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RESEARCH ARTICLE

Research on coupling degree and coupling path between China's carbon emission efficiency and industrial structure upgrading

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Abstract

To coordinate economic development and carbon emission reduction targets, China needs to improve carbon emission efficiency and upgrade the industrial structure. Therefore, it is important to study the coupling degree and coupling path between these two factors in various provinces in China, and thereby promote the development of China's low-carbon economy. We first calculate carbon emission efficiency using the Super-SBM model, then analyze an extended coupling model between carbon emission efficiency and industrial structure upgrading, and finally design the coupling paths using the framework of distribution dynamics. There are three main findings. First, the coupling degree of nearly half the provinces is at the level of mild-to-moderate imbalance recession. And in terms of specific coupling characteristics, nearly half the provinces belong to the type "low-level coordination," with a low development degree and high coordination degree. Second, there is an obvious dynamic imbalance between China's carbon emission efficiency and industrial structure upgrading, and the "low-level trap" of regional carbon emission efficiency is more serious than that of regional industrial structure upgrading. Finally, if the government prioritizes provinces with low carbon emission efficiency, carbon emission efficiency and the coupling efficiency with industrial structure can be improved, which would not only improve the coupling degree within each region but also alleviate the disharmony between regions.

Keywords Carbon emission efficiency · Upgrading industrial structure · Coupling coordination degree model (CCDM) · Cure · Coupling path

Abbreviations

EKC	Environmental Kuznets curve
SDA	Structural decomposition analysis method
LMDI	Logarithmic mean Divisia index
PSM–DID	Propensity score matching–difference in difference
SBM	Slacks-based measure model
DEA	Data envelopment analysis model

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Introduction

The issue of global warming urgently needs to be addressed and solved by all countries in the world, and the massive emissions of greenhouse gases including CO_2 caused by human economic behavior are a key cause of climate warming. As the world's largest CO_2 emitter, China has pledged to peak its carbon emissions by 2030 and reduce its carbon intensity by 60–65% compared with 2005 (Liu et al. 2019; Shao et al. 2016). However, unlike the developed countries that have entered the post-industrial era, China is in the stage of rapid industrialization, and the increasing demand for resources leads directly to rising emissions. In this context, upgrading the industrial structure, improving carbon productivity, and developing a low-carbon economy is an effective way to coordinate China's economic development and carbon emission reduction goals (Yang et al. 2015; Zhang et al. 2018a).

In general, industrial structure upgrading is not only important for improving carbon emission performance and promoting China's green development but also vital to economic growth and quality, as well as a means of improving carbon emission performance (Zhang et al. 2018b). Carbon emissions have a restricting effect on the industrial structure, while the latter has a coercive effect on the former. Within this contradictive relationship, they form a dual coupling by interacting with and influencing each other. Therefore, two questions arise: What is the coupling relationship between carbon emission performance and industrial structure upgrading in China? How can their coupling level be improved? To answer these questions, this study explores the coupling relationship between carbon emission performance and industrial structure upgrading in various provinces of China. First, it reveals the coupling degree, type, and characteristics for each province in an extended coupling model. Second, it designs a coupling path for the first time under the framework of distribution dynamics Finally, it proposes a path to improve the coupling degree from the perspective of dynamic coordination between regional carbon emission efficiency and industrial structure upgrading.

The paper's main contributions to the literature are as follows. First, existing research primarily focuses on the impact of industrial structure on carbon emissions (Wang et al. 2016; Shi et al. 2019; Li et al. 2019; Benjamin and Lin 2020), but rarely considers the latter's impact on the former nor the coordination or coupling of the two. To address this gap, this paper takes China as an example and studies the coupling relationship between carbon emission performance and industrial structure upgrading using an extended coupling model to classify each province according to specific coupling characteristics. Second, although the coupling model is mature, research on the coupling path is lagging behind. It is urgent to design an effective coupling approach to improve the coupling level and coupling efficiency. For this reason, this study adopts a unique method to design the coupling path under the framework of distribution dynamics. This method would enable the Chinese government to take more effective measures to improve the coupling level of carbon emission efficiency and industrial structure upgrading, thereby promoting the development of China's low-carbon economy.

The rest of this study is organized as follows. The "Literature review" section reviews the existing literature. The "Methods and materials" section details the model and data. The "Results and discussion" section presents the empirical results and discussion. Finally, the "Main conclusions and policy suggestions" section presents the conclusions and policy implications.

Literature review

The influencing factors of carbon emissions have been extensively researched. Since the environmental Kuznets curve (EKC) hypothesis was proposed by Grossman and Krueger (1991), the relationship between economic growth and carbon emissions has attracted the attention of many scholars (Atasoy 2017; Wen and Shao 2019). The impact of clean energy and non-clean energy consumption on carbon emissions has also been extensively investigated (Dogan and Seker 2016; Dong et al. 2017; Dong et al. 2019). Some scholars have analyzed and compared the impact factors of carbon emissions from multiple perspectives. For example, Dong et al. (2019) used the Stochastic Impacts by Regression on Population, Affluence, and Technology model to explore the key factors affecting carbon dioxide emissions in 128 countries from 1990 to 2014; they found that, in order of impact on CO_2 emissions, the key impact factors are economic growth, population size, nonrenewable energy, and energy intensity.

So how can carbon emission reduction be achieved? There is a general consensus that adjusting the industrial structure, improving energy efficiency and structure, and technological progress are the three major approaches to improve energy conservation and reduce emissions in China (Foxon 2011; Wang and Feng 2019; Akram et al. 2020). Of the three, the adjustment of industrial structure is considered especially important (Chebbi 2010; Zheng et al. 2019a). From 2010 to 2013, the impact of industrial restructuring on carbon emissions exceeded that of improving energy efficiency. Driven by a series of government-issued policies, China's industrial structure has gradually improved (Li et al. 2017). According to the optimistic estimation of scholars, the contribution of China's industrial restructuring to the carbon intensity target is over 70% (Wang et al. 2014).

