresponding policy implications.

Literature review

Since scholars have gradually realized the importance of resources and the environment for human survival and sustainable economic development, they have incorporated the environment as an essential factor into the economic research framework (Yang et al. 2021). In the subsequent research, many early studies mainly investigated energy-related carbon emissions and its influencing factors (Zhang and Da 2015; Shen et al. 2018), the law of spatio-temporal evolution (Shi et al. 2014; Ding et al. 2019; Wu et al. 2021b), and driving mechanism (Tian et al. 2013; Jiang et al. 2017). In recent years, an increasing number of studies have discussed the carbon emission reduction cost and reduction potential worldwide (Guo et al. 2011; Chen and Xiang 2019; Raza and Lin 2020).

This section reviews the existing literature on the carbon emission reduction potential from the three aspects: measurement of the abatement cost, the concept of the carbon emission reduction potential, and evaluation of the carbon emission reduction potential.

Research on carbon abatement cost measurement

Shadow prices provide a critical way to estimate the marginal abatement cost of undesirable outputs (Zhou et al. 2014). In literature related to the marginal abatement costs, most existing studies generally focused on estimating shadow prices at the national (Lee 2011; Molinos-Senante and Guzmán 2018), regional (Tang et al. 2016b; Zeng et al. 2018; Chen and Jin 2020), or sector level (Wang et al. 2017; Chen and Xiang 2019; Wu et al. 2021c). In previous studies, various methods were employed to estimate the shadow price of pollutants. Färe et al. (1993) first derived the shadow price of undesirable outputs based on the Shephard output distance function. Lee et al. (2002) estimated the shadow prices of sulfur oxides (SOx), nitrogen oxides (NOx), and total suspended particulates (TSP) by formulating the non-parametric production model specific to the directional distance function for the case of a single good output and pollutant. Ke et al. (2008) used the linear programming (LP) approach to compute the shadow prices of SO_2 emissions in China during the 1996–2003 period and found that the shadow price in the west region is the highest. Wei and Zhang (2020) estimated the shadow price of CO_2 and SO_2 by developing a novel partial frontier construction approach that allows the frontier to be differentiable and measured the cost of joint reduction of multiple undesirable outputs by using directional derivatives instead of partial derivatives firstly. Zhang et al. (2020a) applied the dual non-radial DDF to measure the shadow price of the three main atmospheric pollutants (PM2.5, SO_2, and NO_2) for the three major urban agglomerations in China. Wu et al. (2021a) adopted the non-oriented DDF and slack-based measure (SBM) models to estimate the shadow prices of SO_2 and chemical oxygen demand (COD).

The estimation of the carbon shadow price shares the same shadowing pricing procedure as other greenhouse gases, which shifted scholars' attention to estimating carbon shadow price (Zhou et al. 2014). As for literature concerning the carbon abatement cost measurement, there are, for instance, Choi et al. (2012) who employed the dual model of the slack-based data envelopment analysis (DEA) model to estimate the abatement costs of CO_2 emissions. Wang et al. (2011) estimated the marginal CO_2 abatement costs in China with the framework of the non-parametric method. Nevertheless, the non-parametric DEA technique is not well-suited to derive the shadow prices due to its non-differentiability (Färe et al. 2005; Yang et al. 2017). By contrast, the DDF is thought to provide a more flexible method to evaluate the CO_2 marginal abatement costs. The related studies include Tang et al. (2016a), Zhang et al. (2019b), and Ji and Zhou (2020), among others. Furthermore, the quadratic DDF model might be more suitable for a sample that faces mandatory CO_2 emission reduction or prefers to conduct voluntary CO_2 emission reduction (Zhou et al. 2015). Therefore, the quadratic DDF model has been widely employed to evaluate carbon abatement costs in recent years.

Research on carbon emission reduction potential

The CRP has different connotations. The existing studies on defining the carbon dioxide reduction potential from different perspectives can be mainly classified into three categories according to their results. The first strand of literature mainly focuses on the differences in emission reduction of different electricity structure vehicles in the transportation sector. For example, Ketelaer et al. (2014) explored the CO_2 mitigation potential of German commercial transport based on the difference of CO_2 emissions from conventional to electric light commercial vehicles. Zhang et al. (2019a) used the backward analysis to calculate the proportion limit of coal power consumption by urban rail transit and then analyze the emission reduction potential of rail transit under different combinations of electricity consumption structures.

The second strand of literature defines the gap between the CO_2 emissions for the base year and the estimated year under different scenarios as the CO_2 emission reduction potentials of various sectors. For instance, Lin and Xie (2014) calculated the carbon mitigation potential in China′s transport industry under moderate and advanced emission-reduction scenarios. Lin and Ouyang (2014) investigated the reduction potential of CO_2 emissions in the Chinese non-metallic mineral product industry by setting three scenarios. Yu et al. (2016) estimated the carbon abatement potential of China's 43 economic sectors by describing two scenarios, business as usual (BAU) and planned policy. An et al. (2018) relied on four scenario analyses with the aim to estimate the potential of CO_2 emission reduction in the iron and steel industry in China.

The third strand of literature defines the inefficiency level or excesses of carbon dioxide emissions as the CO_2 emission reduction potentials. For example, Choi et al. (2012) employed the non-radial SBM framework to measure the excesses of undesirable output, and they defined the room for improvement in carbon emissions as the CO_2 emission reduction. Wei et al. (2012) established that the abatement potential of CO_2 reflects the inefficiency level of carbon dioxide emission during the production process; the study expected that the richer provinces are normally accompanied by lower CO_2 abatement potential.

There exists enormous potential for China to improve its atmospheric environment (Choi et al. 2020). Several scholars have devoted themselves to evaluate the carbon emission reduction potential in China by using the non-parametric DEA approach. For example, using the DEA model, Guo et al. (2011) evaluated the carbon emission reduction potential in

Chinese provinces, revealing that energy conservation technology promotion and inter-regional technical cooperation can reduce carbon emissions in technically inefficient regions. Further, various extensions of the basic DEA models have been proposed for estimation. Bian et al. (2013) took non-fossil energy as a fixed input and proposed a non-radial DEA approach combining energy structure adjustment and DEA-based target setting together to measure potential CO_2 emission reductions. Choi et al. (2012) employed the SBM of the non-radial DEA model to develop the potential CO_2 emission reduction (PCR) index. In addition, one special case is Wei et al. (2012), who take both equity and efficiency principles into account in evaluating CO_2 abatement capacity. However, it is different from our research. Specifically, we estimate CRP depends on the policymakers' preferences to analyze each province's CRP, rather than how to allocate CO_2 abatement among regions or how much CO_2 should be reduced.

As discussed above, scholars have conducted extensive studies on the concept and evaluation of CRP and found that many regions/sectors have the potential to reduce carbon emissions (Akimoto et al. 2010; Zhu et al. 2020), but still need further exploration. First, existing literature mainly focuses on the excesses of carbon emissions, rather than a comprehensive evaluation system that includes policymakers' preferences, which may lead to an incomplete understanding of the regional CRP. Thus, it must be further explored with additional dimensions and based on the policymakers' preferences. Second, there is a lack of discussion on the spatial-temporal characteristics of CRP and its influencing factors. Finally, scholars mainly focus on the difference between the CO_2 emissions for the base year and the estimated year, but ignore the spatial factors.

Therefore, this paper attempts to provide a comprehensive evaluation of the CRP in 30 Chinese provinces by setting three different scenarios based on Wei et al. (2012) and clarify its determinants. This study also analyzes the spatio-temporal evolution characteristics of CRP under three scenarios. Then, we use the Moran I index to test whether there is spatial autocorrelation of CRP in various provinces. Lastly, based on the theoretical basis of the STIRPAT model, this study constructs the spatial econometric model of regional development factors to investigate the effects of each factor on CRP and estimates the spatially divergent features, with the purpose of providing theoretical support for making policy of promoting regional carbon reduction.

Methodology and data

Measuring the carbon reduction potential

This paper uses a two-step approach to estimate the CRP under three scenarios from 2000 to 2017 in the study. First, we apply the parameterized quadratic function of the DDF method to estimate the carbon shadow price in 30 Chinese provinces from 2000 to 2017. Second, considering three different scenarios differentiated by different policy preferences, we evaluate CRPs (MCRP, FCRP, and ECRP) since 2000. Following the idea of Wei et al. (2012), the calculation of the CRP index is shown in formula (1):

$$CRP = w \times Equity_{it} + (1-w) \times Efficiency_{it} \tag{1}$$

where w is weight reflecting the policymakers' preferences; provincial CRP are evaluated via three scenarios differentiated by policy preferences, $w = 1/2$ under moderation scenario, $w = 2/3$ under fairness scenario, and $w = 1/3$ under efficiency scenario. $Equity_{it}$ and $Efficiency_{it}$ are the index of the development equity and carbon abatement efficiency of province i in year t, respectively. In terms of the development equity index, per capita regional carbon emissions and per capita GDP indicators are both highly recognized fair distribution indicators (den Elzen and Lucas 2005; Pan et al. 2017), in which the former can reflect the equal development rights of the region, and the latter can reflect the ability of the region to pay. Thus, we calculate $Equity_{it}$ by weighting per capita regional carbon emissions and per capita GDP indicators. These two indicators are given equal importance. In terms of the carbon abatement efficiency index, this paper selected carbon emission intensity and carbon abatement cost to reflect the overall efficiency of carbon emission reduction, in which carbon emission intensity is often used to reflect carbon emission efficiency (Sun 2005; Zhang and Wei 2015), and the carbon marginal abatement cost reflects the difficulty level of pollutant reductions (Färe et al. 2006). These two indicators are given equal importance. Areas with high carbon emission intensity and low marginal emission reduction costs can be identified as key pollution reduction areas in practice. All variables are normalized by the "Min–Max" method.[1]

Scenarios analysis assumption

The CRP is a kind of objective reflection related to regional economic development and resource endowments, as well as policymakers' own subjective constraints, as the policymakers' tolerance of regional inequity in carbon emissions impacts carbon emission reduction pressure (Chen et al. 2016). Most existing literature has constructed a comprehensive indicator system encompassing capability, equity, and responsibility (Qin et al. 2017; Dong et al. 2018; Ma et al. 2020), which results in a new research angle that includes both fairness and efficiency simultaneously. Thus, this paper conducts the evaluation of provincial CRP via three scenarios

[1] The "Min–Max" normalization method converts z_i to s_i by $S_i = (z_i - \min z)/(\max z - \min z)$. The variable of the carbon shadow price is reverse transformed.

differentiated by policy preferences. In line with Wei et al. (2012), we set three scenarios as follows: (i) *moderation scenario*, of which fairness and efficiency of carbon emission reduction responsibilities are equally important. A moderation scenario reflects the possible situation; however, the purpose of a moderation scenario is not to provide precise estimates of the regional reduction potential conditions but to clarify the significant factors that contribute to regional carbon emission reduction in the future. Besides, it is the benchmark for setting the other two scenarios; (ii) *fairness scenario*, of which policymakers more focus on the fairness of allocating responsibilities for carbon reduction; and (iii) *efficiency scenario*, of which policymakers pay more attention to carbon reduction efficiency; the province has a higher (lower) capacity to undertake more (less) reduction burden. The main advantage of the scenario analysis is that we can have a relatively accurate examination and a comprehensive analysis on the spatio-temporal distribution of CRP. These features could yield valuable information to policymakers, helping them design better regional environmental policies compatible with low-carbon development.

