Calculation of carbon emission efficiency in China and analysis of influencing factors

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Abstract

Carbon emissions have risen in line with China's economic expansion. The key to sustainable development is finding a way to strike a balance between economic expansion and environmental protection, so improving carbon emission efficiency is vital. This paper uses provincial data from 2010 to 2020 to account for total carbon emissions using the emission factor method and obtains carbon emission efficiency data on this basis. A dynamic spatial Durbin model is then used to empirically test the possible influencing factors. The results show that, firstly, the growth rate of total carbon emissions is generally in line with the growth rate of GDP, indicating that there is no 'decoupling' in the economic system. Second, regional carbon emissions and carbon emission efficiency are not necessarily related. Thirdly, there is a clear spatial effect on carbon emission efficiency. The eastern region has the highest carbon emission efficiency, the western region has the lowest, and the northeastern and central regions have little difference in carbon emission efficiency. Further spatial and temporal migration analysis reveals that five provinces have made the migration between 2010 and 2020. Fourthly, in the short term, the direct and indirect effects of the factors affecting carbon emission efficiency are insignificant, but in the long term, most of the factors have significant direct and indirect effects on carbon emission efficiency. Finally, based on the above research findings, this paper makes policy recommendations.

Introduction

Since the twentieth century, the energy, environmental, and climate problems caused by excessive carbon emissions have become increasingly serious. In order to reduce the global problems caused by carbon emissions, a series of international consensus on low-carbon green development has been reached. The Intergovernmental Panel on Climate Change (IPCC) was established in 1988, and in 1992, it adopted the United Nations Framework Convention on Climate Change (UNFCCC), which laid the groundwork for subsequent national negotiations by emphasising the 'common but differentiated responsibilities' of developing and developed countries. Through the Kyoto Protocol, a number of nations mandated that Parties restrict and reduce their greenhouse gas emissions in accordance with certain, predetermined targets and to submit regular reports beginning in 1997. At the yearly Paris Climate Change Conference in 2015, around 200 parties came to an agreement on the Paris Agreement, which established the post-2020 global climate governance framework with the aim of 'improving climate resilience and low greenhouse gas emission development without endangering food production'. According to the inaugural Global Development Report released by the China International Development Knowledge Centre, 127 countries worldwide have proposed or are preparing to propose

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carbon neutrality targets by May 2022, a range that covers 88% of global CO_2 emissions, 90% of GDP, and 85% of the population (Hu 2021).

Like most countries in the world, China is faced with the trade-off between economic development and energy conservation and emission reduction. China's increasing carbon emissions are occurring in tandem with rapid economic growth. From 2010 to 2020, China's total carbon emissions increased from 6107.45 to 12,553.67 Mt, and GDP increased from 30,173.02 billion yuan to 62,566.22 billion yuan, with an average annual growth rate of carbon emissions of 7.47% and an average annual growth rate of GDP of 7.57% (Fig. 1). How to effectively carry out carbon dioxide emission reduction while maintaining sustained economic growth has become an important issue of Chinese society.

Prior to the Copenhagen Climate Conference in 2009, China set a 2020 greenhouse gas emission control target of a 40–45% reduction in carbon emission intensity compared to 2005 and made it an important binding indicator for examining the sustainable and healthy development of China's national economy and society (Tian and Ma 2020). At the 75th session of the United Nations General Assembly in September 2020, the Chinese government proposed a 'dual carbon' development target: achieving 'peak carbon' by 2030 and 'carbon neutral' by 2060 (Cui et al. 2023a). Achieving the 'two-carbon' target is based on reducing emissions, and improving the efficiency of carbon emissions is key to balancing economic growth and environmental protection.

In order to explore the spatial distribution characteristics and influencing factors of carbon emission efficiency in China, we select relevant data from China Energy Statistical Yearbook, China Statistical Yearbook, and provincial-level Regional Statistical Yearbook from 2010 to 2020 and use spatial measurement methods to analyse the temporal and spatial influences of potential factors on carbon emission efficiency.

Compared to existing studies, this paper contributes the following marginal points. Firstly, some of the existing studies on carbon emissions have the problem of double accounting for primary and secondary energy sources, and the emission factors used are mostly based on international standards. This paper accounts for secondary energy from the perspective of China's national circumstances and uses officially published emission factors, and the measured data can provide data support for related studies. Secondly, the spatial distribution and evolution of the current carbon emission efficiency in China are analysed from a dynamic perspective, which is conducive to grasping the current situation of carbon emission efficiency in time and space and providing support for policy formulation. Thirdly, the dynamic spatial Durbin model is used to further explore the factors influencing the efficiency of carbon emissions, which helps us to find ways to optimise the efficiency of emission control.

The rest of this paper is organised as follows. The "Literature review" section reviews the extant literature. The "Research design" section introduces the model construction and indicators. The "Empirical analysis" section analyses the empirical results. Finally, conclusions and policy implications are summarised in the "Conclusions and policy implications" section.

Literature review

Literature about carbon emission efficiency is mainly divided into two types: One focuses on the carbon emission efficiency measurements, and the other focuses on the analysis of influencing factors.

The definition of carbon emission efficiency from an economic perspective can be divided into two categories: single-factor carbon efficiency and total factor carbon efficiency.