Therefore, the impact of industrial restructuring and upgrading on carbon emissions reduction has become the focus of scholars in China and abroad. According to their different research methods, the relevant studies can be divided into three categories. First, using regression models, He and Wang (2012) and Liu (2012) studied the impact on carbon emissions, with industrial structure as the control variable under the EKC framework. Zhang et al. (2014) analyzed the impact of changes in China's industrial structure on carbon emission intensity with the autoregressive distributed lag method and found that the increased share of the tertiary industry plays an important role in suppressing carbon intensity. Others have used the traditional panel regression model (Wang et al. 2016), spatial econometric model (Shi et al. 2019), panel threshold model (Li et al. 2019), and quantile regression model (Benjamin and Lin 2020) to study the influence of industrial structure on carbon emissions; they have consistently found that the proportion of added value from secondary industry is the main factor affecting China's CO_2 emissions. Li et al.

(2019) also found that this degree of influence was constrained by a region's dependence on natural resources.

The second category of studies examines the drivers of carbon emissions using decomposition methods, mainly based on the input–output model framework (Su and Ang 2015; Zhao et al. 2017; Mi et al. 2015) and the logarithmic mean Divisia index (LMDI) (Ang 2005; Lin and Lei 2015; Ang and Su 2016; Liao et al. 2019). When studying the driving factors of carbon dioxide emissions, a large number of scholars adopt structural decomposition analysis (SDA) under the input–output model framework. For example, Chen et al. (2019) adopted SDA to study the impact of changes in various aspects of industrial structure (such as production structure, aggregate demand structure, trade structure, and investment structure) on CO_2 emissions in the Beijing-Tianjin-Hebei region of China. They found that these changes in industry effectively reduced the growth rate of carbon dioxide emissions during the investigation period, but because of different resource endowment, development stage, and industrial development strategy, each province pursued different decarbonization approaches. Other scholars have used this method to study the impact of industrial structure changes on carbon emissions in China's Yangtze River Delta region (Zhang et al. 2019a), Southwest Economic Zone (Tian et al. 2019), Southern Coastal Economic Zone (Wu et al. 2018), and northeast provinces (Zhang et al. 2018c). In addition, some scholars have used the LMDI method to decompose CO_2 emissions changes and analyze the influence of industrial structure changes and other relevant factors (Zheng et al. 2019b; Huang et al. 2019; Zhang et al. 2019b).

The third category of studies uses methods based on simulation. For example, Song et al. (2018) established a dynamic input–output simulation model to comprehensively explore the potential impact of industrial restructuring on China reaching peak greenhouse gas emissions by 2030. To find a moderate range of economic growth that is conducive to industrial and energy restructuring while also contributing to carbon intensity reduction, Li and Lin (2016) adopted Monte Carlo simulation and found that when GDP growth is between 7 and 8.4%, it can promote the "structural dividend" of industrial structure and energy consumption structure on carbon intensity, predicting that the carbon intensity in 2020 will decrease by nearly 40.60% compared with that in 2005.

In addition, carbon emission reduction targets and policies can impact on the industrial structure (Shao et al. 2019; Yao et al. 2019; Zhang et al. 2019e). The emission reduction targets set by the Chinese government have a reversal force on China's industrial structure (Wang et al. 2019a; Lin et al. 2019). Apart from technological means, it is also important to control carbon emissions through economic means, the most efficient of which include a carbon tax and carbon trading (Zhang et al. 2019c; Zhang et al. 2019d). Hu et al. (2020) used the DID method to detect the effect of policies on energy conservation efficiency and emission reduction; they found that policies could promote carbon emission reduction by improving the technological level and adjusting the industrial structure, with stronger effects in regions with strong law enforcement ability and a high marketization level. Similarly, Zhou et al. (2019) found that emission trading pilots in China reduced carbon intensity by adjusting the industrial structure. These studies show that the establishment of the carbon market will impact on the production of some industries and enterprises in China. Besides helping to achieve the goal of carbon emission control, the carbon market could be beneficial to the elimination of backward production capacity, achieve industrial upgrading, promote low-carbon transformation and sustainable development of enterprises, and also increase the economic dividend generated by the total industrial output value (Zhang et al. 2020), which is of great significance for the early realization of peak carbon emissions in China. In fact, in developed countries, the peak of industrial carbon emissions has been reached through the adjustment of industrial structure and technological progress in energy conservation and emission reduction (Feng et al. 2015). Thus, industrial structure upgrading can reduce carbon emissions and improve industry performance, while environmental policies, like carbon emission policies, can promote industrial structure upgrading.

Overall, the above literature review suggests that carbon emissions and industrial structure constitute a coupled interaction system, affecting and interacting with each other. However, there is a literature gap that numerous studies focus on the impact of industrial structure on carbon emissions, only a few relevant studies focus on the impact of carbon emissions on industrial structure, rarely on the impact of the latter on the former nor the coordination and coupling of the two. Although the coupling model is mature, related research on the coupling path lags considerably. Although Chen and Zhao (2019) examined the coupling degree of industrial structure and ecological environment in Beijing, they did not consider how to achieve better coupling nor study the coupling path. The coupling coordination model is already widely used in various fields, as illustrated by the coupling of socio-economic and resource environments (Cui et al. 2019), the coupling of tourism and low-carbon cities (Wang et al. 2019b) and the coupling of urbanization and the resource environment (Wu et al. 2019). However, these studies mainly focus on measuring coupling degree and do not consider the coupling path.