Measuring the carbon shadow price

The DDF, developed initially by Shephard (1970) and applied by Färe et al. (1993) in empirical fields, has gained tremendous popularity in measuring the abatement cost of pollutants owing to its flexibility. The distance function does not require any assumptions concerning cost minimization or revenue maximization and information on input or output prices. The DDF method allows researchers to simultaneously expand desirable outputs and reduce undesirable outputs based on a given direction vector (Chung et al. 1997). Thus, this paper uses the parameterized quadratic function of the DDF to estimate the carbon shadow price before calculating the CO_2 abatement efficiency index. Following the idea of Chung et al. (1997) and Färe et al. (2005), the directional output distance function can be defined as follows:

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

where $(g_y, -g_b)$ is the direction vector that indicates the direction by which the output combination is scaled. Moreover, we assume a joint-production process in which each observation uses a non-negative vector of inputs denoted as x to produce a non-negative vector of desirable outputs denoted as y and a non-negative vector of undesirable outputs denoted as b. Then, production technology can be represented by the output possibility set $F(x)=\{(y, b): x \text{ can produce } y, \text{ and } b\}$ describing the set of feasible input-output vectors.

In line with Chung et al. (1997), this paper chooses g = (1, -1) as the direction vector to simplify the parameter estimation and satisfies the translation property of the DDF. In addition, we assume that there are $i = 1, \ldots, 30$ provinces in $t = 1, \ldots, T$ years, three inputs (capital, energy consumption, and labor), one desirable output (GDP), and one undesirable output (carbon emissions). The parametric quadratic directional output distance function form can be shown as follows:

$$\begin{aligned}\overrightarrow{D}\left(x_i^t, y_i^t, b_i^t; g_y, -g_b\right) &= \alpha_0 + \sum_{n=1}^{3} \alpha_n x_i^t + \beta_1 y_i^t + \gamma_1 b_i^t \\ &+ \frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3} \alpha_{nn'} x_{ni}^t x_{n'i}^t + \sum_{n=1}^{3} \delta_n x_{ni}^t y_i^t \\ &+ \sum_{n=1}^{3} \nu_n x_{ni}^t b_i^t + \frac{1}{2}\beta_2 \left(y_i^t\right)^2 \\ &+ \frac{1}{2}\gamma_2 \left(b_i^t\right)^2 + \mu y_i^t b_i^t\end{aligned} \tag{3}$$

Following Aigner and Chu (1968), this study uses a deterministic linear programming model to estimate the parameters $(\alpha_0, \alpha_n, \alpha_{nn'}, \delta_n, \nu_n, \beta_2, \gamma_2, \mu)$. The constraint conditions cover the feasibility, monotonicity, translation property, and symmetry property of distance function (Färe et al. 2006), which takes the following Eq. (4):

$$\begin{aligned}&\min \sum_{t=1}^{T}\sum_{i=1}^{30} \overrightarrow{D^t}\left(x_i^t, y_i^t, b_i^t; 1, -1\right) \\ &s.t. \\ &\left.\text{i}\right)\ \overrightarrow{D^t}\left(x_i^t, y_i^t, b_i^t; 1, -1\right) \geq 0, i = 1, \ldots, 30, t = 1, \ldots, T \\ &\left.\text{ii}\right)\ \partial \overrightarrow{D^t}\left(x_i^t, y_i^t, b_i^t; 1, -1\right)/\partial b \geq 0, i = 1, \ldots, 30, t = 1, \ldots, T \\ &\left.\text{iii}\right)\ \partial \overrightarrow{D^t}\left(x_i^t, y_i^t, b_i^t; 1, -1\right)/\partial y \leq 0, i = 1, \ldots, 30, t = 1, \ldots, T \\ &\left.\text{iv}\right)\ \partial \overrightarrow{D^t}\left(x_i^t, y_i^t, b_i^t; 1, -1\right)/\partial x_n \leq 0, i = 1, \ldots, 30, t = 1, \ldots, T \\ &\left.\text{v}\right)\ \widehat{\beta}_1 - \widehat{\gamma}_1 = -1, \widehat{\beta}_2 = \widehat{\gamma}_2 = \widehat{\mu}, \widehat{\delta}_n = \widehat{\nu}_n \\ &\left.\text{vi}\right)\ \alpha_{n'n} = \alpha_{nn'}, n, n' = 1, 2, 3\end{aligned} \tag{4}$$

where the restriction (i) ensures the input-output production set is feasible. The constraint conditions (ii), (iii), and (iv) are due to the monotonicity property for undesirable outputs, desirable outputs, and all inputs, respectively. The parameter restrictions given by (v) are due to the translation property. The last restriction (vi) imposes the symmetry property.

Once the parameters are estimated, we can apply Shepard derivation to derive the relationship between the undesirable output price q and the desirable output p (see Eq. (5)).

$$\begin{aligned}\frac{q}{p} &= -\frac{\partial \overrightarrow{D}\left(x, y, b; g_y, g_b\right)/\partial b}{\partial \overrightarrow{D}\left(x, y, b; g_y, g_b\right)/\partial y} \\ &= -\frac{\gamma_1 + \gamma_2 b + \sum_{n=1}^{3} \nu_n x_n + \mu y}{\beta_1 + \beta_2 b + \sum_{n=1}^{3} \delta_n x_n + \mu b}\end{aligned} \tag{5}$$

Measuring the carbon emission

Carbon emissions of Chinese provinces need to be calculated before calculating the CO_2 abatement efficiency index. According to the IPCC Guidelines for the national reduction potential of pollutant inventories (IPCC 2006), the total fuel-based carbon emissions are estimated according to the following formula (6):[2]

$$CE_i = \sum_{m=1}^{17} EC_{im} \times NCV_{im} \times CC_{im} \times O_{im} \times \frac{44}{12} \tag{6}$$

where CE_i denotes energy-related carbon emissions by fossil fuel's category m in province i, $EC_{im}$is the consumption of fossil fuels m, NCV_{im}, CC_{im}, and O_{im} respectively denote net calorific value[3], carbon content, and oxygenation efficiency (Liu et al. 2015).

Measuring the dynamic evolution characteristic

Kernel density estimation (KDE) is an essential non-parametric estimation method used for point data density visualization, which can describe the actual data distribution based on the data's intrinsic attributes without needing any prior information. Therefore, this paper employs KDE to analyze the dynamic evolution of CRP in China. The KDE can be defined as:

$$\hat{f} = (1/nh)\sum_{i=1}^{n} K((r-R_i)/h) \tag{7}$$

where $\hat{f}$ denotes the kernel density value; h denotes the bandwidth of KDE; $K(r)$ represents the Gaussian kernel function, which is expressed in Eq. (8); r represents the estimating site; and R_i represents the number i sample site.

$$K(r) = \left(1/\sqrt{2\pi}\right) \cdot \exp\left(-r^2/2\right) \tag{8}$$

Spatial econometric model

Spatial autocorrelation model at the global level

To test whether there is a spatial autocorrection in provincial CRP, we adopt the global Moran I index to examine the spatial correction of CRP in 30 Chinese provinces. The spatial autocorrelation index is calculated by Eqs. (9) to (11):

$$I = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}\left(Y_i-\overline{Y}\right)\left(Y_j-\overline{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{9}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\overline{Y}\right)^2 \tag{10}$$

$$\overline{Y} = \frac{1}{n}\sum_{i=1}^{j} Y \tag{11}$$

where I represents the index of global spatial autocorrelation; Y_i and $Y_j$represent the values of CRP in province i and j; n represents the total number of provinces; and W_{ij} represents the spatial weight matrix; this paper sets 30 provinces with neighbors that could be adjacent; W_{ij}=1 if two provinces are neighbors; otherwise, W_{ij}=0. The value range of Moran I is [-1,1], $I < 0$ indicates that there is a negative spatial autocorrelation, and $I > 0$ indicates that there is a positive spatial autocorrelation.

Spatial autocorrelation model at the local scale

This paper uses the local spatial autocorrelation proposed by Anselin (1995) to explore the statistically significant spatial clusters and dispersion of the provincial CRP. The local Moran I index can be calculated using Eq. (12):

$$I_i = \frac{Y_i-\overline{Y}}{S^2}\sum_{j=1, j\neq i}^{n} W_{ij}\left(Y_j-\overline{Y}\right) \tag{12}$$

where$I_i$represents the local Moran I, and the other symbols represent the same as in Eqs. (9) to (11). When I_i is significantly positive, it indicates that there exists local positive spatial autocorrelation, and the province is surrounded by provinces with similar properties. When the province and its adjacent provinces are all found with a high value of CRP, it is called high-high (H-H) agglomeration; otherwise, it is called low-low (L-L) agglomeration. When I_i is significantly negative, it indicates that there exists spatial discretization. When the province with a high value of CRP is surrounded by provinces with low value, it is called high-low (H-L) agglomeration; otherwise, it is called low-high (L-H) agglomeration.

Spatial panel model

The spatial panel model predominantly includes the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). As a general form of SLM and SEM, SDM considers the spatial correlation of dependent variables and independent variables simultaneously. SLM mainly explores

[2] Different from considering 7 energy types, it is found that the measurement accuracy is significantly improved after supplementing ten types of energy consumption data by constructing the accuracy improvement rate index; the results are presented as supplementary material.

[3] Liu et al. (2015) pointed out that the carbon emission factor in the IPCC report is approximately higher than the value in China's "United Nations Framework Convention on Climate Change (UNFCCC)" report. Therefore, we use the net calorific value provided in the China Energy Statistical Yearbook, which is more suitable for China's national conditions.

Table 1 Input-output indicators

Indicators	Category	Specific indicators
Input indicators	Labor	Total number of the year-end employees
	Energy consumption	Total energy consumption and is converted into standard coal equivalent
	Capital	Fixed asset investment*
Output indicators	Desirable output	The actual GDP and is converted into the 2000 base period price
	Undesirable output	Carbon emissions calculated by Eq. (6)

* The capital input variable was calculated by the perpetual inventory method based on the 2000 base period fixed asset investment of each province

whether the independent variables in a region are affected by the dependent and independent variables in adjacent regions. Therefore, this study chooses SDM to examine the geographical space feature of CRP under moderation, fairness, and efficiency scenarios. The model is constructed as follows:

$$CRP_{it} = \alpha + \rho \sum_{j=1}^{n} W_{ij}CRP_{jt} + \beta X_{it} + \theta \sum_{j=1}^{n} W_{ij}X_{jt} + \varepsilon_{it} \quad (13)$$

where X_{it} represents the independent variables; W_{ij} is the spatial weight matrix; $\sum_{j=1}^{n} W_{ij}CRP_{jt}$,$\sum_{j=1}^{n} W_{ij}X_{jt}$ denote the spatial lag terms of the dependent variable$CRP_{it}$and independent variables, which allows us to investigate the spillover effects of different variables;ρ is the spatial lag autoregressive coefficient; β is the estimated coefficient of the independent variable; θ represents the coefficient of the space-lag term of the independent variable; and ε_{it} is a random perturbation term.

Variables and data

Variable selection in measuring carbon reduction potential

In terms of the variables in measuring carbon shadow price, input indicators are capital, labor force, and energy consumption. Besides, the actual GDP was adopted as a desirable output indicator, and carbon emissions were determined as an undesirable output indicator (see Table 1). In terms of the variables in measuring the CRP, we select per capita regional carbon emissions and per capita GDP to construct the development equity index. Besides, we select carbon emission intensity and carbon shadow price to construct the carbon abatement efficiency index (see Table 2).

Influencing factors of carbon reduction potential

Many factors influence CRP. Existing studies combined with the STIRPAT model show that population, economic development, industrial structure, research and development (Dietz and Rosa 1994; Cheng et al. 2020), energy structure (Yu et al. 2018), and energy efficiency are the main factors influencing carbon emission. On the basis of the work of Shahbaz et al. (2016), the increase in domestic openness will attract more foreign investments and high energy demand for production (Wang and Zheng 2020), so we also consider openness and employ the ratio of total import and export to GDP to represent it, in which the total import and export volumes are converted into RMB. Thus, we select population size, economic development, industrial structure, low-carbon innovation, energy structure, energy efficiency, and economic opening rate as explanatory variables to analyze the influencing factors of CRP (see Table 3).