Fig. 1 GDP and carbon emission growth 2010–2020
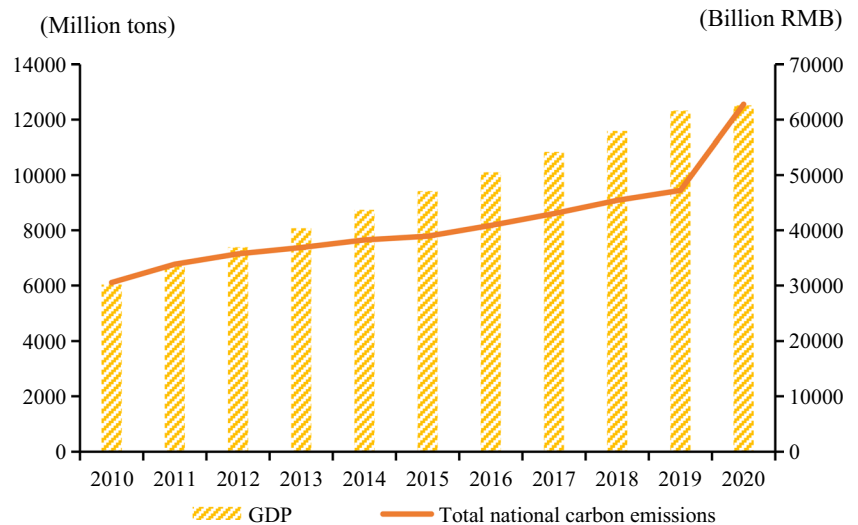
Kaya and Yokobori (1993) were the first to define carbon efficiency from a single factor perspective as the ratio of gross domestic product (GDP) to carbon emissions over a period of time. Sun (2005) also used carbon productivity as a proxy variable for carbon efficiency to measure the effectiveness of national energy conservation and emission reduction. Some scholars used carbon dioxide produced per unit of energy consumption as a criterion for evaluating the efficiency of carbon emissions Mielnik and Goldemberg 2014; Ang 1999), but this approach tends to ignore the link between energy consumption and external factors and has certain limitations. The starting point for carbon efficiency accounting is carbon emission accounting. Overall, methods for measuring carbon emissions include field measurements, material balance and emission factor methods, life cycle methods, and input–output methods (Xie et al. 2014). The most widely used method in academia is the emission factor method (Kone and Buke 2019; Liu et al. 2017; Wang et al. 2017), as the actual measurement method is labour-intensive and the material balance method requires high requirements for basic data. Emission factors are mostly referred to the survey data published by the IPCC. Ramanathan (2002) treated carbon emissions as an undesired output, proposing that the total factor productivity (TFP) assessment would be more comprehensive and reasonable. In the framework of efficiency analysis, the more common efficiency evaluation methods include Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Since the SFA method requires a specific frontier function for the boundary, an inappropriate functional form can lead to biased estimation results. The DEA method fills this gap well by not only not requiring a specific functional form, but also by being able to handle multiple input and output indicators, so most efficiency evaluations of carbon emissions tend to use improved DEA models (Gao et al. 2021; Kong et al. 2019; Sun and Huang 2020; Zhang et al. 2018; Zhang et al. 2020; Zhou et al. 2019).

One part of the impact factor research focuses on finding the causes of carbon emissions through factor decomposition, while the other part focuses on empirical testing. The basis for decomposition in studies of the decomposition of carbon emissions from impact factors is the core factor influencing changes in carbon emissions. The most used methods are exponential decomposition and structural decomposition. The use of exponential decomposition in the energy sector began to emerge after the 1970s, and scholars found that economic development (Cheng et al. 2013; Zhou et al. 2019; Wang et al. 2010) and energy mix (Ge et al. 2022; Gu et al. 2022; Shao and Zhang 2019) have a direct and significant impact on carbon emissions. The difference between the structural decomposition method and the exponential decomposition method is that the former does not rely on input–output tables, but only requires sectoral aggregated data. For example, Lu et al.

(2013) used the LMDI-based 'two-level full decomposition method' to decompose China's carbon emissions from 1994 to 2008 and analysed the impact of four major factors on carbon emissions, namely energy structure, energy intensity, industrial structure, and gross output value, from the perspective of industrial structure.

Based on the decomposition of the influencing factors, some scholars have further incorporated the decomposition results into their empirical analysis. Current research in direct empirical evidence has focused on both the regional and industry sector levels. Studies at the regional level have focused on the national level (Qu 2012), and some studies have also focused on empirical analysis of the factors influencing carbon efficiency in several key regions (Yao and Liu 2010; Nie and Yao 2022). Studies on carbon efficiency at the industry level have mostly covered the manufacturing and construction industries (Qu and Li 2017b; Zhang and Yu 2015; Hui and Su 2018), with a small number of studies covering the service sector (Wang et al 2022; Nie and Yao 2022). Additionally, several research have concentrated on the impacts of technological progress (Lei et al. 2020), urbanisation (Zhang and Chen 2021; Wang and Cheng 2020), foreign trade (Zhang et al. 2018; Zhu and Du 2013), and environmental regulation (Li and Ma 2019) on the efficiency of carbon emissions.

It is clear from the above-mentioned literature that there is a wealth of research on carbon emissions, which can help to clarify the current situation of carbon emissions in China and the mechanisms of their impact. But even so, there are still shortcomings in the current study, mainly in two aspects. Firstly, the existing carbon emission efficiency measurement index system often uses carbon emission factors based on developed countries' standards, which are difficult to reflect the real situation in China. Second, there may be path-dependent effects of carbon emissions between regions, and to circumvent potential endogeneity problems (Tian and Ma 2020; Shao and Zhang 2019), we include the lagged one-period value of carbon emission efficiency as an explanatory variable in the regression model and construct a dynamic spatial Durbin model for empirical analysis.

Research design

Model construction

Static panel model

A general panel benchmark regression model is first developed to empirically analyse the impact of each factor on carbon emissions:

$$CEE_{it} = \alpha + \beta_0 gov + \beta_1 energy + \beta_2 cindus$$
$$+ \beta_3 fie + \beta_4 infrastructure + \beta_5 tech \qquad (1)$$
$$+ \beta_6 avpergdp + \mu_i + \gamma_t + \varepsilon_{it}$$

where CEE_{it} is the measured carbon emission efficiency of the i province in year t. $gov, energy, cindus, fie, infrastructure, tech,$ and $avpergdp$ represent government constraints, energy structure, industrial organisation, openness, infrastructure, technology level, and regional GDP per capita, respectively. μ_i is a regional effect, γ_t is a time effect, and ε_{it} is a random error term.