Therefore, we study the coupling relationship between carbon emission performance and industrial structure upgrading in China and design a coupling path under the framework of distribution dynamics, promoting improvements in the low-carbon economic development of each province.

Methods and materials

Coupling research, in contrast to traditional causality research that does not distinguish coupling from coordination clearly, uses systemic thinking to analyze the interaction and synergistic relationship between two systems. Lu and Zhou (2013) expanded the concept of coupling research for the first time, clearly distinguishing the two aspects of system development and coordination. It postulates that the former reflects the evolution of the system from low to high, while the latter emphasizes the interaction and development of various elements within the system, both of which constitute the coupling relationship between the systems. Therefore, this study explores the coupling relationship and coupling of the two systems of carbon emission efficiency and industrial structure upgrading in China, using the extended coupling model, and then, it introduces the distribution dynamics analysis and design of the coupling path from the perspective of slowing down the "low-level trap," which means those regions cannot change the situation for a long time and realizing the dynamic coordination between regions.

Coupling coordination model

(1) System development model

Coupling is the unification of coordination and development. Although the linear function is usually used to set up the system development model, it is considered that this setting lacks reasonable economic assumptions. Therefore, this study draws on the setting method of Lu and Zhou (2013) and the assumption of the development function including the strict pseudo-concavity and constant returns to scale. Under this assumption, the development function uses the Cobb-Douglas form, as follows:

$$T = \lambda f(x)^{\alpha} g(y)^{1-\alpha} \tag{1}$$

where $f(x)$ is the normalized carbon emission efficiency; $g(y)$ is the normalized level of the upgrading of the industrial structure; λ is the exogenous variable; and α and $1-\alpha$ reflect the importance of carbon emission efficiency and the industrial structure upgrading in the overall system.

(2) System coordination model

This study draws on the research results of Li et al. (2014) who use the deviation coefficient to describe the coordination between the systems and obtains the model of the degree of coordination of the measurement system. Referring to the practice of Lu and Zhou (2013), the coefficient of variation can be converted to the formula:

$$C_v = \sqrt{2(1-C)} \tag{2}$$

where

$$C = \left[\frac{4f(x)g(y)}{\left(f(x)+g(y)\right)^2}\right]^2 \tag{3}$$

where (3) is the system coordination degree. According to Fig. 1, when the deviation coefficient of the two systems of an area $C_v = 0$, the system coordination degree $C = 1$, $f(x) = g(y)$at this time, and the coordinate point of the area is located on the 45-degree line C_0 from the origin. Correspondingly, areas where $f(x) > g(y)$-and$f(x) < g(y)$ are located beyond or beneath C_0. For those areas with the same non-zero coordination degree, the coordinate points are approximately on a straight line starting from the coordinate origin and having a slope of less than 45 degrees, such as line C_1 and line C_2 in Fig. 1. Moreover, the area where the coordinate point falls on the C_0 symmetric line has the same degree of coordination.

(3) Coupling model

Coordination degree C measures the deviation of carbon emission efficiency and the level of industrial structure upgrading, but it cannot reflect the development level of the two. The development function T measures the level of development, but it cannot reflect the coordination of the two. For example, a region may have a "low-level coordination" situation with a high degree of coordination but a low level of development (point A in Fig. 2). Because of $C_1 = C_2$, the coordination degree of point E is the same as that of point D. However, the former is higher than the latter. Although the three points (A, B, C) have the same degree of development, there still is a difference in coordination among them (B > D > C). It can be seen that there are various situations in the coordination and development level of the comprehensive system of "carbon emission efficiency–industrial structure upgrading" in various regions. It is not enough to examine

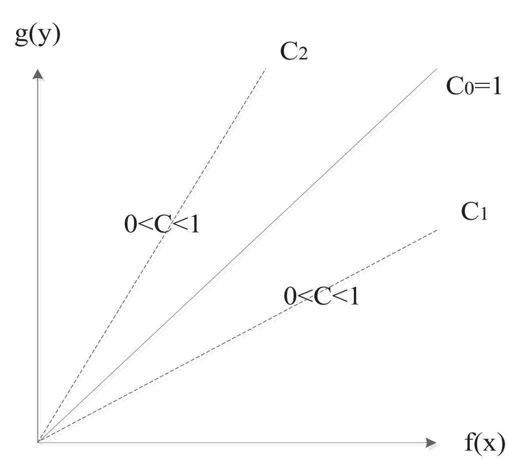


Fig. 1 Graphic analysis of coordination degree

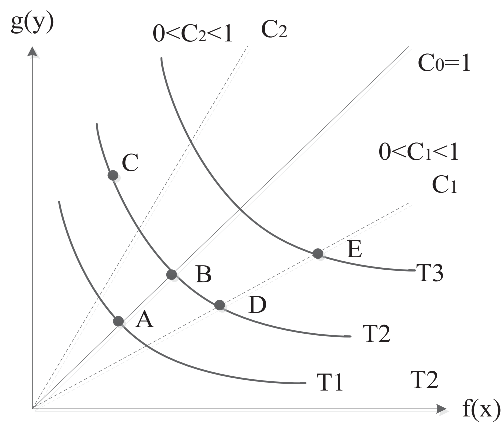


Fig. 2 Graphic analysis of coupling degree

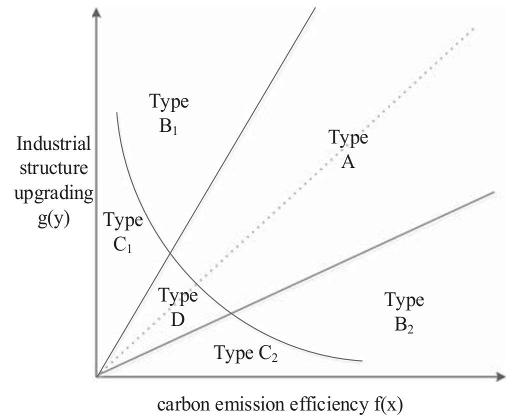


Fig. 3 Coupling types of carbon emission efficiency and industrial structure upgrade

the degree of development or of coordination but rather, it is necessary to examine the coupling relationship between the two at the same time. For that, the coupling degree formula of this study is shown in Eq. (4) (Li et al. 2014).

$$D = \sqrt{C \times T} \tag{4}$$

Different coupling degrees correspond to different coupling types (Chen and Zhao 2019; Cui et al. 2019), as shown in Table 1.