It is worth noting that low-carbon innovation plays a vital role in the process of carbon reduction (Zhang et al. 2017; Du et al. 2019). The government could realize the emission reduction target by deploying clean energy technologies and encouraging investments in low-carbon projects (Jordaan et al. 2017). Considering patent data provide a number of valuable information on the patent's technological content and citations, patents are still the most commonly used proxy for studying innovation activities in the scientific literature (Park 2014; Albino et al. 2014). Besides, combined patent classification (CPC), jointly promulgated by the European Patent Office and the United States Patent Office, has become one of the most popular patent classification systems since 2013 (Wang et al. 2020). The Y02 section in the CPC system includes patents for technologies or applications that mitigate or adapt to climate change. Thus, here, we use the number of CPC-Y02 patent applications to represent low-carbon innovation in different Chinese provinces; then, we collect the data of patent applications from the IncoPat database[4]. To avoid heteroscedasticity and consider the low amount of low-carbon innovation applications in some regions, this study takes the logarithm of the number of patent applications plus one as the proxy variable.

[4] http://www.incopat.com

Table 2 Variables in measuring the CRP

Indexes	Category	Specific indicators
Development equity	Per capita regional carbon emissions	The ratio of carbon emissions to population
	Per capita GDP	The real GDP per capital
Carbon abatement efficiency	Carbon emission intensity	The ratio of carbon emissions to GDP
	Carbon shadow price	Carbon shadow price calculated by Eqs. (2)–(5)

Data sources

We collect data from many official sources. Such as the China Statistical Yearbook (2001-2018), the China Energy Statistical Yearbook (2001-2018), the China Environmental Statistics Yearbook, the Statistical Yearbook of each province (2001–2018), and the National Bureau of Statistics official website database (2001–2018). The number of patent applications was obtained from the Incopat patent search platform, and the search scope is in the low-carbon field applied for in the China Patent Office (SIPO) from 2000 to 2017. Based on data availability, this paper excludes Hong Kong, Macao, Taiwan, and Tibet due to its data that are missing. In summary, the data sample comprises panel data from 30 provinces and 18 years, which produces a balanced panel with 540 observations.

Spatio-temporal evolution characteristics of carbon reduction potential

Temporal characteristics of carbon reduction potential

Time series characteristics of carbon reduction potential

This paper conducts a temporal analysis of data to explore the Spatio-temporal differences and changes of CRP. We use MATLAB software to classify and summarize the CRP and ranking of various provinces in China. We select 2001, 2006, 2008, 2011, and 2017 as typical years[5]. In addition, the Chinese mainland is divided into three groups (eastern, central, and western) to analyze the regional variations of average CRP under moderation (Table 4), fairness (Table 5), and efficiency (Table 6) scenarios.

There are differences in the CRP among different provinces/regions under three different scenarios:

(i) *Moderation scenario*. The average MCRP in all regions decreased from 0.334 in 2001 to 0.312 in 2017, decreased significantly from 2006 to 2008, but volatility increased between 2008 and 2017. In terms of subregions, the MCRP in the three regions has been increasing first and then gradually decreasing. The average MCRP in the eastern region is higher than that of the other two regions. The average growth rate of MCRP was found the lowest in the eastern region, followed by the central and the western regions, with average annual growth rates of 0.10%, 1.40%, and 1.80%, respectively. In terms of provinces, the provinces Shanxi, Inner Mongolia, and Ningxia were ranked as the top three places for the average MCRP with values of 0.534, 0.431, and 0.418, respectively. However, the bottom three provinces for the average MCRP were Guangxi, Hainan, and Jiangxi, with values of 0.213, 0.221, and 0.222, respectively.

(ii) *Fairness scenario*. The average FCRP in all regions increased from 0.251 in 2001 to 0.331 in 2017, decreased quickly from 2006 to 2008, and increased from 2008 to 2017. In terms of subregions, the FCRP in the three regions showed a fluctuating upward trend. The FCRP in the eastern region was found the highest, followed by the central and the western regions. The eastern region had the fastest average growth rate of the three regions, with average annual growth rates of 2.09%, 0.69%, and 0.52%, respectively. In terms of provinces, the provinces Shanxi, Inner Mongolia, and Shanghai were ranked as the top three places for the average FCRP with values of 0.471, 0.404, and 0.398, respectively. However, the bottom three provinces for the average FCRP were Guangxi, Jiangxi, and Yunnan, with values of 0.167, 0.175, and 0.180, respectively.

(iii) *Efficiency scenario*. The average ECRP in all regions decreased from 0.417 in 2001 to 0.296 in 2017. In terms of subregions, the ECRP in the three regions showed a fluctuating downward trend. The ECRP in the eastern region showed relatively lower degrees from 2000 to 2006, while it increased sharply and became the highest after 2008. The average growth rate of ECRP was found the highest in the eastern region, while the central and the western regions exhibited negative growth, with average annual growth rates of 1.58%, − 2.94%, and − 3.56%, respectively. In terms of provinces, the provinces Shanxi, Ningxia, and Inner Mongolia were ranked as the top three places for the average ECRP with values

[5] The change trend plots of carbon reduction potential under moderation, fairness, and efficiency scenarios between 2000 and 2017 are presented in supplementary material.

Table 3 Influencing factors of CRP

Explanatory variables	Abbreviation	Unit	Remarks
Population size	*POP*	-	The logarithm of population
Economic development	*GDP*	100 million yuan	Real GDP
Industrial structure	*IND*	%	The proportion of the secondary industry to the tertiary industries
Low-carbon innovation	*GREEN*	-	The logarithm of the number of patent applications plus one
Energy structure	*ES*	%	The ratio of coal consumption to energy consumption
Energy efficiency	*EE*	%	The GDP created by the energy consumption per unit.
Economic opening rate	*OPEN*	%	The ratio of total import and export to GDP

Table 4 China's regional MCRP and ranking in 2001, 2006, 2008, 2011, and 2017

Region	Province	2001	Rank	2006	Rank	2008	Rank	2011	Rank	2017	Rank	Mean
Eastern	Beijing	0.355	8	0.386	8	0.292	10	0.262	14	0.273	15	0.305
	Tianjin	0.375	5	0.417	6	0.318	7	0.349	7	0.362	8	0.365
	Hebei	0.337	12	0.378	9	0.315	8	0.346	8	0.295	12	0.335
	Liaoning	0.382	4	0.418	5	0.350	5	0.389	3	0.375	6	0.384
	Shanghai	0.395	3	0.441	4	0.375	3	0.381	4	0.417	3	0.396
	Jiangsu	0.281	23	0.325	20	0.295	9	0.345	9	0.371	7	0.313
	Zhejiang	0.273	27	0.328	18	0.285	11	0.305	11	0.308	10	0.284
	Fujian	0.281	24	0.322	21	0.235	19	0.251	17	0.276	14	0.269
	Shandong	0.293	19	0.345	14	0.328	6	0.373	6	0.381	5	0.336
	Guangdong	0.256	30	0.311	25	0.283	12	0.317	10	0.324	9	0.283
	Hainan	0.273	28	0.297	28	0.200	28	0.146	30	0.168	27	0.221
	Mean	0.318	-	0.361	-	0.298	-	0.315	-	0.323	-	
Central	Shanxi	0.506	1	0.605	1	0.473	1	0.470	2	0.570	1	0.534
	Jilin	0.335	13	0.359	12	0.254	16	0.255	16	0.234	18	0.284
	Heilongjiang	0.345	11	0.369	10	0.282	13	0.288	12	0.261	16	0.309
	Anhui	0.315	15	0.316	23	0.222	22	0.218	20	0.212	19	0.257
	Jiangxi	0.286	22	0.302	27	0.193	29	0.171	27	0.168	26	0.222
	Henan	0.301	17	0.330	17	0.259	14	0.284	13	0.243	17	0.284
	Hubei	0.299	18	0.319	22	0.223	21	0.228	19	0.211	20	0.252
	Hunan	0.280	25	0.311	24	0.211	26	0.205	22	0.192	23	0.235
	Mean	0.333	-	0.364	-	0.265	-	0.265	-	0.261	-	
Western	Chongqing	0.291	20	0.307	26	0.211	27	0.204	23	0.207	21	0.238
	Sichuan	0.269	29	0.294	29	0.213	25	0.214	21	0.200	22	0.238
	Guizhou	0.360	7	0.386	7	0.248	17	0.194	24	0.187	24	0.281
	Yunnan	0.290	21	0.333	16	0.216	23	0.182	26	0.151	30	0.230
	Shaanxi	0.306	16	0.334	15	0.236	18	0.246	18	0.295	13	0.282
	Gansu	0.350	9	0.351	13	0.231	20	0.191	25	0.173	25	0.259
	Qinghai	0.320	14	0.327	19	0.214	24	0.162	29	0.161	29	0.234
	Ningxia	0.499	2	0.484	2	0.357	4	0.378	5	0.382	4	0.418
	Xinjiang	0.348	10	0.367	11	0.258	15	0.258	15	0.300	11	0.305
	Inner Mongolia	0.369	6	0.442	3	0.383	2	0.480	1	0.468	2	0.431
	Guangxi	0.277	26	0.292	30	0.179	30	0.169	28	0.161	28	0.213
	Mean	0.334	-	0.356	-	0.250	-	0.243	-	0.244	-	
All	Mean	0.334	-	0.373	-	0.294	-	0.311	-	0.312	-	

Table 5 China's regional FCRP and ranking in 2001, 2006, 2008, 2011, and 2017

Region	Province	2001	Rank	2006	Rank	2008	Rank	2011	Rank	2017	Rank	Mean
Eastern	Beijing	0.298	5	0.345	7	0.290	7	0.278	12	0.316	11	0.298
	Tianjin	0.304	4	0.372	4	0.319	5	0.380	6	0.426	4	0.361
	Hebei	0.247	10	0.301	8	0.269	9	0.311	9	0.289	15	0.284
	Liaoning	0.296	6	0.352	6	0.322	4	0.380	4	0.395	6	0.35
	Shanghai	0.347	3	0.413	2	0.381	2	0.401	3	0.478	3	0.398
	Jiangsu	0.212	19	0.272	15	0.266	10	0.327	8	0.391	7	0.286
	Zhejiang	0.210	21	0.276	14	0.260	11	0.291	10	0.327	10	0.261
	Fujian	0.206	22	0.255	18	0.209	17	0.244	15	0.303	14	0.241
	Shandong	0.217	16	0.287	10	0.290	8	0.343	7	0.387	8	0.299
	Guangdong	0.196	26	0.258	16	0.249	12	0.289	11	0.327	9	0.253
	Hainan	0.190	29	0.218	28	0.166	28	0.143	30	0.185	24	0.186
	Mean	0.248	-	0.304	-	0.275	-	0.308	-	0.348	-	
Central	Shanxi	0.376	1	0.502	1	0.424	1	0.442	2	0.581	1	0.471
	Jilin	0.244	12	0.280	12	0.221	14	0.246	14	0.255	17	0.246
	Heilongjiang	0.254	8	0.292	9	0.245	13	0.270	13	0.273	16	0.267
	Anhui	0.220	15	0.231	24	0.175	24	0.188	21	0.206	21	0.204
	Jiangxi	0.197	25	0.219	27	0.152	29	0.149	28	0.167	28	0.175
	Henan	0.211	20	0.249	20	0.210	16	0.243	16	0.232	18	0.229
	Hubei	0.213	17	0.240	23	0.183	20	0.205	19	0.216	20	0.208
	Hunan	0.194	27	0.228	26	0.168	26	0.177	23	0.189	23	0.188
	Mean	0.239	-	0.280	-	0.222	-	0.240	-	0.265	-	
Western	Chongqing	0.205	23	0.229	25	0.176	23	0.192	20	0.223	19	0.201
	Sichuan	0.185	30	0.214	29	0.167	27	0.181	22	0.192	22	0.188
	Guizhou	0.246	11	0.278	13	0.191	19	0.164	25	0.183	25	0.218
	Yunnan	0.200	24	0.242	21	0.169	25	0.156	27	0.149	30	0.18
	Shaanxi	0.213	18	0.250	19	0.195	18	0.224	18	0.304	13	0.236
	Gansu	0.244	13	0.257	17	0.183	21	0.167	24	0.169	27	0.205
	Qinghai	0.225	14	0.241	22	0.178	22	0.160	26	0.176	26	0.194
	Ningxia	0.368	2	0.382	3	0.315	6	0.380	5	0.417	5	0.37
	Xinjiang	0.254	9	0.284	11	0.220	15	0.243	17	0.313	12	0.263
	Inner Mongolia	0.269	7	0.367	5	0.361	3	0.490	1	0.517	2	0.404
	Guangxi	0.190	28	0.209	30	0.139	30	0.148	29	0.160	29	0.167
	Mean	0.236	-	0.268	-	0.208	-	0.228	-	0.255	-	
All	Mean	0.251	-	0.305	-	0.264	-	0.298	-	0.331	-	

of 0.598, 0.466, and 0.459, respectively. However, the bottom three provinces for the average ECRP were Hainan, Guangxi, and Jiangxi, with values of 0.257, 0.259, and 0.268, respectively.