Spatial panel model

It has been shown that carbon emissions, as one of the externalities of economic development, will spread between regions in response to natural climatic conditions, as well as technological progress and industrial shifts, so there may be a more obvious correlation effect of carbon emissions in space. In addition, inter-regional competition for growth may also indirectly contribute to the spatial correlation of carbon emissions between regions (Zhang and Cheng 2009; Li and Qi 2011). Construction of a spatial econometric model incorporates all forms of the following:

$$\begin{cases} CEE_{it} = \alpha + \rho \sum_{j=1, j \neq i}^{n} W_{ij} CEE_{jt} + \beta X_{it} + \theta \sum_{j=1}^{n} W_{ij} X_{ijt} + \mu_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = \varphi \sum_{j=1, j \neq i}^{n} W_{ij} \varepsilon_{jt} + \mu_{it} \end{cases} \quad (2)$$

where CEE_{it} is the measured carbon emission efficiency of i province in year t, W_{ij} is the spatial panel weight matrix, X_{it} is the independent variable for i province in year t, μ_i is the area effect, γ_t is the time effect, ε_{it} is the random error term, ρ is the spatial autoregressive coefficient, and φ is the spatial autocorrelation coefficient. If $\rho \neq 0, \theta = 0, \varphi = 0$, then Eq. (2) is a spatial autoregressive model (SAR); if $\rho = 0, \theta = 0, \varphi \neq 0$, then Eq. (2) is a spatial error model (SEM); if $\rho \neq 0, \theta \neq 0, \varphi = 0$, then Eq. (2) is a spatial Durbin model (SDM).

Description of variables and data sources

A total of 30 provinces and regions, including 21 provinces, 4 municipalities directly under the Central Government, and 5 autonomous regions, are involved in the estimation and empirical analysis of carbon emission intensity, while Taiwan Province, Tibet Autonomous Region, Hong Kong, and Macao Special Administrative Region are not included due to lack of data. The data spans the period 2010–2020. The indicators covered in the text are sourced from the China Energy Statistical Yearbook, the China Statistical Yearbook, and the Regional Statistical Yearbooks at the provincial level.

The energy data in this paper is sourced from 2010 to 2020 China Statistical Yearbook. The China Statistical Yearbook is the most comprehensive and authoritative statistical yearbook in China. The main text is generally divided into more than 20 chapters covering population, people's livelihood, prices, employment, fixed asset investment, and national economic accounts, with slight adjustments in different years according to different situations of economic and social development. The chapter 'Energy' includes the main contents of energy production, consumption, and variety, energy production, etc. In this paper, we have selected the data of 'Energy consumption by industry'. Regarding Volume 2, Chapter 6 of the National Greenhouse Gas Inventories developed by the Intergovernmental Panel on Climate Change (IPCC), CO_2 emissions can be found by the following equation:

$$C_t = \sum_{i=1}^{n} C_{i,t} = \sum_{i=1}^{n} E_{i,t} \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \qquad (3)$$

where C_t is the CO_2 emissions, $E_{i,t}$ is the energy consumption, and NCV_i is the average low-level heat generation of various energy sources, from the General Rules for Calculating Comprehensive Energy Consumption. CEF_i and COF_i are derived from the Provincial Greenhouse Gas Emissions Inventory, which is more relevant to China's specific situation by modifying the carbon emission factors according to China's national conditions and energy mix than other international greenhouse gas emission inventories. CEF_i is the carbon content per unit calorific value, which measures the number of carbon emissions per unit of energy produced during the combustion or use of each energy source, and COF_i is the carbon oxidation factor, which measures the efficiency of oxidative combustion of the carbon in coal combustion to CO_2. The ratio 44/12 represents CO_2 molecular weight/carbon molecular weight.

As the units of the various energy sources are not uniform, it is necessary to convert them uniformly to standard coal, with the conversion factors derived from the General Rules for Calculating Comprehensive Energy Consumption. For clarity of presentation, the various data are summarised in Table 1.

It should be noted that the measurement of carbon emissions from electricity is based on data published by the National Energy Administration. One kilowatt hour of electricity requires the consumption of about 1/3 kg of standard coal, which corresponds to the production of 0.86 kg of CO_2.

Based on the above method, the total carbon emissions data at the inter-provincial level for 2010–2020 are obtained and then divided by the deflated regional GDP for each year to obtain the carbon emission efficiency indicators at the provincial level.

Regarding the drivers of carbon productivity, the following seven factors have been selected based on relevant studies (Dong et al. 2020; Ge et al. 2022; Guo et al. 2022; Zhang and Chen 2021; Cui et al. 2023b):

(1) Government intervention. Government intervention is measured using the general local budget revenue over the upper regional GDP.
(2) Energy structure. The energy structure is expressed using the proportion of coal consumption to total primary energy consumption.
(3) Industrial structure. The industrial structure is measured by the proportion of value added in the secondary industry to GDP.
(4) Openness. The total imports and exports of foreign-invested enterprises are used.
(5) Traffic condition. The traffic condition is measured using the area of reason.
(6) Technology level. Technological progress is expressed using the number of patents granted.
(7) Wealth per capita. Wealth per capita is measured by dividing the gross regional product by the number of resident population at the end of the year.

All variables relating to wealth levels are adjusted using 2000 as the base period, total foreign investment is converted to RMB amounts using the current year's exchange rate, and all variables are logarithmised. Descriptive statistics for the variables are shown in Table 2.

Empirical analysis

Analysis of the results of carbon emission efficiency accounting

In terms of the average total carbon emissions from 2010 to 2020, there are large differences between regions, with the top five provinces being Shandong, Guangdong, Jiangsu, Hebei, and Zhejiang, corresponding to average total carbon emissions of 780.68 Mt, 660.94 Mt, 656.69 Mt, 599.22 Mt, and 433.55 Mt. In total, they account for 37.96% of the average total carbon emissions of the 30 provinces. The five provinces with the lowest average

carbon emissions are Chongqing, Ningxia, Jilin, Qinghai, and Hainan, corresponding to average total carbon emissions of 125.43 Mt, 107.89 Mt, 104.01 Mt, 73.34 Mt, and 36.49 Mt. The average carbon emission efficiency shows large differences among provinces, and there is no obvious correlation between the average carbon emission efficiency ranking and the total carbon emission ranking. The top five provinces among the 30 provinces in terms of average carbon emission efficiency are Beijing, Chongqing, Heilongjiang, Shanghai, and Hunan, corresponding to an average carbon emission efficiency of 0.991 (yuan/ton), 0.887 (yuan/ton), 0.867 (yuan/ton), 0.842 (yuan/ton), and 0.819 (yuan/ton). The bottom five provinces are Hebei, Shanxi1, Xinjiang, Qinghai, and Ningxia, corresponding to an average carbon emission efficiency of 0.302 (yuan/ton), 0.259 (yuan/ton), 0.258 (yuan/ton), 0.178 (yuan/ton), and 0.130 (yuan/ton) (Fig. 2).