Coupled path approach

To improve the coupling degree of those areas with a low coupling degree, this study first classifies the regions based on the connotation characteristics of coupling. Second, the coupling relations of all regions are divided into four types according to the average degree of coordination and development: higher coordination and higher development (type A), lower coordination and higher development (type B), lower coordination and lower development (type C), and higher coordination and lower development (type D).

Based on the classification of Fig. 3, this study determines the coupling improvement path of China's "carbon emission efficiency–industrial structure upgrading" under the framework of distributed dynamics. Distributed dynamics shows the dynamic evolution of regional distribution from a long-term perspective, including the overall dynamic change of distribution (nuclear density curve characterization) and the internal dynamic change of distribution (the transfer probability matrixes). Therefore, from the prospective of internal dynamics, this study compares the regional carbon emission efficiency with the dynamic changes in the industrial structure among regions to compare the degree of "catch up" and "cure" among the regions. If the former curing degree is high, it indicates that the "long-term low efficiency" of China's regional carbon emission efficiency is more serious than the "long-term low level" of the regional industrial structure, and the carbon emission efficiency is inconsistent with the industrial structure upgrading dynamics among regions. Thus, when improving the coupling level of carbon emission efficiency and industrial structure upgrading in each region, the government should balance the dynamic coordination, such as starting with a more solidified party, supporting low-level regions, and giving priority to solving the "low-level trap" problem. The concrete ways are as follows:

Path 1: If the curing degree of regional carbon emission efficiency is more serious than the upgrading of the industrial structure, the central government should focus on supporting those regions with low carbon emission efficiency long term. For example, in B, C, and D regions,

Table 1 Coupling types corresponding to coupling values

Negative coupling (offset decay)		Positive coupling (coordinated development)	
D value	Coupling type	*D* value	Coupling type
0.00~0.09	Extreme disordered recession	0.50~0.59	Barely coordinated development
0.10~0.19	Severe disordered recession	0.60~0.69	Junior coordinated development
0.20~0.29	Moderate disordered recession	0.70~0.79	Intermediate coordinated development
0.30~0.39	Mild disordered recession	0.80~0.89	Well-coordinated development
0.40~0.49	On the verge of disordered recession	0.90~1.00	Highly coordinated development

supporting priority refers to B_1 and C_1 regions and especially those provinces with low carbon emission efficiency. By doing this, the coupling paths from B_1 to A and from C_1 to A can be realized. Its significance is reflected in two aspects: First, it can solve the serious solidification problems of carbon emission efficiency in China, avoiding the low-level carbon emission efficiency "trap" and achieving dynamic coordination between carbon emission efficiency and industrial structure upgrading. Second, it can generate incentive effects for type D regions, which are currently at low levels of development by improving their industrial structure, so they can become type B_1 or C_1 regions, thereby receiving government support and ultimately joining the regions with a high degree of development and coordination, by achieving a coupling path of $D \rightarrow B_1 \rightarrow A$ or $D \rightarrow C_1 \rightarrow A$.
Path 2: When the degree of solidification of the regional industrial structure is more serious, the central government should focus on supporting areas where the industrial structure has been at a low level for a long time. Specifically, it should focus on supporting B_2 and C_2 areas and take the coupling path of $B_2 \rightarrow A$ or $C_2 \rightarrow A$. Its significance is similar to that of path 1.

The measurement of carbon emission efficiency, industrial structure upgrading, and curing degree

Carbon emission efficiency measurement: super-efficiency SBM model with undesired output

Tone (2001) proposed a DEA model (a non-radial and non-angular efficiency measurement model) based on the SBM model. Compared with that of the traditional data envelopment analysis model (CCR–DEA model and BBC–DEA model), a variable of relaxation is added into the objective function in the SBM model, and the efficiency is a maximization of the actual benefit rather than the benefit ratio. However, since the efficiency value of the effective decision unit cannot be determined, Tone (2002, 2003) further proposes the super-efficiency SBM model and incorporates the unexpected output into the SBM model to fit the actual production process and effectively measure the environmental efficiency in production. Referring to the ideas of existing scholars (Yan et al. 2017), this study incorporates carbon dioxide emission as an unexpected output into the super-efficient SBM model to measure the carbon emission efficiency. Considering the super-efficient SBM model with undesired output is relatively mature, this study does not make a specific introduction to it; for its mathematical formula, please refer to the relevant literature (Yan et al. 2017; Zhou et al. 2018).

Industrial structure upgrade level measurement

The literature mainly measures the upgrading of the industrial structure from the perspective of advancement and rationalization (Li et al. 2019). Industrial upgrading refers to a change in the overall industry with the improvement of efficiency. In order to reflect the research purpose of this study and fit the coupling connotation of carbon emission performance and industrial structure upgrading properly, this study draws on the practice of Xu and Jiang (2015) by using the industrial structure level index to represent the level of industrial structure upgrading.

The calculation formula is as follows:

$$\text{upgrade} = \sum_{i=1}^{3} I_i \times i = I_1 \times 1 + I_2 \times 2 + I_3 \times 3 \tag{5}$$

where I_i is the proportion of the output value of the I_ith industry to the GDP. The larger index reflects a higher level of industrial structure upgrading in the region.