Overall, the eastern region's economy is more developed, and its average CRP is obviously higher than that of the other two regions, indicating that there is still a lot of space for reducing carbon emissions in the eastern region; meanwhile, the relatively underdeveloped economy makes carbon reduction potential very low in most provinces in the central and western regions. In terms of provinces, the above analysis demonstrates that the top two provinces for the average CRP are Shanxi and Inner Mongolia; while Guangxi and Jiangxi have been the bottom two provinces in China, indicating that the CRP shows a slight polarization in the central and western regions, the polarization may result from various factors such as the level of economic development, the proportion of heavy industries, the consumption of high-carbon energy, and production technology. Hence, it is necessary to research how to enhance carbon reduction capacity effectively in most provinces and make more room for carbon emission reduction.

Table 6 China's regional ECRP and ranking in 2001, 2006, 2008, 2011, and 2017

Region	Province	2001	Rank	2006	Rank	2008	Rank	2011	Rank	2017	Rank	Mean
Eastern	Beijing	0.411	15	0.426	13	0.294	16	0.246	21	0.229	17	0.312
	Tianjin	0.446	7	0.463	7	0.317	10	0.318	11	0.298	10	0.368
	Hebei	0.426	12	0.455	8	0.361	7	0.381	5	0.301	9	0.386
	Liaoning	0.469	4	0.484	5	0.378	4	0.399	4	0.354	5	0.417
	Shanghai	0.443	8	0.469	6	0.368	5	0.361	8	0.357	4	0.395
	Jiangsu	0.349	28	0.377	26	0.325	8	0.363	7	0.350	6	0.340
	Zhejiang	0.336	29	0.379	25	0.310	12	0.318	12	0.288	11	0.306
	Fujian	0.356	25	0.389	22	0.261	23	0.257	17	0.249	16	0.298
	Shandong	0.368	22	0.403	18	0.367	6	0.402	3	0.375	3	0.374
	Guangdong	0.316	30	0.365	30	0.316	11	0.345	9	0.322	8	0.314
	Hainan	0.356	26	0.376	27	0.234	29	0.150	30	0.151	29	0.257
	Mean	0.289	-	0.417	-	0.321	-	0.322	-	0.298	-	
Central	Shanxi	0.637	1	0.708	1	0.523	1	0.498	1	0.560	1	0.598
	Jilin	0.427	11	0.437	12	0.287	17	0.263	16	0.213	19	0.321
	Heilongjiang	0.435	10	0.447	10	0.318	9	0.305	13	0.249	15	0.351
	Anhui	0.411	14	0.402	19	0.269	20	0.249	19	0.217	18	0.309
	Jiangxi	0.376	21	0.385	24	0.234	28	0.194	27	0.169	26	0.268
	Henan	0.391	17	0.410	17	0.309	13	0.324	10	0.254	14	0.338
	Hubei	0.386	18	0.398	20	0.263	22	0.251	18	0.206	21	0.296
	Hunan	0.365	23	0.393	21	0.253	25	0.233	22	0.195	22	0.283
	Mean	0.428	-	0.448	-	0.307	-	0.290	-	0.258	-	
Western	Chongqing	0.377	20	0.385	23	0.245	27	0.216	24	0.191	24	0.276
	Sichuan	0.353	27	0.374	29	0.260	24	0.248	20	0.209	20	0.288
	Guizhou	0.474	3	0.494	4	0.306	14	0.224	23	0.191	23	0.345
	Yunnan	0.380	19	0.424	14	0.263	21	0.208	26	0.154	28	0.281
	Shaanxi	0.399	16	0.419	15	0.277	19	0.268	15	0.286	13	0.328
	Gansu	0.455	6	0.445	11	0.279	18	0.215	25	0.176	25	0.314
	Qinghai	0.415	13	0.412	16	0.249	26	0.163	29	0.145	30	0.273
	Ningxia	0.629	2	0.587	2	0.398	3	0.376	6	0.347	7	0.466
	Xinjiang	0.441	9	0.450	9	0.296	15	0.272	14	0.287	12	0.348
	Inner Mongolia	0.469	5	0.516	3	0.405	2	0.469	2	0.419	2	0.459
	Guangxi	0.364	24	0.375	28	0.220	30	0.190	28	0.162	27	0.259
	Mean	0.433	-	0.444	-	0.291	-	0.259	-	0.233	-	
All	Mean	0.417	-	0.441	-	0.325	-	0.324	-	0.293	-	

Dynamic evolution analysis of carbon reduction potential

The dynamic evolution analysis results provide information for the current distributions of CRP and the variation in the provincial gap. Thus, we employ KDE to reveal the dynamic evolution of provincial CRP for 2001, 2006, 2008, 2011, and 2017. Figures 1, 2, and 3 show the Kernel density estimations, drawn by Stata 15.0, for MCRP, FCRP, and ECRP, respectively.

According to Figs. 1, 2, and 3, the following features are evident by comparing the dynamic evolution of the MCRP, FCRP, and ECRP. Firstly, as seen from the trend of the KDE curve, the curves and their centers of three scenarios moved slightly to the right from 2001 to 2006 and then moved to the left after 2006, suggesting that the CRP gradually increased first and then gradually decreased during the study period. Secondly, as seen from the kurtosis of the KDE curve, the peaks and ranges of three different scenario curves experienced varying degrees of change. The modes where the MCRP and ECRP were low evolved from a wide to sharp one from 2001 to 2006, with the height ascending, revealing that the regional gap of MCRP and ECRP was shrinking at this stage. Furthermore, the dispersion range slightly widened after 2006, with the height descending, indicating that the gap

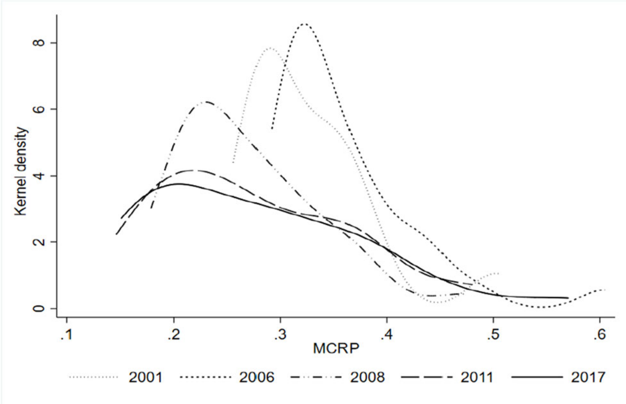

Fig. 1 Kernel density plot of China's MCRP in selected years

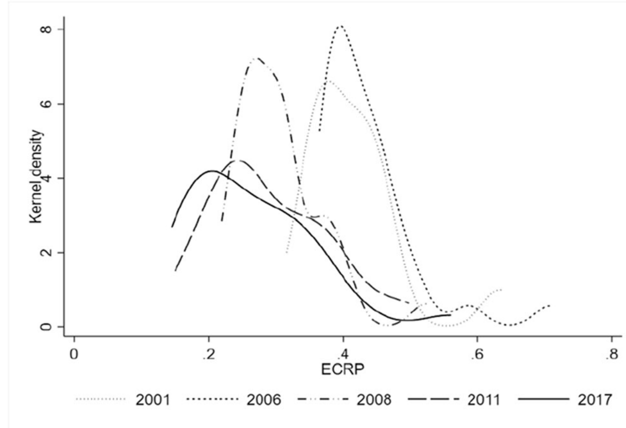

Fig. 3 Kernel density plot of China's ECRP in selected years

among CRPs of different provinces was enlarging. Thirdly, as seen from the shapes of the KDE curve, the curves of fairness and efficiency scenario for 2001, 2006, and 2008 were bi-modal and showed a rise at the right end, while those for 2011 and 2017 were unimodal. Besides, the curve of the moderation scenario was unimodal and with several lumps in the long right tail, which means that the CRP shows slight polarization.

Overall, provincial CRPs in China were enhancing from 2001 to 2008, with the provincial gap of MCRP and ECRP enlarged from 2001 to 2008 and bi-polarization tendency was weakened during 2011 and 2017. The peak of the curve in 2017 was the lowest and smoothest, which means that inter-provincial CRP level disparity in China was the narrowest in 2017.

Spatial characteristics of carbon reduction potential

Global spatial autocorrelation

This study tests the spatial correlation of MCRP, FCRP, and ECRP from 2000 to 2017. Table 7 presents the results of the global Moran index; the global Moran indices of CRP are positive at least at the 5% level of significance, indicating a significant positive spatial autocorrelation among the 30 provinces over time. The spatial dependence of MCRP, FCRP, and ECRP has shown a significant growth trend since 2000, but after 2011, the Moran I index began to decline fluctuating, indicating that the spatial autocorrelation of regional CRP has weakened after 2011. Moreover, the spatial correlations in 2009, 2010, and 2011 were relatively large, which indicates that the spatial dependence of CRP has an inverted "U" pattern, which first increases and then weakens.

Specifically, (i) the global Moran I index of MCRP increased from 0.136 in 2000 to 0.296 in 2010 and then showed a downward trend, which proves the strong geographic

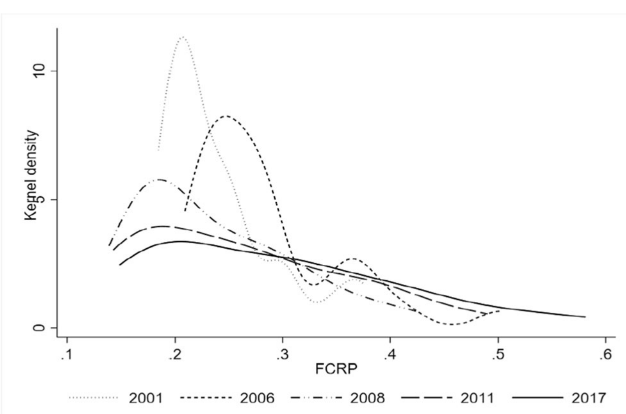

Fig. 2 Kernel density plot of China's FCRP in selected years

Table 7 The Moran's I index of CRP in China (2000–2017)

Year	*MCRP*	P value	*FCRP*	P value	*ECRP*	P value
2000	0.136**	0.032	0.166**	0.016	0.135**	0.030
2001	0.149**	0.022	0.183***	0.010	0.145**	0.021
2002	0.143**	0.026	0.180**	0.011	0.140**	0.026
2003	0.100*	0.066	0.123**	0.042	0.107*	0.056
2004	0.138**	0.027	0.191***	0.007	0.126**	0.035
2005	0.187***	0.006	0.248***	0.001	0.156**	0.013
2006	0.189***	0.005	0.253***	0.001	0.152**	0.013
2007	0.203***	0.004	0.255***	0.001	0.171**	0.011
2008	0.286***	0.000	0.317***	0.000	0.249***	0.001
2009	0.294***	0.000	0.321***	0.000	0.260***	0.001
2010	0.296***	0.000	0.317***	0.000	0.265***	0.001
2011	0.295***	0.000	0.304***	0.000	0.278***	0.001
2012	0.285***	0.000	0.294***	0.000	0.268***	0.001
2013	0.232***	0.001	0.245***	0.001	0.217***	0.002
2014	0.251***	0.001	0.257***	0.001	0.239***	0.001
2015	0.221***	0.003	0.225***	0.003	0.214***	0.003
2016	0.256***	0.001	0.257***	0.001	0.250***	0.001
2017	0.234***	0.002	0.257***	0.001	0.222***	0.003

Note: *, **, and *** represent the passing significant level of 10%, 5%, and 1%, respectively dependence and spatial autocorrelation in provincial CRP; (ii) the global Moran I index of FCRP had been fluctuant increasing from 2000 to 2009 and then showed a fluctuant downward trend after 2009; and (iii) the global Moran I index of ECRP increased fluctuant from 0.135 in 2000 to 0.278 in 2011 and then showed a fluctuant downward trend.