Overall, there is an upward trend in national and regional carbon emission efficiency, but a significant decline in both 2020, possibly due to the impact of an exogenous shock, the novel coronavirus in 2019. The eastern region has the highest carbon emission efficiency, exceeding the national level in all years; the central region ranks second, and the gap between the central region and the national level begins to widen after 2015; the north-eastern region ranks third, and from 2013 onwards, the northeastern region begins to exceed the national level in carbon emission efficiency; and the ministry has the lowest carbon emission efficiency, which is significantly lower than the national carbon emission efficiency level in all years (Fig. 3).

Table 2 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
cee	330	−0.674	0.515	−2.572	0.236
gov	330	−2.194	0.257	−2.84	−1.406
energy	330	−0.401	0.427	−3.595	−0.007
cindus	330	1.289	0.416	−0.085	2.176
fie	330	24.419	2.552	16.666	28.63
infrastructure	330	9.794	0.808	7.213	11.535
tech	330	10.016	1.47	5.576	13.473
avpergdp	330	15.331	0.836	12.89	17.058

Table 1 Carbon dioxide emission data

Energy	Equivalent standard coal factor	NCV_i	CEF_i	COF_i
Coking coal	0.9714 (standard coal/kg)	28,435 kJ/(6800 kcal)/kg	29.5	0.93
Petrol	1.4714 (standard coal/kg)	43,070 kJ/(10,300 kcal)/kg	18.9	0.98
Paraffin	1.4714 (kcal/kg)	43,070 kJ/(10,300 kcal)/kg	19.6	0.98
Diesel	1.4571 (kcal/kg)	42,652 kJ/(10,200 kcal)/kg	20.2	0.98
Fuel oil	1.4286 (kcal/kg)	41,816 kJ/(10,000 kcal)/kg	21.1	0.98

Spatial correlation analysis of inter-provincial carbon emission efficiency

The ability to use spatial measures of carbon emission efficiency depends on whether the data is spatially significant. The two main analytical methods for measuring spatial correlation are $Moran's I$ index and $Geary\ C$ index. Compared to the $Geary\ C$ index, the $Moran's I$ index is less affected by deviations from a normal distribution, so the $Moran's I$ index method is used for analysis in this paper.

$$Global\ Moran's I = \frac{n}{\sum_i^n \sum_j^n W_{ij}} \times \frac{\sum_i^n \sum_j^n W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_{i=1}^n (X_i - \overline{X})^2} \quad (4)$$

where X_i is the observed value of province i, W_{ij} is the spatial weight matrix after normalisation, and the $Moran's I$ index takes values between -1 and 1. At a given level of significance, $Moran's I > 0$ indicates a positive correlation,

$Moran's I < 0$ indicates a negative correlation, and $Moran's I$ close to 0 indicates that the observations are spatially randomly distributed and not correlated.

$$Local\ Moran's I = \frac{n^2}{\sum_i^n \sum_j^n W_{ij}} \times \frac{(X_i - \overline{X})\sum_i^n \sum_j^n W_{ij}(X_j - \overline{X})}{\sum_{i=1}^n (X_i - \overline{X})^2} \quad (5)$$

where the variables have the same meaning as $global\ Moran's I$ and the relationship between the two exists $\sum_{i=1}^n Local\ Moran's I = n \times global\ Moran's I$.

The spatial weight matrix is an adjacency weight matrix based on the number of nearest neighbours, assigning a weight of 1 to the 10 closest units and a weight of 0 to the others.

$$W_{ij} = \begin{cases} 1, \text{The distance between } i \text{ and } j \text{ is less than 10} \\ 0, \text{The distance between } i \text{ and } j \text{ is less than 10} \end{cases} \quad (6)$$

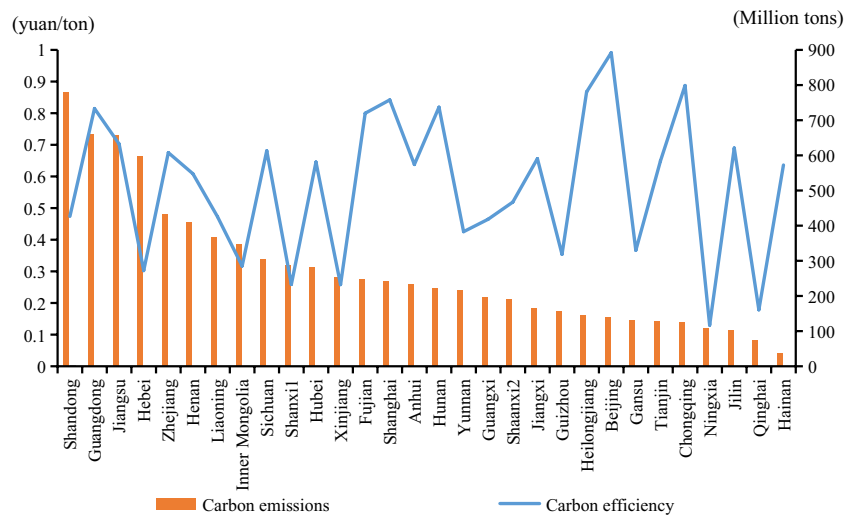**Fig. 2** Average total carbon emissions and average carbon efficiency 2010–2020
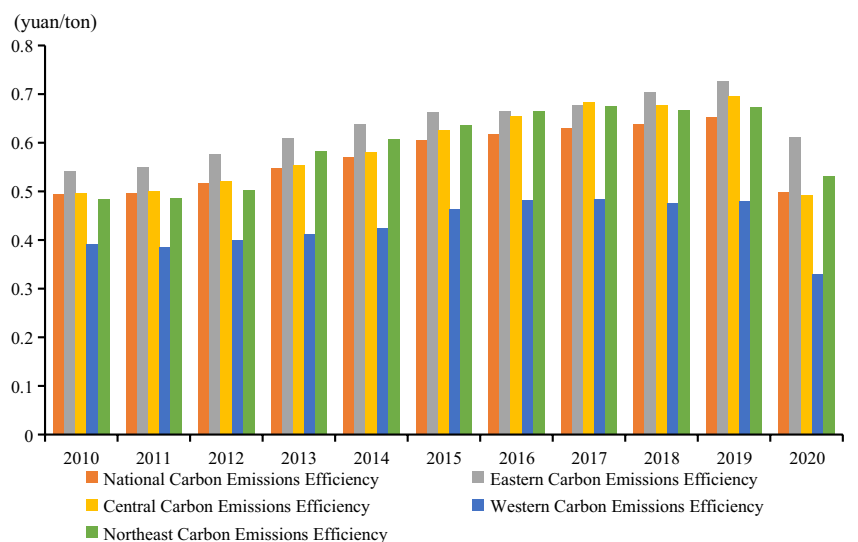

Fig. 3 Carbon emission efficiency

According to Eq. (4), the *Global Moran'sI* values of inter-provincial carbon emission efficiency from 2010 to 2020 are measured based on the use of spatial weights based on the number of nearest neighbours. The results in Table 3 show that the *Global Moran'sI* values for 2010–2020 are all significantly positive at the 1% level, so the spatial distribution pattern of inter-provincial carbon emission efficiency in China has a strong spatial aggregation, and the possible spatial correlation between regions should be given due attention when conducting research on inter-provincial carbon emission efficiency.