Regional cure degree measure: club convergence index

Based on the club convergence index proposed by Zhou and Zhou et al. (2018) and the detection of the solidification and comparative analysis of solidification degree of China's regional carbon emission efficiency and regional industrial structure upgrading, the structure of the club convergence index is as follows:

First, calculate the Markov transition probability matrix. The probability value of the Markov transition probability matrix for d-year is $P_{ij}^{t,t+d} = \{X_{t+d} = j | X_t = i\}$, which indicates the probability of the j-type province of the i-type in the d-year. Secondly, construct a club convergence index with variable duration, which combines the scale of different types of regions (clubs) and their degree of convergence. The d-year club convergence index is Formula (6):

$$\text{CCL}^d = p_{11}^d \times \text{rat}_1 + p_{22}^d \times \text{rat}_2 + \cdots + p_{kk}^d \times \text{rat}_k \tag{6}$$

where p_{kk}^d is the degree of convergence of the k club in d-years and rat_k is the proportion of such clubs.

Data description and source

Based on the availability of data and the need for empirical analysis, this study selects 29 provinces (cities, districts) as research objects, studied from 1997 to 2016, excluding the provinces of Hainan (for lack of 1952 GDP data) and Tibet (for lack of energy data). This study calculates carbon emission efficiency based on input, expected output, and undesired output data and then calculates the level of industrial structure upgrading based on the output value data of tertiary industries.

The explanation of data processing and data sources are as follows.

In the input data, capital stock measures capital input. According to the research of Wang et al. (2013), we calculate the capital stock of each province in 1952 and use the perpetual inventory method to estimate the missing data. In the perpetual inventory process, the fixed asset investment price index represents the total fixed capital formation of each province to the comparable prices of 1952. The total number of employees in the three industries measures the labor input at the end of the year. The total energy consumption and the carbon emissions of each province measure the energy input and the unexpected output. Since there are no official or authoritative carbon emission data in various provinces in China, we use the method of Yao et al. (2015) to calculate the total carbon emissions, according to the burning of fossil fuels, the consumption of cement, and the corresponding carbon emission factor in various provinces. The calculation formula is $C = \sum C_i = \sum e_i \cdot \varepsilon_i$, where e_i represents the consumption of resources and ε_i is the corresponding CO_2 emission factors. The CO_2 emission coefficients of coal, coke, gasoline, kerosene, diesel, fuel oil, natural gas, and cement are 1.647, 2.848, 3.045, 3.174, 3.15, 3.064, 21.670, and 0.527, respectively (tons of CO_2/ton or tons of CO_2/100 million cubic meters). In terms of data sources, annual energy data come from the "China Energy Statistics Yearbook." The labor data come from the statistical yearbooks of the provinces. All other data are from the Guotai'an Database.

Results and discussion

Coupling analysis of regional carbon emission efficiency and industrial structure upgrading in China

Measurement of carbon emission efficiency and industrial upgrading level

This study measures the carbon emission efficiency of 29 provinces in China from 1997 to 2016 by using the super-efficiency DEA model with undesired output and calculates the level of industrial structure upgrading in each province. With the help of ArcGIS software, this study visualizes the average level of each province during the inspection period and classifies them into four categories using natural breaks. The results are shown in Figs. 4 and 5.

In Fig. 4, we can see that China's regions having low carbon emission efficiency are mainly in the central and western regions, especially in the northwest. It should be noted that Yunnan is at the first level with the highest carbon emission efficiency, which may be related to the province's restrictions on high-energy-consuming industries and the emphasis on the ecological environment. The carbon emissions efficiency of the eastern provinces is relatively high, and all provinces are at least the second level, with Shanghai at the first level and Beijing, Tianjin, Fujian, and other provinces at the second. The northwest side of the Heihe-Tengchong Line is at a third level, while the southeast side is relatively high. In Fig. 5, there is a certain difference between the spatial distribution of industrial structure upgrading and the efficiency of carbon emissions. Under the classification method of natural breaks, there are only two regions at the first level, namely Beijing and Shanghai, and three religions at the second level, namely Tianjin, Guangdong, and Zhejiang, which means that the provinces in China's coastal religions generally have a high level of industrial structure. However, the spatial distribution gradient characteristics of the provinces with lower levels of industrial structure upgrading are not obvious, since those provinces are located not only in the central and southwestern regions but also on the northern border. In summary, the above analysis shows that the chronology of China's carbon emission efficiency and level of industrial structure upgrading is not consistent with its spatial distribution pattern. Therefore, it is necessary to delve into the coordination and coupling relationship between the provinces' carbon emission efficiency levels and industrial structure upgrading to improve carbon emission efficiency and industrial structure more effectively in various regions.

The coupling degree measurement of carbon emission efficiency and industrial structure upgrading

We use Formula (4) to calculate the coupling degree of each province year by year. It should be noted that in this study, industrial structure upgrading and carbon emission efficiency are equally important to local areas. Therefore, in Formula (1), $\alpha = 0.5$ and $\lambda = 1$.

According to the coupling type corresponding to the coupling degree in Table 1, the coupling degree of carbon emission efficiency and industrial structure upgrading is relatively low in China's provinces, and there are only eight regions in the forward coupling, where Shanghai has the highest coupling degree with good quality coordination. Followed by Tianjin (intermediate coordinated development) and Beijing (primary coordinated development), the other five provinces, namely Zhejiang, Fujian, Jiangsu, Liaoning, and Chongqing, are in a reluctantly coordinated development level.