Local spatial autocorrelation

To reveal the spatial local auto-correlation and distribution pattern of China's provincial CRP, we draw Moran scatter plots for only 2009 and 2017 owing to the limited space available (see Figs. 4, 5, and 6). The first and the third quadrants, with H-H-type provinces and L-L-type provinces, respectively, indicate the province with high/low CRP is surrounded by provinces with high/low CRP, while the second and the fourth quadrants, with L-H-type provinces and H-L-type provinces, respectively, show the polarization characteristics.

It can be seen from the figure that most provinces with high CRP are located mainly in the eastern and central region (quadrant I) under three scenarios, such as Shanxi, Tianjin, Liaoning, and other provinces. These provinces possess abundant natural resources and increasingly close regional cooperation mechanisms, all of which have a positive effect on the surrounding province (Chen et al. 2020). Cluster provinces with low CRP are concentrated in the western region (quadrant III), including Guansu and Yunnan, and other provinces, as may result from most provinces in the western region which have underdeveloped economies and lower emission efficiency. L-H type was mainly distributed in Anhui, Jilin, and Henan. For these provinces, technical exchanges and cooperation with neighboring provinces could be strengthened to improve CRP. H-L type was prevalent in Guangdong and Jiangsu. These provinces are relatively rich in economy and energy technology, so that they could help their neighboring areas to increase carbon reduction capability through regional cooperation.

Specifically, (i) the sum of H-H-type and L-L-type provinces accounts for 73.3% (22 provinces) of the provinces in 2017, up from 63.3% (19 provinces) in 2009, which means that the spatial clustering is increasing, and the spatial polarization feature of provinces' MCRP appeared. For instance, Shanghai transformed from H-L type in 2009 to H-H type in 2017, as may result from Shanghai which has a positive radiative effect and its neighboring developing new sustainable clean technologies to increase CRP. (ii) The sum of H-H-type and L-L-type provinces accounts for 60% (18 provinces) of the provinces in 2017, down from 70% (21 provinces) in 2009, which means that the spatial clustering of provinces' FCRP is decreasing, and the spatial polarization feature weakened. (iii) The sum of H-H-type and L-L-type provinces accounts for 73.3% (22 provinces) of the provinces in 2017, down from 76.6% (23 provinces) in 2009, indicating that the spatial clustering of provinces' FCRP is increasing slightly.

Empirical results

Model selection

Before conducting spatial analysis, the first step is to focus attention on the selection of spatial econometric models.

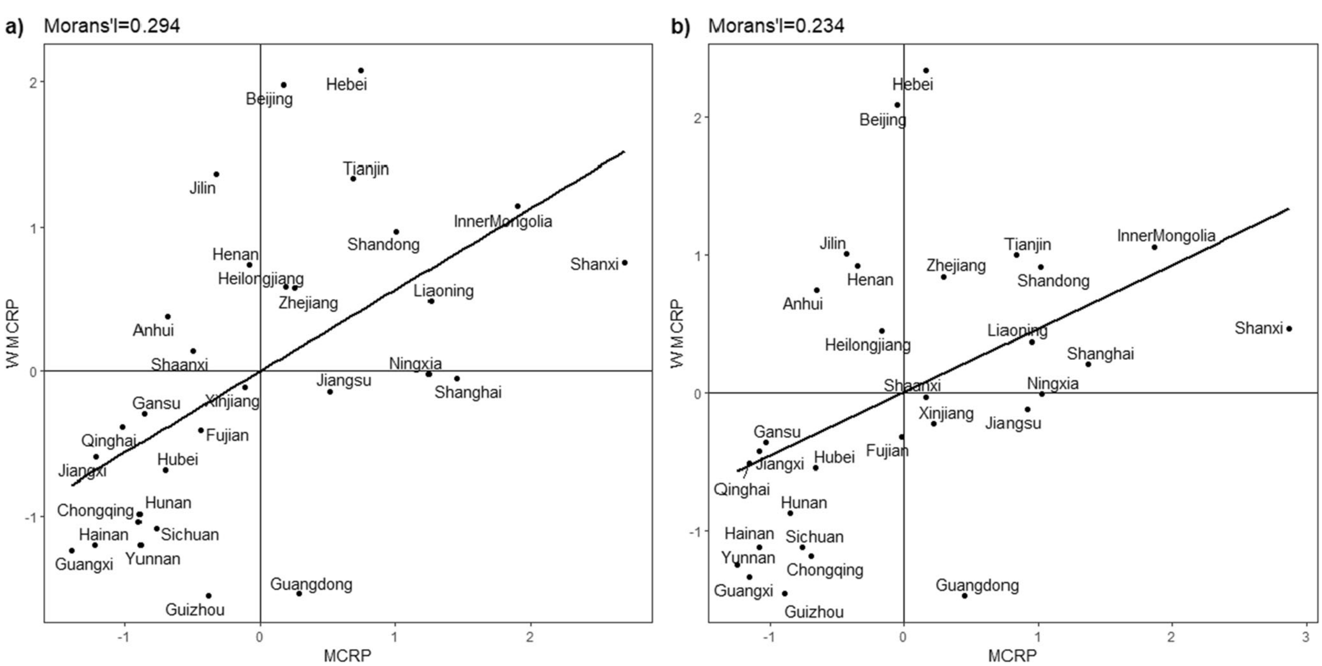

Fig. 4 Moran scatter plots of MCRP in 2009 and 2017

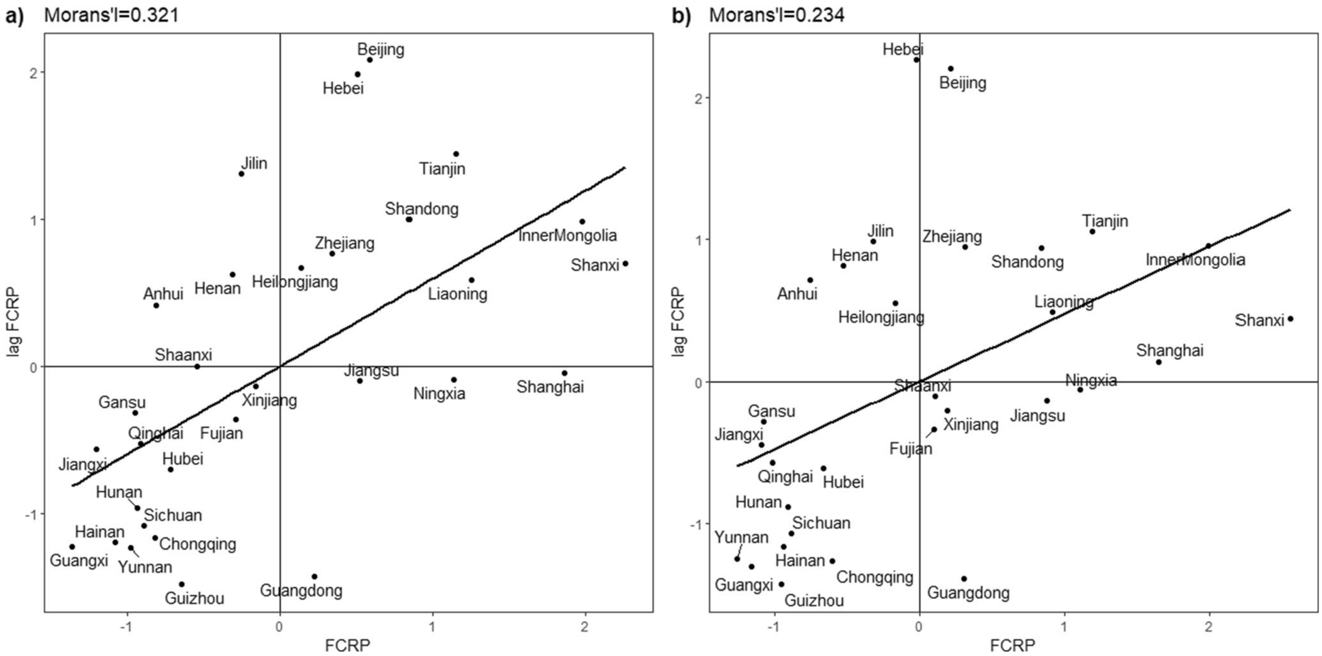

Fig. 5 Moran scatter plots of FCRP in 2009 and 2017

Firstly, we employed the Lagrange multiplier (LM) test to examine whether a spatially lagged dependent variable (LM spatial lag) or a spatially autocorrelated error term (LM spatial error) should be included in the model. According to the LM test results (Table 8), the LM-lag and LM-error test statistics are significant at the 1% level of significance, which indicates that the spatial model is a more appropriate specification than the non-spatial model. Then, the robust LM-lag and the robust LM-error statistics are significant, with a significance level of at least 1%, indicating that the factors affecting CRP include not only independent variables and their lag terms but also some unobservable error terms. Secondly, this paper conducted the likelihood ratio (LR) test to test further the existence of spatial effects. According to Table 8, the LR test results show that the SDM is estimated as this study preferred specification. Finally, it is essential to judge whether the correct panel data specification is a random effect or a fixed effect model through the Hausman test. The Hausman test statistics is significant at