To further obtain local specific spatial characteristics, the Moran spatial scatter diagram for each year can be obtained according to Eq(5). Figure 4 shows the spatial scatter diagram of carbon emission efficiency in 2010 and 2020. The horizontal coordinate of the scatter plot represents the standardised level of carbon emission efficiency for each province, while the vertical coordinate

is used to represent the level of carbon emission efficiency for each province weighted by the spatial weight matrix, which measures the level of spatial lag in carbon emission efficiency for each province. The scatter plot of Moran's I 2000 shows that 67% (20) of the provinces have similar spatial correlations, of which 43% (13) are in quadrant I 'high carbon emission efficiency — high spatial lag' and 23% (7) are in quadrant III 'HH: Low carbon emission efficiency — low spatial lag'. In the scatter plot of Moran's I 2020, 73% (22) of the provinces have similar spatial correlations, of which 50% (15) are in quadrant I 'HH: high carbon efficiency — high spatial lag' and 16.67% (5) are in quadrant III 'LL: low carbon efficiency — low spatial lag'. The above results indicate that there is a significant positive spatial spillover effect on carbon emission efficiency and that China's regional carbon emission efficiency is mainly characterised not only by spatial dependence in terms of local spatial correlation, but also by a small amount of spatial heterogeneity (Table 4).

Further spatio-temporal migration analysis reveals that five provinces experience migration during the period 2010–2020. The migration direction of HL→HH for Heilongjiang and Tianjin is mainly due to the increase in carbon emission efficiency in their neighbouring province of Liaoning, which has led to an increase in high carbon emission efficiency in the vicinity of the two provinces. The migration direction for Shaanxi2 is HL→LL, indicating a decrease in the province's own carbon emission efficiency. Shandong's migration direction is HH→LH, mainly due to a decrease in the efficiency of its own carbon emissions (Fig. 5). The direction of migration in Liaoning is LH→HH, indicating that the province has achieved a leap in carbon emission efficiency driven by its neighbouring provinces.

Table 3 Spatial autocorrelation

Year	I	$E(I)$	$SD(I)$	Z	p-value
2010	0.200	−0.035	0.057	4.134	0.000
2011	0.204	−0.035	0.056	4.241	0.000
2012	0.215	−0.035	0.057	4.403	0.000
2013	0.209	−0.035	0.057	4.289	0.000
2014	0.213	−0.035	0.057	4.358	0.000
2015	0.189	−0.035	0.057	3.943	0.000
2016	0.182	−0.035	0.057	3.823	0.000
2017	0.182	−0.035	0.057	3.807	0.000
2018	0.195	−0.035	0.057	4.029	0.000
2019	0.197	−0.035	0.057	4.066	0.000
2020	0.178	−0.035	0.057	3.729	0.000

Moran scatterplot (Moran's I = 0.2001 and P-value = 0.0000)
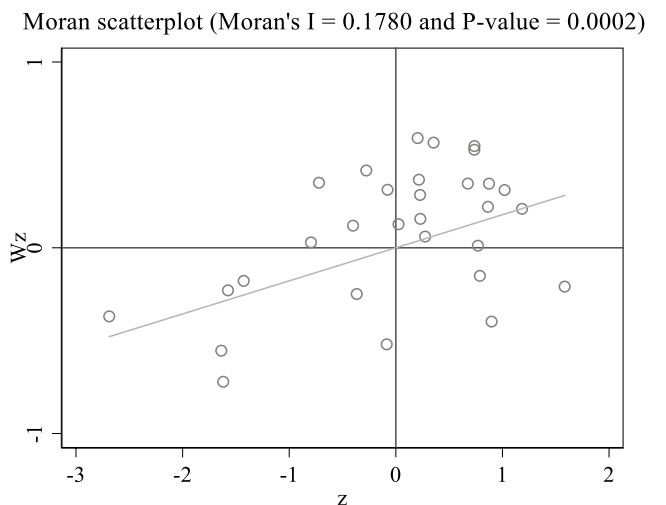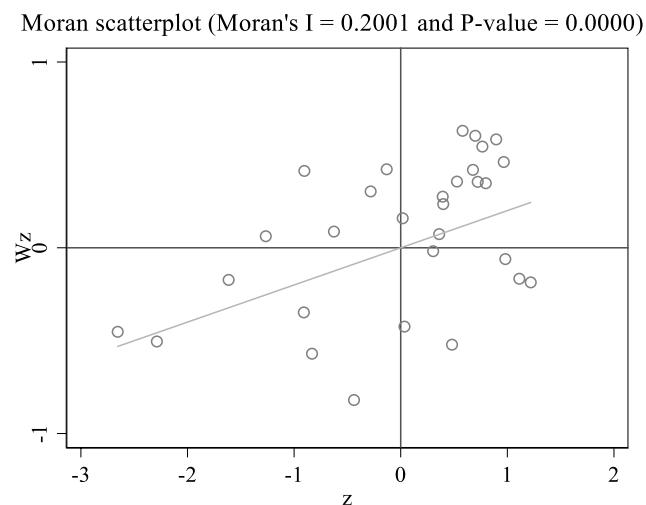
Moran scatterplot (Moran's I = 0.1780 and P-value = 0.0002)

Fig. 4 Spatial scatter plot of carbon efficiency (2010, 2020)