Furthermore, in those regions with the disordered recession, there are eight provinces with moderately disordered recession (0.1~0.2) which are mainly in the west of China and a few in the central region. The second type includes the mildly dysfunctional recession (0.3~0.4) areas, including Heilongjiang and Jilin in the northeast; Gansu, Ningxia, and Shaanxi in the northwest; and Shandong, Guangdong, Hubei, and Hunan provinces (0.4~0.5). Guizhou and Henan (the type of extreme imbalance) and Guangxi (the type of severely

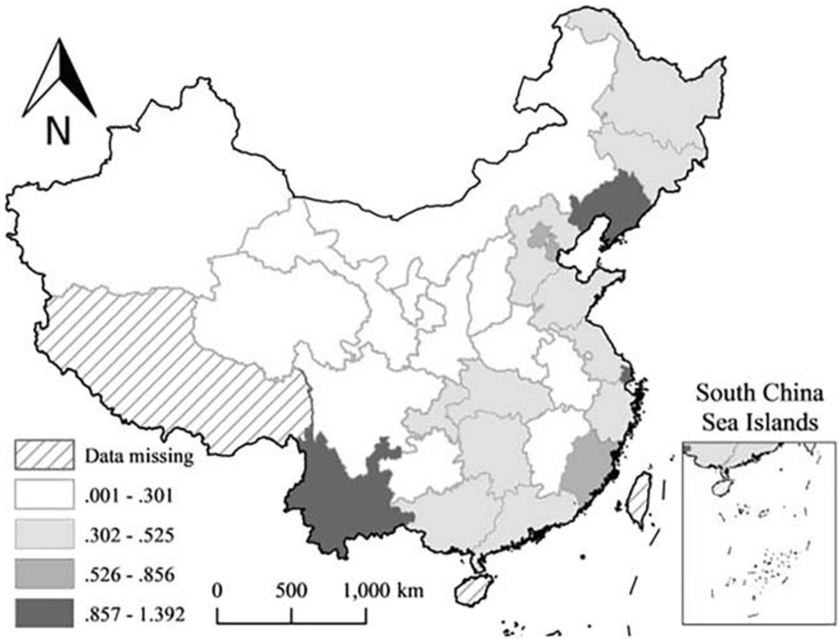


Fig. 4 The spatial pattern of carbon emission efficiency in China

degraded recession) are the three provinces with the lowest degree of coupling, which shows that the degree of coupling of carbon emission efficiency and industrial structure upgrading of all provinces in China is low on the whole, and the spatial differentiation is clear. In addition, from the perspective of the four major regions, the coupling degree in the eastern region is much higher than that in other regions, and the positive coupling is more than 0.5 during the inspection period. The northeast region, the central region, and the western region follow behind. In particular, the mean value of the coupling degree in the central and western regions is only 0.282 and 0.226, respectively, which is less than half of that in the eastern region and has great room for improvement.

In terms of time, except for the coupling degree of Beijing, Chongqing, Sichuan, and Anhui provinces, the other regions have shown a downward trend. The Xinjiang Uygur Autonomous Region suffered the biggest declines, which fell 11.409% between 1997 and 2016, from the verge of disordered recession (0.405) to the level of extreme disordered recession (0.041). The provinces with larger annual declines include

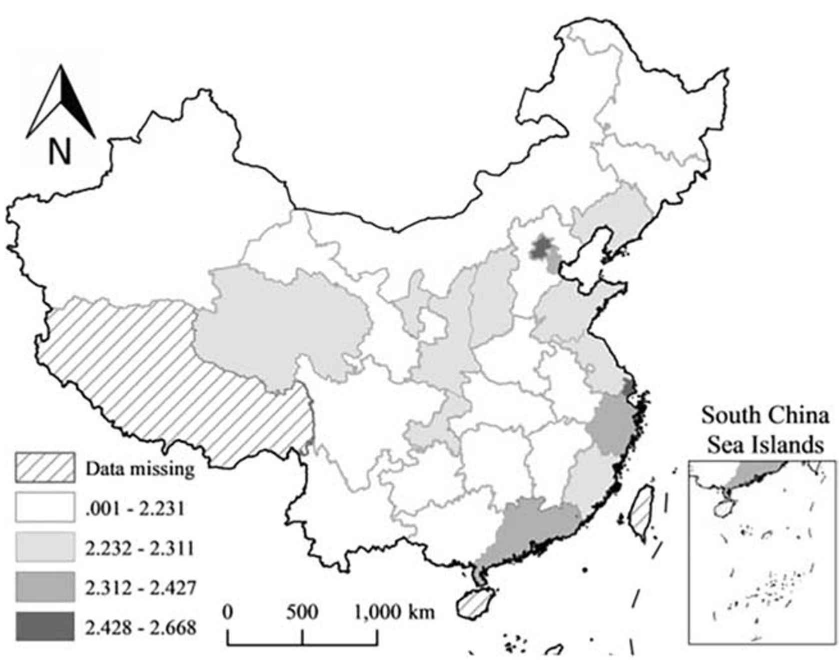


Fig. 5 Spatial pattern of upgrading industrial structure level in China. Notes: Figs. 4 and 5 are based on the standard map of GS (2016) No. 2921 downloaded from the Standard Map Service website of the National Surveying and Mapping Geographic Information Bureau. The base map has no modification (Fig. 6 is the same)

Henan (− 5.837%), Ningxia (− 5.072%), and Qinghai (− 4.791%). The rate of decline in the four regions is inversely proportional to the efficiency level, with the western region declining the fastest and the central, the northeast, and the eastern regions falling behind. The northeast region began to decline from positive coupling to negative coupling after 2000.

In short, the degree of coupling of the "carbon emission efficiency–industrial structure upgrading" system in various provinces in China has not yet reached the ideal level, but generally shows a downward trend, which should be carefully considered by the government.