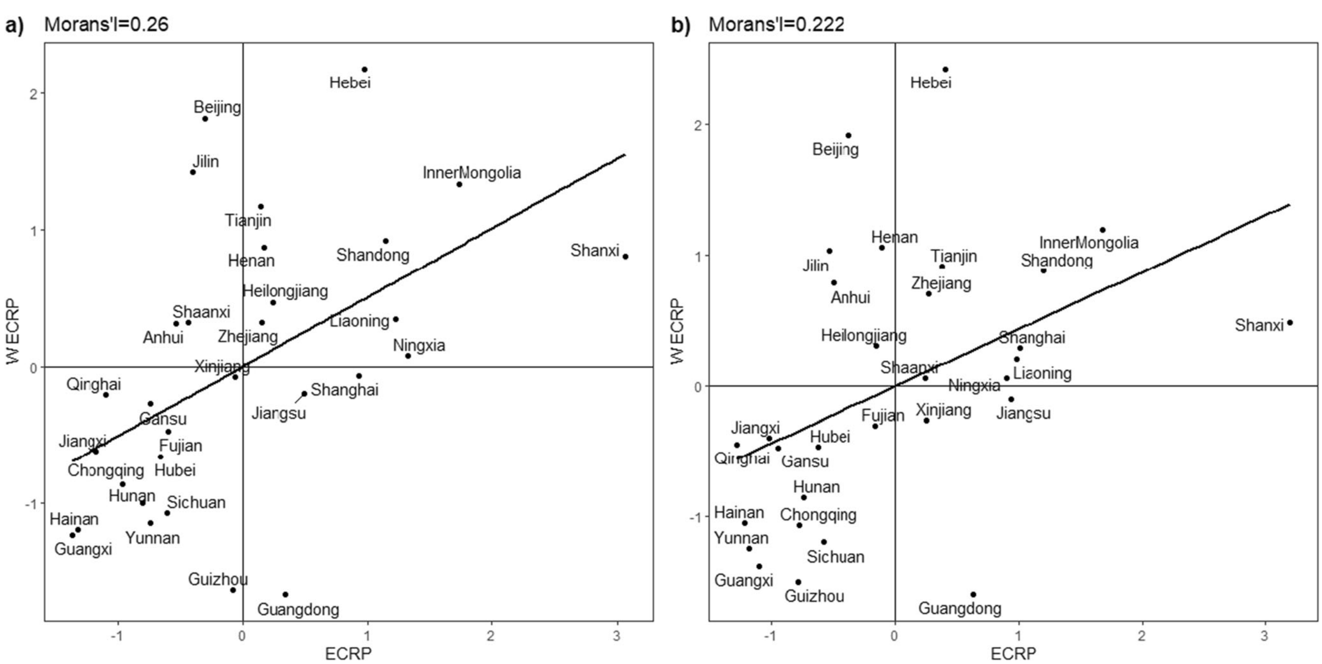

Fig. 6 Moran scatter plots of ECRP in 2009 and 2017

Table 8 The test of the spatial measurement model

Model	Test type	*MCRP*	*FCRP*	*ECRP*
Spatial error	Lagrange multiplier	197.168***	245.450***	183.139***
	Robust Lagrange multiplier	21.281***	34.657***	41.232***
Spatial lag	Lagrange multiplier	228.789***	288.402***	158.570***
	Robust Lagrange multiplier	52.902***	77.609***	16.663***
	LR-SDM-SAR	42.280***	56.180***	37.400***
	LR-SDM-SEM	49.380***	52.990***	48.830***
	Hausman	12.260*	17.390***	20.220***

Note: *, **, and *** represent the passing significant level of 10%, 5%, and 1%, respectively

the 1% level of significance, which indicates that this paper should use the SDM of fixed effect (Table 8).

Results of spatial Durbin estimation

For a spatial econometric model, the estimated coefficients of independent variables are not of great significance. What really needs to be explained are the direct effects and indirect effects of independent variables in space. As the estimation coefficients of explanatory variables do not represent the marginal effects of the independent variables on the dependent variable, we estimate the direct and indirect effects of independent variables on the dependent variable following LeSage and Pace (2009). Table 9 reports on the results of the estimated coefficients of the influencing factors affecting CRP under various scenarios, in which columns (1)–(3), columns (4)–(6), and columns (7)–(9) represent the result under moderation, fairness, and efficiency scenario, respectively.

According to Table 9, the regression coefficients of *GDP* on MCRP, FCRP, and ECRP are positive at the 1% level of significance; *W_GDP* has a negative and significant effect. The direct effects of *GDP* are significantly positive, and the indirect effects of *GDP* are significantly negative, which indicates that economic development has significant spatial spillover effects. Improving regional economic development in local provinces can significantly increase local CRP, but it may inhibit neighboring provinces' CRP, which may result from economic growth promoting the local accumulation of various resource, and then, siphon effect has caused the neighboring province to face the pressure of losing resources and innovative elements, leading to the potential space for carbon emission reduction that has been compressed. Thus, economic development is the main factor for enhancing the local CRP.

The regression coefficient of *IND* is negative at the 1% level of significance, and the direct and indirect effects of *IND* on MCRP, FCRP, and ECRP are negative and significant. We can conclude that adjusting the industrial structure in local provinces can increase local and neighboring provinces' carbon reduction potential. Most Chinese provinces' development mode is relatively rough and their industrial structure is relatively backward for a long time. Furthermore, many scholars established that the secondary industry is the leading producer of carbon emissions (Cole et al. 2008; Cheng et al. 2018). Due to many companies in the secondary industry that are generally characterized by high energy consumption and high carbon emission, improvement of industrial structure facilitates the flow of various factors from low-efficiency sectors to high-efficiency sectors (Zhou et al. 2013), which additionally increases the potential of carbon emission reduction. Therefore, industrial structure optimization is an effective way to improve provincial carbon emission reduction potential and reduce regional carbon emissions.

From the spillover effect decomposition analysis, *GREEN* has a negative effect on FCRP in local provinces, while *GREEN* has a positive effect on ECRP in local and neighboring provinces. These results indicate that improving low-carbon technologies can contribute to the local carbon emission reduction and provide critical support for local CRP under the efficiency scenario; in contrast, enhancing low-carbon innovation capability could restrain the local CRP under the fairness scenario. Low-carbon innovation can bring about an improvement in energy factor utilization and rapid development in new products. Especially in the process of increasing CRP by low-carbon technological progress, it is the efficiency-driven policy that plays the primary role. Therefore, we conclude that low-carbon innovation is a critical path that the province uses to increase local CRP and promote low-carbon transformation in the adjacent provinces from the perspective of efficiency.

The regression coefficient of *ES* is positive at the 1% level of significance, and direct effect coefficients of *ES* on MCRP, FCRP, and ECRP are positive at the 1% level of significance, indicating that energy structure optimization has significant spatial spillover effects. However, only under the efficiency scenario the indirect effect coefficient is 0.197, which is not significant, suggesting that adjustment of energy structure in local provinces has only marginally contributed to adjacent provinces' ECRP. The energy consumption structure in China is dominated by coal (Lin and Wang 2020); coal consumption is the major source of greenhouse gas emissions and

Table 9 The spatial effect estimation results

Scenarios	*MCRP*			*FCRP*			*ECRP*		
	SDM	Direct effects	Indirect effects	SDM	Direct effects	Indirect effects	SDM	Direct effects	Indirect effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP	0.164***	0.155***	-0.207***	0.219***	0.205***	-0.279***	0.110***	0.103***	-0.147*
	(6.232)	(5.840)	(-2.638)	(9.015)	(8.276)	(-3.509)	(3.642)	(3.441)	(-1.741)
IND	-0.067***	-0.067***	-0.027***	-0.057***	-0.057***	-0.030***	-0.078***	-0.077***	-0.025**
	(-7.292)	(-7.435)	(-2.582)	(-6.666)	(-6.779)	(-2.736)	(-7.394)	(-7.550)	(-2.340)
GREEN	0.001	0.002	0.020	-0.007*	-0.007*	0.006	0.009*	0.010**	0.034**
	(0.246)	(0.479)	(1.607)	(-1.861)	(-1.730)	(0.474)	(1.955)	(2.214)	(2.444)
ES	0.120***	0.131***	0.277**	0.094***	0.111***	0.367***	0.145***	0.152***	0.197
	(5.162)	(5.448)	(2.347)	(4.383)	(4.889)	(3.033)	(5.444)	(5.602)	(1.578)
EE	0.025***	0.026***	0.018*	0.020***	0.020***	0.009	0.030***	0.031***	0.026**
	(9.640)	(9.782)	(1.669)	(8.278)	(8.207)	(0.834)	(10.196)	(10.458)	(2.246)
OPEN	-0.009	-0.008	0.024	-0.007	-0.005	0.041*	-0.011	-0.010	0.009
	(-1.301)	(-1.073)	(1.023)	(-1.143)	(-0.756)	(1.741)	(-1.382)	(-1.258)	(0.363)
POP	-0.022	0.005	0.648***	0.013	0.044	0.654***	-0.055	-0.032	0.646***
	(-0.586)	(0.133)	(6.378)	(0.385)	(1.237)	(6.389)	(-1.304)	(-0.732)	(5.929)
W_GREEN	0.015			0.007			0.025**		
	(1.534)			(0.768)			(2.157)		
W_GDP	-0.205***			-0.270***			-0.148**		
	(-3.619)			(-5.188)			(-2.257)		
W_ES	0.167**			0.213***			0.119		
	(1.992)			(2.735)			(1.241)		
W_EE	0.006			-0.001			0.013		
	(0.733)			(-0.104)			(1.399)		
W_OPEN	0.019			0.029**			0.008		
	(1.199)			(2.009)			(0.456)		
W_POP	0.482***			0.436***			0.519***		
	(5.725)			(5.493)			(5.505)		
ρ	0.290***			0.351***			0.239***		
	(4.110)			(5.018)			(3.352)		
δ^2	0.001***			0.001***			0.001***		
	(16.303)			(16.232)			(16.346)		
Wald	42.69***			54.84***			37.80***		
	(0.000)			(0.000)			(0.000)		

Note: *, **, and *** represent the passing significant level of 10%, 5%, and 1%, respectively

environmental problems (Wang et al. 2012). The higher consumption of the province will provide more room for carbon emission reduction. Hence, switching to renewable energy and improving the coal-based energy structure would provide essential support for local carbon emission reduction.

According to Table 9, it can be seen that the increase in energy efficiency will significantly increase (1% significance level) local CRP under three scenarios, while only under the fairness scenario the indirect effect coefficient is 0.009, which is not significant. The results show that energy efficiency has a significantly positive impact on the surrounding areas' CRP except for the fairness scenario. The main reason is that the improvement of energy efficiency brings effective energy utilization (Jin et al. 2017). Due to the demonstration effect on neighboring areas, provinces with low energy efficiency usually strive to bring in technology promotion strategies, practical experiences of local policies of provinces with high efficiency (Song et al. 2018). Therefore, energy efficiency can be regarded as the vital factor of enhancing carbon reduction potential.

The direct effects of *OPEN* and *POP* on MCRP, FCRP, and ECRP were not significant; the indirect effects of *POP* are significantly positive under three scenarios, indicating that openness cannot significantly increase CRP, especially the openness that deviates from the green development orientation which is not conducive to regional emission reduction. Moreover, the effect of population size on CRP is not limited to local provinces and can enhance carbon reduction potential across provinces through population movement.

Conclusions and policy implications

Conclusions

This study evaluates the carbon shadow price and the CRP index under the three scenarios of moderation, fairness, and efficiency. Based on the evaluation data, we analyze the spatial-temporal patterns and dynamic evolution of provincial CRP from 2001 to 2017 in China. Then, we employ exploratory spatial data analysis and SDM to explore the influencing factors of CRP under three different scenarios. The main conclusions are as follows.

First, there are differences between different provinces/regions' CRPs under three different scenarios from 2000 to 2017. The average MCRP and average ECRP showed a gradual downward trend, while the average FCRP showed an upward volatility trend. There are also substantial differences between the regions. MCRP and FCRP in the eastern region were found the highest, whereas ECRP in the eastern region was the highest after 2008. Further, there exists a slight polarization in the central and western regions.

Second, the spatial autocorrelation test indicated that the provinces with a similar CRP showed a significant geographic agglomeration, and the agglomeration effect was strengthened first and then weakened over time. Besides, most provinces with high CRP are located mainly in the eastern and central regions, such as Shanxi and Inner Mongolia. These provinces possess abundant natural resources and have a positive effect on the surrounding province. Cluster provinces with low CRP are concentrated in the western region. These provinces have underdeveloped economies.

Lastly, through the SDM analysis and spillover effect decomposition, we conclude that improvements in regional CRP not only depend on economic development, industrial structure adjustment, and energy efficiency elevation, but also involve energy structure optimization, low-carbon innovation, and population. It is noteworthy that there are differences in the effects of low-carbon innovation under different scenarios. The low-carbon innovation provides critical support for local CRP under the efficiency scenario but restrains the local CRP under the fairness scenario.

Policy implications

Based on the above conclusions, the policy implications for regional carbon reduction potential improvement are as follows.

Firstly, the central government should fully consider the heterogeneity of factors such as economic development, resource conditions, and carbon emission potentials in various regions when formulating carbon reduction policies. The government must emphasize local conditions, make the ex ante scenario assessment, pay more attention to areas with high CRPs, and appropriately control areas with low CRPs. For example, the leading coal production provinces with low marginal abatement costs, Shanxi, Inner Mongolia, etc., should assume higher carbon reduction targets to unlock the carbon reduction potential, while underdeveloped provinces with slow energy structure adjustments, such as Hainan and Qinghai, should assume looser carbon reduction constraints. Overall, the government should guide innovation and human resource flow to the central and western regions and high-carbon areas with high emission reduction potential to improve emission reduction efficiency while reducing total social costs.