Table 4 Distribution of regional clusters

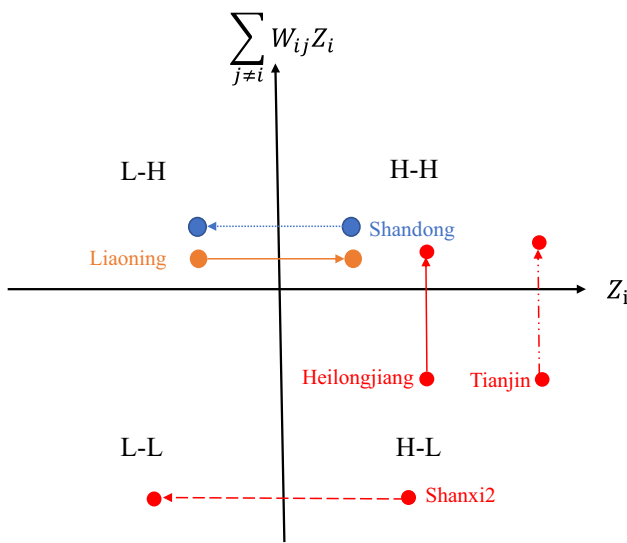| Year	Category	Area
2010	HH	Jilin, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Hainan
	LH	Hebei, Liaoning, Guangxi, Guizhou, Yunnan
	LL	Shanxi1, Inner Mongolia, Gansu, Qinghai, Ningxia, Xinjiang
	HL	Beijing, Tianjin, Heilongjiang, Chongqing, Sichuan Province, Shaanxi2
2020	HH	Tianjin, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Henan, Hubei, Hunan, Guangdong, Hainan
	LH	Hebei, Shandong, Guangxi, Guizhou, Yunnan
	LL	Shanxi1, Inner Mongolia, Shaanxi2, Gansu, Qinghai, Ningxia, Xinjiang
	HL	Beijing, Chongqing, Sichuan

Fig. 5 Transition in carbon efficiency

Table 5 Results of the general panel data model

	Mixed Ols	FE	RE
gov	-0.959^{***}	0.132	0.0503
	(0.151)	(0.126)	(0.112)
energy	-0.0507	-0.108^{***}	-0.118^{***}
	(0.0653)	(0.0387)	(0.0381)
cindus	-0.533^{***}	-0.0105	-0.0873
	(0.110)	(0.115)	(0.0935)
fie	0.118^{***}	0.0446^{***}	0.0571^{***}
	(0.0117)	(0.0169)	(0.0136)
infrastructure	-0.436^{***}	-0.221^{**}	-0.270^{***}
	(0.0564)	(0.0918)	(0.0824)
tech	0.0182	-0.144^{***}	-0.112^{***}
	(0.0314)	(0.0333)	(0.0309)
avpergdp	0.464^{***}	0.771^{***}	0.710^{***}
	(0.0676)	(0.113)	(0.0938)
_cons	-8.025^{***}	-9.722^{***}	-9.008^{***}
	(0.580)	(1.187)	(0.886)
N	330	330	330
Adj. R^2	0.659	0.275	

Analysis of the results of the ordinary panel data model

Table 5 shows the results of the mixed OLS estimation under the non-panel model and the regression results for the ordinary panel. The *F*-test is used to determine whether there is a significant difference between the 'mixed regression' and the 'fixed effects'. The results indicate that the *F*-statistic is significant at the 1% level, and the fixed effects panel model should be used. The LM test is then used to determine whether there is a significant difference between the 'mixed regression' and the 'random effects'. The results show that the LM statistic is significant at the 1% level and that the random effects panel model is better than the mixed regression model. Further Hausman tests are conducted for both the fixed effects panel model and the random effects panel model, and the results show that the *p*-value is less than 0.01, so the test results of the fixed effects panel model should prevail.

In the fixed effects model, the regression coefficients are positive but insignificant for government intervention; negative at the 1% level for energy; negative but insignificant for industrial; positive at the 1% level for foreign investment; negative at the 5% level for infrastructure; negative at the 1% level for technology level; and positive at the 1% level for regional wealth per capita.

Analysis of the results of the spatial econometric data model

To select a more appropriate spatial econometric model, this paper firstly performs an LM test on the regression results (see Table 6 for the results). The test results show that LM-lag and LM-error are significant at the 1% significance level, and Robust LM-lag and Robust LM-error are significant at

the 5% significance level, indicating that the empirical evidence should choose a more extensive spatial Durbin model. The results of the LR test indicate that the spatial Durbin model (SDM) does not degenerate into a spatial error model (SEM) or a spatial autoregressive (SAR) model. Further considering the potential estimation bias due to regional differences and time factors, as well as the applicability of fixed effects models for analysing specific individuals, the two-way fixed effects spatial Durbin model is used for estimation in this paper.

The two-way fixed spatial Durbin model is expressed as follows:

$$y = \alpha + \rho Wy + \beta X + \theta WX + \mu + \varphi + \varepsilon \tag{7}$$

where y is the explanatory variable, ρ is the spatial autoregressive coefficient, W is the spatial weight matrix, X is the matrix of exogenous explanatory variables, μ is the individual fixed effect, φ is the time fixed effect, and ε is the residual term.

The dynamic spatial model is based on the static spatial model with the addition of lagged terms in time and space for the object of study. At the same time, this model can solve the problems of endogeneity, autocorrelation of data in time for each province, and spatial dependence between observations at a certain point in time in the static spatial model, thus making the model estimation more accurate and reliable.

Based on the fact that static spatial models do not capture the short-term effects of each explanatory variable and also ignore the effects of potential factors, Elhorst (2010) showed that incorporating spatial lagged terms into the model can address potential endogeneity issues, obtain unbiased estimators, and estimate both the long-term direct and indirect effects, as well as estimate short-term direct and indirect effects. With the introduction of the spatial lag term, the spatial Durbin model can be expressed as follows:

$$y_t = \iota y_{t-1} + \rho Wy_t + \eta Wy_{t-1} + \beta X_t + \theta WX_t + \mu + \varphi + \varepsilon_t \tag{8}$$

The regression results of the dynamic spatial Durbin model with two-way fixed effects are given in Table 7.

The results show that the model with a significant one-period lag of carbon emission efficiency is significantly positive at the 1% level, indicating that provinces have significant inertia in their development patterns in terms of carbon emission efficiency improvement. The coefficient of the spatial lag of carbon emission efficiency, rho, is significantly positive at the 1% level, which is consistent with the spatial correlation analysis. In the short term, the direct and indirect effects of the factors affecting carbon efficiency are not significant, but in the long term, most of the factors have significant direct and indirect effects on carbon efficiency.