Coupling path of regional carbon emission efficiency and industrial structure upgrading in China

Analysis of dynamic coordination of regional carbon emission efficiency and industrial structure in China

This study examines the coordination between regional carbon emission efficiency and industrial structure upgrading from the perspective of the internal dynamics of distribution. By referring to the club convergence index constructed by zhou and zhou (2018) under the framework of distribution dynamics, this paper estimates and compares the differences in the degree of horizontal curing between the two over the long term. As the implementation of coordinated regional development policy takes time, this study determines the club convergence indices of different periods. Considering the various ways that discretizing dynamic results can get different distributions, the club convergence indices are calculated based on the mean and the median discretization.

With reference to the discretization method of Du et al. (2018), this study divides districts into four types (clubs) by taking as the dividing points 50%, 100%, and 150% of the mean or median of each year. The higher the value indicates the higher the degree of solidification and the deficiency of the government's adjustment. Therefore, it is necessary to strengthen the adjustment to achieve regional coordination. Table 2 shows the calculation results of the club convergence index of carbon emission efficiency and industrial structure upgrading for different durations in China.

In Table 2, it shows that no matter what the discretization is, the club convergence index of China's regional carbon emission efficiency is larger than the club convergence index of industrial structure upgrading, and this difference has been increasing with time. It also indicates that from a dynamic point of view, there is a clear disharmony between the interregional carbon emission efficiency and industrial structure upgrading. The former shows different solidification characteristics, while the latter holds high fluidity, which indicates some "weak regions" may perform better in industrial structure upgrading as the time goes by, showing a certain catch-up behavior, but may face the "inefficiency trap" of carbon emissions. Thus, although the country has attached importance to energy, to the environment, and to carbon emission reduction problems, the effect of coordinating regional industrial upgrading is significantly better than that of regional carbon emission efficiency measures, which may be related to the government's "feasible measures" for the former and the concept that "development is an absolute principle" for the latter. Therefore, the government should work harder to strengthen the coordination of energy efficiency and carbon emission efficiency among regions, not only valuing energy and environmental issues from a conceptual perspective but also proposing some practical measures, such as support for areas that have been at a low level for a long time. The further revelation is that when improving China's coupling of carbon emission efficiency and industrial structure upgrading, the government should focus on regions with low coupling efficiency and start by improving their carbon emission efficiency. It cannot only improve the coupling degree of the region but also alleviate the curing problem of carbon emission efficiency among regions.

Table 2 Club convergence index of carbon efficiency and upgrading industrial structure for different durations

Duration	Divided by the mean			Divided by the median		
	Carbon emission efficiency	Industrial structural upgrading	Difference	Carbon emission efficiency	Industrial structural upgrading	Difference
$k = 1$	0.947	0.866	0.082	0.920	0.819	0.102
$k = 2$	0.927	0.784	0.144	0.889	0.716	0.172
$k = 3$	0.899	0.734	0.164	0.846	0.655	0.191
$k = 4$	0.869	0.705	0.164	0.800	0.627	0.172
$k = 5$	0.841	0.655	0.186	0.756	0.584	0.172
Mean value	0.897	0.749	0.148	0.842	0.680	0.162

Coupling path between China's carbon emission efficiency and industrial structure upgrading

Classification of specific coupling types of carbon emission efficiency and industrial structure upgrading in various regions of China This paper classifies the following provinces according to the specific coupling characteristics of China's carbon emission efficiency and industrial structure upgrading. In addition, it presents an averaged scatter plot of the normalized carbon emission efficiency and industrial structure upgrade level of each province and classifies the provinces according to the coordination level and the mean value of the development level of all regions. The result is shown in Figs. 6 and 7.

The curve in Fig. 7 is the average development level of each province during the inspection period. The two straight lines with 45-degree line symmetry are the average coordination level of each province during the inspection period, and thus, the coupling characteristics of the system of the "carbon emission efficiency–industrial structure upgrading" in various regions of China can be divided into the following four types:

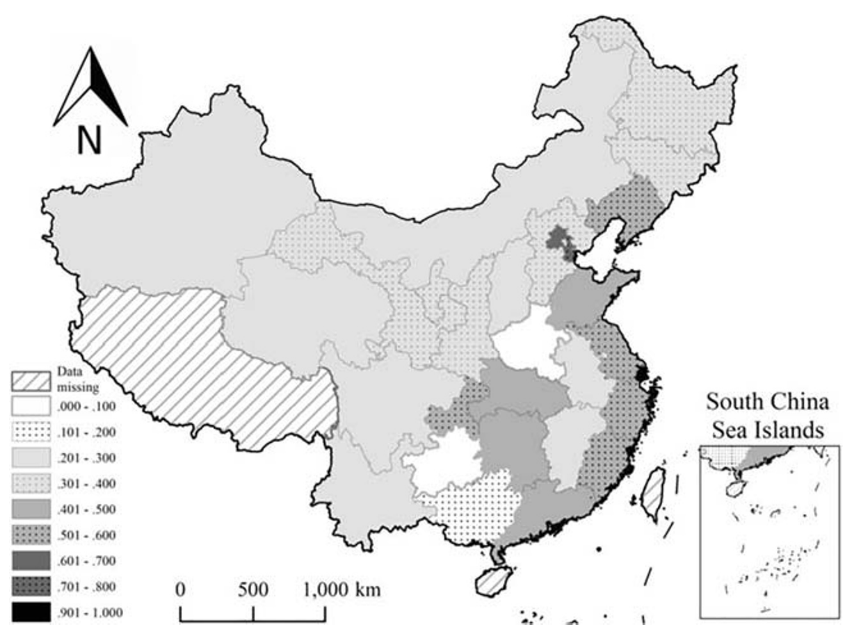
Type A: coupling type with a high degree of development and coordination. Such regions include Shanghai, Tianjin, Zhejiang, Jiangsu, Fujian, and Chongqing, which are mainly located in the coastal areas of China. With a high degree of development and coordination of the carbon emission efficiency and industrial structure upgrading, they are the benchmark areas for the development of a low-carbon economy in China. Although the coupling degree of Shanghai is higher than that of Tianjin, its development degree is higher, while its coordination degree is lower than that of Tianjin, as depicted in Fig. 7.