Secondly, emphasize the cross-regional collaboration of carbon emission control. The "spillover" of social capital, talents, and low-carbon technology makes it easy to achieve the goal of inter-regional coordinated development of carbon reduction. To break the current situation of low carbon reduction potential among the western regions, carbon reduction strategies should be established based on "joint prevention and control." Specifically, for H-L agglomeration areas, strengthening the leading role in developed economic areas, such as Guangdong and Jiangsu, and reinforcing the spillover of capital, environmental protection technologies, and other factors to enhance the radiation effect from the "center" to the "periphery" should be established. For low-low agglomeration areas with underdeveloped economies, such as Guangxi and Gansu, CRP could be enhanced by encouraging develop clean energy (e.g., photovoltaic, wind energy, tidal energy) and increasing special fund support and guarantee to weaken the siphon effect.

Thirdly, explore the carbon reduction paths characterized by sustainable and low-carbon development governed in multiple dimensions. The study shows that improvement in economic development, industrial structure, and energy efficiency elevation will not only effectively enhance the local CRP but also have a significant spatial spillover effect. Therefore, it is essential to optimize energy efficiency and explore economic growth paths characterized by sustainable and low-carbon development. On the one hand, through tax incentives and low-interest loans, the government can encourage and support the local research institutes and enterprises in developed areas to carry out the production, transformation, and application of low-carbon innovation, which is an indispensable strategy for advancing energy efficiency. Meanwhile, the government could introduce voluntary energy efficiency standards for various sectors, especially high-carbon industries, to stimulate industrial energy efficiency improvements. On the other hand, the government could vigorously promote the application of clean energy in transport, industry, and construction through financial subsidies and pollution penalties to get rid of coal dependence gradually. Simultaneously, we should formulate relevant policies to guide enterprises to transition toward the tertiary industry to accelerate de-industrialization progress. In particular, the government should increase subsidies for outstanding talents and foster regional knowledge collaboration.

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Author contribution All authors contributed to the study conception and design. Zhangwen Li acquired, analyzed, and interpreted the data; drafted the article or revised it critically for important intellectual content; and was a major contributor in writing the manuscript. Caijiang Zhang revised it critically for intellectual content and approved the version to be published. Yu Zhou acquired the data and made substantial contributions to the conception or design of the work. All authors read and approved the final manuscript.

Data availability The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable

Competing interests The authors declare no conflict of interest.

References

Aigner DJ, Chu SF (1968) On estimating the industry production function. Am Econ Rev 58:826–839

Akimoto K, Sano F, Homma T, Oda J, Nagashima M, Kii M (2010) Estimates of GHG emission reduction potential by country, sector, and cost. Energy Policy 38:3384–3393. https://doi.org/10.1016/j.enpol.2010.02.012

Albino V, Ardito L, Dangelico RM, Messeni Petruzzelli A (2014) Understanding the development trends of low-carbon energy technologies: A patent analysis. Appl Energy 135:836–854. https://doi.org/10.1016/j.apenergy.2014.08.012

An R, Yu B, Li R, Wei Y-M (2018) Potential of energy savings and CO_2 emission reduction in China's iron and steel industry. Appl Energy 226:862–880. https://doi.org/10.1016/j.apenergy.2018.06.044

Anselin L (1995) Local indicators of spatial association—LISA. Geogr Anal 27:93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Bian Y, He P, Xu H (2013) Estimation of potential energy saving and carbon dioxide emission reduction in China based on an extended non-radial DEA approach. Energy Policy 63:962–971. https://doi.org/10.1016/j.enpol.2013.08.051

Chen H, Chen W (2019) Potential impacts of coal substitution policy on regional air pollutants and carbon emission reductions for China's building sector during the 13th Five-Year Plan period. Energy Policy 131:281–294. https://doi.org/10.1016/j.enpol.2019.04.047

Chen B, Jin Y (2020) Adjusting productivity measures for CO2 emissions control: evidence from the provincial thermal power sector in China. Energy Econ 87:104707. https://doi.org/10.1016/j.eneco.2020.104707

Chen J, Xiang D (2019) Carbon efficiency and carbon abatement costs of coal-fired power enterprises: a case of Shanghai, China. J Clean Prod 206:452–459. https://doi.org/10.1016/j.jclepro.2018.09.087

Chen J, Cheng S, Song M, Wu Y (2016) A carbon emissions reduction index: integrating the volume and allocation of regional emissions. Appl Energy 184:1154–1164. https://doi.org/10.1016/j.apenergy.2016.03.032

Chen J, Xu C, Cui L, Huang S, Song M (2019) Driving factors of CO2 emissions and inequality characteristics in China: a combined decomposition approach. Energy Econ 78:589–597. https://doi.org/10.1016/j.eneco.2018.12.011

Chen Y, Zhu B, Sun X, Xu G (2020) Industrial environmental efficiency and its influencing factors in China: analysis based on the Super-SBM model and spatial panel data. Environ Sci Pollut Res 27:44267–44278. https://doi.org/10.1007/s11356-020-10235-y

Chen Z, Zhao W, Zheng H (2021) Potential output gap in China's regional coal-fired power sector under the constraint of carbon emission reduction. Energy Policy 148:111888. https://doi.org/10.1016/j.enpol.2020.111888

Cheng Z, Li L, Liu J (2018) Industrial structure, technical progress and carbon intensity in China's provinces. Renew Sust Energ Rev 81:2935–2946. https://doi.org/10.1016/j.rser.2017.06.103

Cheng M, Shao Z, Gao F, Yang C, Tong C, Yang J, Zhang W (2020) The effect of research and development on the energy conservation potential of China's manufacturing industry: the case of east region. J Clean Prod 258:120558. https://doi.org/10.1016/j.jclepro.2020.120558

Choi Y, Zhang N, Zhou P (2012) Efficiency and abatement costs of energy-related CO2 emissions in China: a slacks-based efficiency measure. Appl Energy 98:198–208. https://doi.org/10.1016/j.apenergy.2012.03.024

Choi Y, Yang F, Lee H (2020) On the unbalanced atmospheric environmental performance of major cities in China. Sustainability 12:5391. https://doi.org/10.3390/su12135391

Chung YH, Färe R, Grosskopf S (1997) Productivity and undesirable outputs: a directional distance function approach. J Environ Manag 51:229–240. https://doi.org/10.1006/jema.1997.0146

Cole MA, Elliott RJR, Wu S (2008) Industrial activity and the environment in China: an industry-level analysis. China Econ Rev 19:393–408. https://doi.org/10.1016/j.chieco.2007.10.003

den Elzen MGJ, Lucas PL (2005) The FAIR model: a tool to analyse environmental and costs implications of regimes of future commitments. Environ Model Assess 10:115–134. https://doi.org/10.1007/s10666-005-4647-z

Dietz T, Rosa EA (1994) Rethinking the environmental impacts of population, affluence and technology. Hum Ecol Rev 1:277–300

Ding L, Yang Y, Wang W, Calin AC (2019) Regional carbon emission efficiency and its dynamic evolution in China: a novel cross efficiency-malmquist productivity index. J Clean Prod 241:118260. https://doi.org/10.1016/j.jclepro.2019.118260

Dong F, Long R, Yu B, Wang Y, Li J, Wang Y, Dai Y, Yang Q, Chen H (2018) How can China allocate CO_2 reduction targets at the provincial level considering both equity and efficiency? Evidence from its Copenhagen Accord pledge. Resour Conserv Recycl 130:31–43. https://doi.org/10.1016/j.resconrec.2017.11.011

Du K, Li P, Yan Z (2019) Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. Technol Forecast Soc Change 146:297–303. https://doi.org/10.1016/j.techfore.2019.06.010

Färe R, Grosskopf S, Lovell CAK, Yaisawarng S (1993) Derivation of shadow prices for undesirable outputs: a distance function approach. Rev Econ Stat 75:374–380

Färe R, Grosskopf S, Noh D-W, Weber W (2005) Characteristics of a polluting technology: theory and practice. J Econ 126:469–492. https://doi.org/10.1016/j.jeconom.2004.05.010

Färe R, Grosskopf S, Weber WL (2006) Shadow prices and pollution costs in U.S. agriculture. Ecol Econ 56:89–103. https://doi.org/10.1016/j.ecolecon.2004.12.022

Guo X-D, Zhu L, Fan Y, Xie B-C (2011) Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. Energy Policy 39:2352–2360. https://doi.org/10.1016/j.enpol.2011.01.055

Huang Y-H, Wu J-H (2021) Bottom-up analysis of energy efficiency improvement and CO2 emission reduction potentials in the cement industry for energy transition: an application of extended marginal abatement cost curves. J Clean Prod 296:126619. https://doi.org/10.1016/j.jclepro.2021.126619

IPCC (2006) IPCC Guidelines for national greenhouse gas inventories. https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html. Accessed 5 Mar 2021

Ji DJ, Zhou P (2020) Marginal abatement cost, air pollution and economic growth: evidence from Chinese cities. Energy Econ 86:104658. https://doi.org/10.1016/j.eneco.2019.104658

Jiang J, Ye B, Xie D, Tang J (2017) Provincial-level carbon emission drivers and emission reduction strategies in China: combining multilayer LMDI decomposition with hierarchical clustering. J Clean Prod 169:178–190. https://doi.org/10.1016/j.jclepro.2017.03.189

Jin L, Duan K, Shi C, Ju X (2017) The impact of technological progress in the energy sector on carbon emissions: an empirical analysis from China. Int J Environ Res Public Health 14:1505. https://doi.org/10.3390/ijerph14121505

Jordaan SM, Romo-Rabago E, McLeary R, Reidy L, Nazari J, Herremans IM (2017) The role of energy technology innovation in reducing greenhouse gas emissions: a case study of Canada. Renew Sust Energ Rev 78:1397–1409. https://doi.org/10.1016/j.rser.2017.05.162

Ke T-Y, Hu J-L, Li Y, Chiu Y-H (2008) Shadow prices of SO2 abatements for regions in China. Agric Resour Econ 5(2):59–78

Ketelaer T, Kaschub T, Jochem P, Fichtner W (2014) The potential of carbon dioxide emission reductions in German commercial transport by electric vehicles. Int J Environ Sci Technol 11:2169–2184. https://doi.org/10.1007/s13762-014-0631-y

Lee M (2011) Potential cost savings from internal/external CO2 emissions trading in the Korean electric power industry. Energy Policy 39:6162–6167. https://doi.org/10.1016/j.enpol.2011.07.016

Lee J-D, Park J-B, Kim T-Y (2002) Estimation of the shadow prices of pollutants with production/environment inefficiency taken into account: a nonparametric directional distance function approach. J Environ Manag 64:365–375. https://doi.org/10.1006/jema.2001.0480

LeSage JP (2008) An introduction to spatial econometrics. Rev Déconomie Ind:19–44. https://doi.org/10.4000/rei.3887

LeSage JP, Pace RK (2009) Introduction to spatial econometrics. CRC press, Boca Raton

Lin B, Ouyang X (2014) Analysis of energy-related CO2 (carbon dioxide) emissions and reduction potential in the Chinese non-metallic mineral products industry. Energy 68:688–697. https://doi.org/10.1016/j.energy.2014.01.069

Lin B, Wang Y (2020) Does energy poverty really exist in China? From the perspective of residential electricity consumption. Energy Policy 143:111557. https://doi.org/10.1016/j.enpol.2020.111557

Lin B, Xie C (2014) Reduction potential of CO2 emissions in China′s transport industry. Renew Sust Energ Rev 33:689–700. https://doi.org/10.1016/j.rser.2014.02.017