Due to the inclusion of spatially lagged explanatory and explained variables, the dynamic SDM cannot fully reflect the relationship between the explanatory and explained variables, and the interaction information contained in the model should be further analysed by direct, indirect, and total effects.

The spatial regression model partial differential approach addresses the problem that the spatial Durbin model regression coefficients do not directly explain the spatial spillover effects. Referring to Lesage and Pace (2009), Elhorst (2010), and others, partial differential equations are used to calculate the direct and indirect effects of the respective variables.

$$\Delta y_t = (I - \rho W)^{-1}[(\iota - 1)I + (\rho + \eta)W]y_{t-1} + (I - \rho W)^{-1}\beta X_t +$$

Table 6 Results of spatial measurement tests

Indicator	Statistical values	p-value
LM-lag	26.627	0.000
Robust LM-lag	6.384	0.012
LM-error	24.919	0.000
Robust LM-error	4.676	0.031
LR-SDM-SAR	29.79	0.0001
LR-SDM-SEM	29.78	0.0001

Table 7 Dynamic spatial Durbin model results

	Main	WX
L.cee	2.529***	
	(0.0695)	
L.Wcee	14.60***	
	(0.413)	
gov	3.196***	19.76***
	(0.147)	(0.727)
energy	−0.319***	−1.493***
	(0.0312)	(0.222)
cindus	2.227***	15.09***
	(0.120)	(0.680)
fie	−0.208***	−0.669***
	(0.0148)	(0.0630)
infrastructure	0.773***	3.562***
	(0.0627)	(0.272)
tech	−0.281***	−1.166***
	(0.0260)	(0.126)
avpergdp	−1.615***	−5.555***
sigma2_e	0.00557***	
	(0.000411)	

$$(I - \rho W)^{-1} W X_t + (I - \rho W)^{-1}(\mu + \varphi + \varepsilon_t) \qquad (9)$$

The partial derivative of the k_{th} explanatory variable in the X vector at a particular point in time can be expressed in matrix form as follows:

$$\left[\begin{array}{cccc} \frac{\partial \Delta y_t}{\partial x_{1k}} & \frac{\partial \Delta y_t}{\partial x_{2k}} & \cdots & \frac{\partial \Delta y_t}{\partial x_{nk}} \end{array} \right]_t = \left[\begin{array}{ccc} \frac{\partial \Delta y_1}{\partial x_{1k}} & \cdots & \frac{\partial \Delta y_1}{\partial x_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \Delta y_n}{\partial x_{1k}} & \cdots & \frac{\partial \Delta y_n}{\partial x_{nk}} \end{array} \right] = (I - \rho W)^{-1}(\beta_k + \theta_k W)$$

$$(10)$$

The elements on the diagonal of the $n \times n$ matrix represent the effects of the region's explanatory variables on the region's explanatory variables in the short run and are referred to as short-term direct effects. The other elements represent the effects of other region's explanatory variables on the region's explanatory variables and are referred to as short-term indirect effects (Table 8).

According to the results in Table 9, in the long run, government regulation has a catalytic effect on local carbon emission efficiency improvement, but the influence of government factors from neighbouring regions has a dampening effect on local carbon emission efficiency improvement. Government intervention is an effective means of compensating for market failures, and in the process of economic

development, governments are often faced with the trade-off between environmental protection and regional development. Under a system of fiscal decentralisation, the choices made by neighbouring regional governments will often inform the actions of the local government.

The energy has a dampening effect on local carbon emission efficiency improvement, but the energy of neighbouring regions has a significant positive spatial spillover effect on local carbon emission efficiency. This may be caused by the increased share of coal in the neighbouring regions, which provides part of the local energy consumption demand.

The industrial structure has no significant effect on local carbon emission efficiency, and the industrial structure of the neighbouring regions can reduce local carbon emission efficiency. This suggests that a high proportion of secondary industries in the neighbouring regions will affect the improvement of local carbon emission efficiency, due to the linkage of industrial chains that often exist between regions.

Foreign investment has a significant positive direct and spatial spillover effect. Total foreign investment can increase regional capital stock and affect carbon efficiency through technological upgrading and production transformation.

Traffic conditions have a significant inhibitory effect on the carbon emission efficiency of local and neighbouring regions. The growth of the population stock has, to some extent, increased the rigid demand for transport, which in turn has led to growing carbon emissions.

The level of technology is one of the key factors in improving the efficiency of carbon emissions, with a clear direct impact and spatial spillover effect. The region can improve its carbon efficiency by learning from and emulating the advanced technology levels of neighbouring regions.

The increase in the level of per capita wealth is not conducive to the improvement of local carbon emission efficiency but has a significant positive spatial spillover effect. Wealth levels

Table 8 Effect decomposition methods

Effect	Formula
Short-term direct effects	$[(I - \rho W)^{-1}(\beta_k I_n)]^{\overline{d}}$
Short-term indirect effects	$[(I - \rho W)^{-1}(\beta_k I_n)]^{\overline{rusm}}$
Long-term direct effects	$[(1 - \iota)I - (\rho + \eta)W)]^{-1}(\beta_k I_n)^{\overline{d}}$
Long-term indirect effects	$[(1 - \iota)I - (\rho + \eta)W)]^{-1}(\beta_k I_n)^{\overline{rusm}}$

Table 9 Results of the decomposition of direct and indirect effects

	SR direct	SR Indirect	SR total	LR direct	LR Indirect	LR total
gov	51.00	− 137.1	− 86.10	3.001*	− 4.323**	− 1.322***
	(1088.9)	(1726.1)	(1387.5)	(1.751)	(1.753)	(0.0434)
energy	− 4.332	9.395	5.064	− 0.474*	0.579**	0.105***
	(90.78)	(134.9)	(103.3)	(0.268)	(0.268)	(0.0133)
cindus	37.54	− 102.9	− 65.33	1.584	− 2.583**	− 0.999***
	(805.5)	(1288.6)	(1042.0)	(1.054)	(1.053)	(0.0407)
fie	− 1.933	5.734	3.801	− 0.423**	0.473**	0.0506***
	(39.75)	(65.58)	(54.06)	(0.199)	(0.199)	(0.00379)
infrastructure	9.860	− 26.90	− 17.04	1.167**	− 1.417**	− 0.250***
	(207.3)	(326.5)	(261.3)	(0.580)	(0.577)	(0.0162)
tech	− 3.273	8.458	5.185	− 0.482*	0.566**	0.0839***
	(68.05)	(108.7)	(87.79)	(0.257)	(0.256)	(0.00708)
avpergdp	− 16.72	47.29	30.57	− 3.104**	3.517**	0.413***
	(346.8)	(547.1)	(438.6)	(1.576)	(1.572)	(0.0361)

and environmental protection are difficult to balance over a period of time, and a large part of the increase in local per capita wealth is driven by high energy-consuming and high-polluting industries. The economic development of neighbouring regions will enhance local carbon emission efficiency, probably because high-polluting enterprises have relocated to regions with relatively advanced economic development.

Conclusions and policy implications

Economic growth is often accompanied by an increase in carbon emissions, so striking a balance between economic growth and environmental protection has become a key to sustainable development. In the field of carbon emissions, it is important to note that it is not only the total amount of carbon emissions that should be concerned but also the efficiency of carbon emissions.

Based on the accounting of carbon emissions, this paper further calculates the carbon emission efficiency and empirically analyses the influencing factors of carbon emissions using the dynamic spatial Durbin model. Accordingly, the findings of this paper are as follows:

(1) The results of carbon accounting show that China's total carbon emissions increase from 6107.45 to 12,553.67 Mt during the period 2010–2020, with the growth rate of total carbon emissions basically in line with the growth rate of GDP, indicating that there is no 'decoupling' in the economic system.

(2) The average carbon emission efficiency shows large differences among provinces, and there is no obvious correlation between the average carbon emission efficiency ranking and the total carbon emission ranking. The top five provinces among the 30 provinces in terms of average carbon emission efficiency are Beijing, Chongqing, Heilongjiang, Shanghai, and Hunan

(3) There is a clear spatial effect on carbon efficiency. Overall, there is an upward trend in national and regional carbon efficiency, but a significant decline in both 2020, possibly due to the impact of an exogenous shock. On the whole, the eastern region has the highest carbon emission efficiency, which is higher than the national carbon emission efficiency level in all years; the western region has the lowest carbon emission efficiency, which is lower than the national carbon emission efficiency level in all years. The northeast and central regions are not very different from each other.

(4) Further spatial and temporal migration analysis reveals that five provinces have made the migration during the period 2010–2020. The migration direction of HL→HH for Heilongjiang and Tianjin is mainly due to the increase in carbon emission efficiency of their neighbouring province, Liaoning, which has led to an increase in the high carbon emission efficiency of the neighbouring two provinces. The migration direction for Shaanxi2 is HL→LL, indicating a decrease in the province's own carbon emission efficiency. Shandong's migration direction is HH→LH, mainly due to the decrease in its own carbon emission efficiency. Liaoning's migration direction is LH→HH, indicating that the province has achieved a jump in carbon emission efficiency driven by its neighbouring provinces.

(5) The results of the dynamic spatial Durbin model regression show that in the short term, the direct and indirect effects of the factors affecting carbon efficiency are not significant, but in the long term, most of the factors have a significant direct and indirect effect on carbon emission efficiency. Government regulation, foreign investment, and technology level all have direct effects that increase local carbon emission efficiency, but energy structure, transportation status, and per capita wealth level have direct effects that reduce it, and industrial structure has no apparent impact on local carbon emission. In terms of spillover effects, energy structure, foreign investment, technology level, and per capita wealth level have positive spatial spillover effects, while government regulation, industrial structure, and transportation status have negative spatial spillover effects.

Based on the above findings, this paper makes the following policy recommendations:

Policy formulation should take into account regional differences, and carbon reduction strategies should be focused and implemented in a differentiated manner. There are significant differences in total carbon emissions and carbon emission efficiency between regions in China, and the ability to coordinate governance should be strengthened. Based on the carbon emission efficiency of each province, the carbon emission efficiency benchmarks of Beijing, Chongqing, Heilongjiang, Shanghai, and Hunan should be used as a basis to increase the exchange of governance experience with other provinces in order to improve the overall level of China's environmental pollution control efficiency. For the eastern regions with a high level of marketisation, the government should give full play to the market's resource allocation role, while for the central and western and northeastern regions with a low level of marketisation, the focus should be on the government's intervention function.

Carbon emission control measures are a long-term process and the long-term impact of policies should be considered. The two factors of foreign investment and technology level have a significant positive direct impact and spatial spillover effect. Therefore, it is necessary to increase efforts to introduce foreign investment, to do a good job in screening and

managing the introduction of foreign investment, and to pay attention to avoiding the problem of 'pollution paradise' that may be caused by trade. Develop technological innovation policies to encourage research units and enterprises to increase their RD efforts, while promoting inter-regional technology exchange and cooperation to better exploit the spillover effects of technology. Optimise the energy mix, increase the proportion of green energy consumption, reduce the proportion of China's traditional coal-based fossil energy consumption, adopt clean production technologies, and increase the ratio of energy inputs to output. Optimise the industrial structure, adhere to sustainable economic development strategies, focus on heavy industrial enterprises with high energy consumption and pollution, and eliminate backward production capacity, while paying attention to the coordinated development of light and heavy industries. Promote the decarbonisation of transport, formulate strategies for the construction of low-carbon transport infrastructure, encourage the use of new energy vehicles, and improve energy efficiency in transport. Promote integrated and interactive development between regions, narrow regional development gaps, and guide the rational flow of factors across regions.

The following are some of the paper's limitations: First, the paper only measures direct carbon emissions due to data constraints, which could cause the conclusions to be understated. Second, this study solely considers the link between carbon emissions and economic growth when using carbon productivity as a defining variable for carbon emission efficiency. In the future, efforts will be made to use the input–output method to enhance this article and to investigate important economic development regions such the Chengdu-Chongqing Economic Circle, Yangtze River Delta, and Beijing-Tianjin-Hebei from a total factor perspective.

Author contribution Yuan Ma: conceptualisation, formal analysis, writing — original draft. Zi-ran Zhang: financial support, preliminary review, project administration. Yu-ling Yang: methodology, framework recommendations.

Declarations

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