Liu Z, Guan D, Wei W, Davis SJ, Ciais P, Bai J, Peng S, Zhang Q, Hubacek K, Marland G, Andres RJ, Crawford-Brown D, Lin J, Zhao H, Hong C, Boden TA, Feng K, Peters GP, Xi F, Liu J, Li Y, Zhao Y, Zeng N, He K (2015) Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature 524:335–338. https://doi.org/10.1038/nature14677

Liu Y, Qu Y, Lei Z, Wang W (2020) Multi-sector reduction potential of embodied carbon emissions in China: a case study of Liaoning province. Environ Dev Sustain 22:5585–5602. https://doi.org/10.1007/s10668-019-00441-1

Ma G, Li X, Zheng J (2020) Efficiency and equity in regional coal decapacity allocation in China: a multiple objective programming model based on Gini coefficient and Data Envelopment Analysis. Res Policy 66:101621. https://doi.org/10.1016/j.resourpol.2020.101621

Molinos-Senante M, Guzmán C (2018) Reducing CO2 emissions from drinking water treatment plants: a shadow price approach. Appl Energy 210:623–631. https://doi.org/10.1016/j.apenergy.2016.09.065

Pan X, den Elzen M, Höhne N et al (2017) Exploring fair and ambitious mitigation contributions under the Paris Agreement goals. Environ Sci Pol 74:49–56. https://doi.org/10.1016/j.envsci.2017.04.020

Park JY (2014) The evolution of waste into a resource: examining innovation in technologies reusing coal combustion by-products using patent data. Res Policy 43:1816–1826. https://doi.org/10.1016/j.respol.2014.06.002

Qin Q, Liu Y, Li X, Li H (2017) A multi-criteria decision analysis model for carbon emission quota allocation in China's east coastal areas: efficiency and equity. J Clean Prod 168:410–419. https://doi.org/10.1016/j.jclepro.2017.08.220

Raza MY, Lin B (2020) Decoupling and mitigation potential analysis of CO2 emissions from Pakistan's transport sector. Sci Total Environ 730:139000. https://doi.org/10.1016/j.scitotenv.2020.139000

Shahbaz M, Loganathan N, Muzaffar AT, Ahmed K, Ali Jabran M (2016) How urbanization affects CO2 emissions in Malaysia? The application of STIRPAT model. Renew Sust Energ Rev 57:83–93. https://doi.org/10.1016/j.rser.2015.12.096

Shen L, Wu Y, Lou Y, Zeng D, Shuai C, Song X (2018) What drives the carbon emission in the Chinese cities?—a case of pilot low carbon city of Beijing. J Clean Prod 174:343–354. https://doi.org/10.1016/j.jclepro.2017.10.333

Shephard RW (1970) Theory of cost and production functions Princeton University press. Princeton University press

Shi Y, Sasai T, Yamaguchi Y (2014) Spatio-temporal evaluation of carbon emissions from biomass burning in Southeast Asia during the period 2001–2010. Ecol Model 272:98–115. https://doi.org/10.1016/j.ecolmodel.2013.09.021

Song M, Chen Y, An Q (2018) Spatial econometric analysis of factors influencing regional energy efficiency in China. Environ Sci Pollut Res 25:13745–13759. https://doi.org/10.1007/s11356-018-1574-5

Song Y, Huang J, Zhang Y, Wang Z (2019) Drivers of metal consumption in China: an input-output structural decomposition analysis. Res Policy 63:101421. https://doi.org/10.1016/j.resourpol.2019.101421

Sun JW (2005) The decrease of CO2 emission intensity is decarbonization at national and global levels. Energy Policy 33:975–978. https://doi.org/10.1016/j.enpol.2003.10.023

Tang K, Gong C, Wang D (2016a) Reduction potential, shadow prices, and pollution costs of agricultural pollutants in China. Sci Total Environ 541:42–50. https://doi.org/10.1016/j.scitotenv.2015.09.013

Tang K, Yang L, Zhang J (2016b) Estimating the regional total factor efficiency and pollutants' marginal abatement costs in China: a parametric approach. Appl Energy 184:230–240. https://doi.org/10.1016/j.apenergy.2016.09.104

Tian X, Chang M, Tanikawa H, Shi F, Imura H (2013) Structural decomposition analysis of the carbonization process in Beijing: a regional explanation of rapid increasing carbon dioxide emission in China. Energy Policy 53:279–286. https://doi.org/10.1016/j.enpol.2012.10.054

Wang Y, Zheng Y (2020) Spatial effects of carbon emission intensity and regional development in China. Environ Sci Pollut Res 28:14131–14143. https://doi.org/10.1007/s11356-020-11557-7

Wang Q, Cui Q, Zhou D, Wang S (2011) Marginal abatement costs of carbon dioxide in China: a nonparametric analysis. Energy Procedia 5:2316–2320. https://doi.org/10.1016/j.egypro.2011.03.398

Wang K, Wei Y-M, Zhang X (2012) A comparative analysis of China's regional energy and emission performance: which is the better way to deal with undesirable outputs? Energy Policy 46:574–584. https://doi.org/10.1016/j.enpol.2012.04.038

Wang K, Che L, Ma C, Wei Y-M (2017) The shadow price of CO2 emissions in China's iron and steel industry. Sci Total Environ 598:272–281. https://doi.org/10.1016/j.scitotenv.2017.04.089

Wang Y, Zhao T, Wang J, Guo F, Kan X, Yuan R (2019) Spatial analysis on carbon emission abatement capacity at provincial level in China from 1997 to 2014: an empirical study based on SDM model. Atmospheric Pollut Res 10:97–104. https://doi.org/10.1016/j.apr.2018.06.003

Wang W, Li Y, Lu N, Wang D, Jiang H, Zhang C (2020) Does increasing carbon emissions lead to accelerated eco-innovation? Empirical evidence from China. J Clean Prod 251:119690. https://doi.org/10.1016/j.jclepro.2019.119690

Wei X, Zhang N (2020) The shadow prices of CO2 and SO2 for Chinese coal-fired power plants: a partial frontier approach. Energy Econ 85:104576. https://doi.org/10.1016/j.eneco.2019.104576

Wei C, Ni J, Du L (2012) Regional allocation of carbon dioxide abatement in China. China Econ Rev 23:552–565. https://doi.org/10.1016/j.chieco.2011.06.002

Wei C, Löschel A, Liu B (2015) Energy-saving and emission-abatement potential of Chinese coal-fired power enterprise: a non-parametric analysis. Energy Econ 49:33–43. https://doi.org/10.1016/j.eneco.2015.02.002

Wei W, Cai W, Guo Y, Bai C, Yang L (2020) Decoupling relationship between energy consumption and economic growth in China's provinces from the perspective of resource security. Res Policy 68:101693. https://doi.org/10.1016/j.resourpol.2020.101693

Wu D, Li S, Liu L, Lin J, Zhang S (2021a) Dynamics of pollutants' shadow price and its driving forces: an analysis on China's two major pollutants at provincial level. J Clean Prod 283:124625. https://doi.org/10.1016/j.jclepro.2020.124625

Wu S, Hu S, Frazier AE (2021b) Spatiotemporal variation and driving factors of carbon emissions in three industrial land spaces in China from 1997 to 2016. Technol Forecast Soc Change 169:120837. https://doi.org/10.1016/j.techfore.2021.120837

Wu Y, Yu J, Song M, Chen J, Hou W (2021c) Shadow prices of industrial air pollutant emissions in China. Econ Model 94:726–736. https://doi.org/10.1016/j.econmod.2020.02.014

Xia F, Zhang X, Cai T, Wu S, Zhao D (2020) Identification of key industries of industrial sector with energy-related CO2 emissions and analysis of their potential for energy conservation and emission reduction in Xinjiang, China. Sci Total Environ 708:134587. https://doi.org/10.1016/j.scitotenv.2019.134587

Yang L, Tang K, Wang Z, An H, Fang W (2017) Regional eco-efficiency and pollutants' marginal abatement costs in China: a parametric approach. J Clean Prod 167:619–629. https://doi.org/10.1016/j.jclepro.2017.08.205

Yang F, Choi Y, Lee H (2021) Life-cycle data envelopment analysis to measure efficiency and cost-effectiveness of environmental regulation in China's transport sector. Ecol Indic 126:107717. https://doi.org/10.1016/j.ecolind.2021.107717

Yu S, Agbemabiese L, Zhang J (2016) Estimating the carbon abatement potential of economic sectors in China. Appl Energy 165:107–118. https://doi.org/10.1016/j.apenergy.2015.12.064

Yu S, Zheng S, Li X (2018) The achievement of the carbon emissions peak in China: the role of energy consumption structure optimization. Energy Econ 74:693–707. https://doi.org/10.1016/j.eneco.2018.07.017

Zeng S, Jiang X, Su B, Nan X (2018) China's SO2 shadow prices and environmental technical efficiency at the province level. Int Rev Econ Financ 57:86–102. https://doi.org/10.1016/j.iref.2018.02.014

Zhang Y-J, Da Y-B (2015) The decomposition of energy-related carbon emission and its decoupling with economic growth in China. Renew Sust Energ Rev 41:1255–1266. https://doi.org/10.1016/j.rser.2014.09.021

Zhang N, Wei X (2015) Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. Appl Energy 146:409–420. https://doi.org/10.1016/j.apenergy.2015.01.072

Zhang Y-J, Hao J-F, Song J (2016) The CO2 emission efficiency, reduction potential and spatial clustering in China's industry: evidence from the regional level. Appl Energy 174:213–223. https://doi.org/10.1016/j.apenergy.2016.04.109

Zhang Y-J, Peng Y-L, Ma C-Q, Shen B (2017) Can environmental innovation facilitate carbon emissions reduction? Evidence from China. Energy Policy 100:18–28. https://doi.org/10.1016/j.enpol.2016.10.005

Zhang L, Long R, Chen H (2019a) Carbon emission reduction potential of urban rail transit in China based on electricity consumption structure. Resour Conserv Recycl 142:113–121. https://doi.org/10.1016/j.resconrec.2018.11.019

Zhang W, Zhang N, Yu Y (2019b) Carbon mitigation effects and potential cost savings from carbon emissions trading in China's regional industry. Technol Forecast Soc Change 141:1–11. https://doi.org/10.1016/j.techfore.2018.12.014

Zhang N, Wu Y, Choi Y (2020a) Is it feasible for China to enhance its air quality in terms of the efficiency and the regulatory cost of air pollution? Sci Total Environ 709:136149. https://doi.org/10.1016/j.scitotenv.2019.136149

Zhang Y, Wang W, Liang L, Wang D, Cui X, Wei W (2020b) Spatial-temporal pattern evolution and driving factors of China's energy efficiency under low-carbon economy. Sci Total Environ 739:140197. https://doi.org/10.1016/j.scitotenv.2020.140197

Zhou X, Zhang J, Li J (2013) Industrial structural transformation and carbon dioxide emissions in China. Energy Policy 57:43–51. https://doi.org/10.1016/j.enpol.2012.07.017

Zhou P, Zhou X, Fan LW (2014) On estimating shadow prices of undesirable outputs with efficiency models: a literature review. Appl Energy 130:799–806. https://doi.org/10.1016/j.apenergy.2014.02.049

Zhou X, Fan LW, Zhou P (2015) Marginal CO2 abatement costs: findings from alternative shadow price estimates for Shanghai industrial sectors. Energy Policy 77:109–117. https://doi.org/10.1016/j.enpol.2014.12.009

Zhu Q, Li X, Li F, Zhou D (2020) The potential for energy saving and carbon emission reduction in China's regional industrial sectors. Sci Total Environ 716:135009. https://doi.org/10.1016/j.scitotenv.2019.135009

Zuberi MJS, Patel MK (2017) Bottom-up analysis of energy efficiency improvement and CO2 emission reduction potentials in the Swiss cement industry. J Clean Prod 142:4294–4309. https://doi.org/10.1016/j.jclepro.2016.11.178