Type B: coupling type with a high degree of development and low degree of coordination. This coupling type can be further divided into B_1 and B_2 subclasses. The former, such as Yunnan province and Liaoning province, are low in coordination due to the lag of carbon emission efficiency, while the latter subclass, such as Beijing and Guangdong province, are mainly caused by the lag of industrial structure upgrading. These regions should take more targeted measures to make up for their shortcomings in low-carbon economic development.

Type C: coupling type with a low degree of development and coordination. It can also be further divided into C_1 and C_2 subclasses. The former is caused mainly by lagging carbon emission efficiency, while the latter is caused mainly by lagging industrial structure upgrading. The regions belonging to C_1 include Guizhou, Qinghai, and Shanxi, and the provinces belonging to C_2 include Henan and Guangxi, among others. These regions are the "vulnerable areas" in the development of China's low-carbon economy, which also have great potential and room for improvement in coupling degree.

Type D: coupling type with a low degree of development and a high degree of coordination. This type includes 14 of China's provinces, which represent the overall state of the coupling relationship between China's carbon emissions and the efficiency of the industrial structure upgrading. Typically, type D includes Sichuan, Anhui, Jiangxi, the Inner Mongolia Autonomous Region, Xinjiang, and other provinces. It shows that regional carbon efficiency measures and industrial structure

Fig. 6 Spatial pattern of coupling degree between carbon efficiency and upgrading industrial structure in China



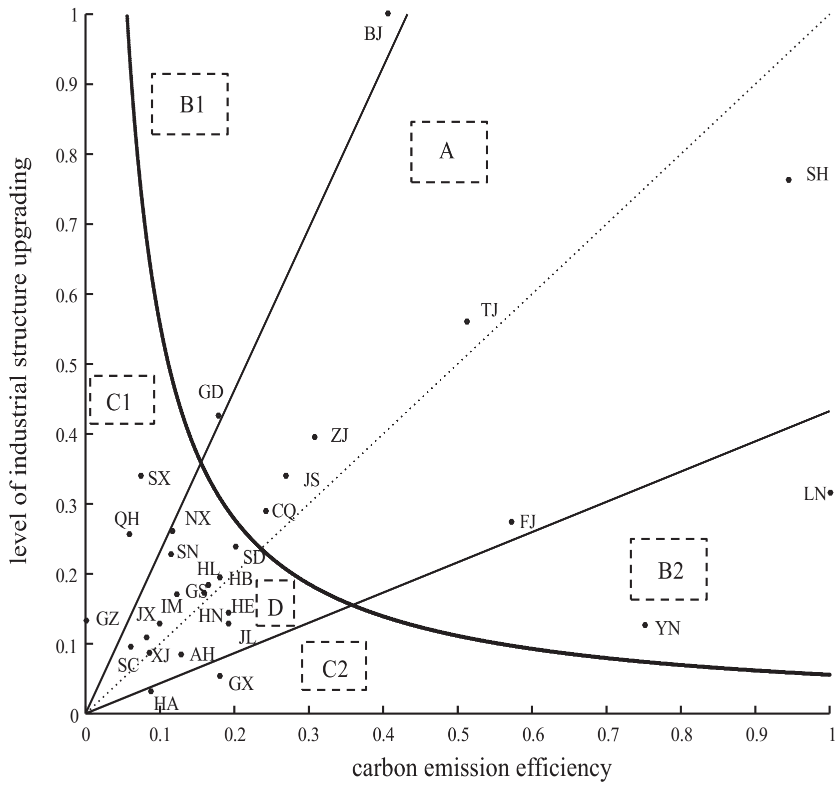


Fig. 7 The classification of coupling types of carbon efficiency and industrial structure upgrading in different regions. Abbreviation of the provinces: BJ, Beijing; ZJ, Zhejiang; FJ, Fujian; SH, Shanghai; TJ, Tianjin; CQ, Chongqing; HLJ, Heilongjiang; JL, Jilin; HB, Hebei; LN, Liaoning; XJ, Xinjiang; GS, Gansu; QH, Qinghai; SX, Shanxi; SX, Shanxi; NX, Ningxia; HN, Henan; SD, Shandong; JS, Jiangsu; AH, Anhui; HN, Hunan; HB, Hubei; SC, Sichuan; JS, Jiangsi; GD, Guangdong; FJ, Fujian; GX, Guangxi; GZ, Guizhou; YN, Yunnan

upgrading systems are not well coordinated. The possible causes of the above situation may be primarily due to the interaction between regional carbon efficiency and the upgrading of the industrial structure, which is likely to happen in the type D situation, namely low-carbon efficiency and low level of industrial structure upgrading, therefore contribute to a higher level of coordination degree and a low level of coordination. It also indicates that the carbon emission efficiency and industrial structure upgrading levels are low in many regions of China, so measures are necessary to break such low-quality coordination. Second, these low-level coordination regions lack the motivation to escape the "trap." Perhaps, it is because when these regions periodically break out of the low coordination level, it may result in an inaccessible degree of development and worsen the degree of coordination.

The coupling path between carbon emission efficiency and industrial structure upgrading in various regions of China Based on the analysis of the first and second part of the paper, the government should adopt the strategy of path 1, as the degree of solidification of China's carbon emission efficiency is significantly greater than the upgrading of the industrial structure.

Specifically, the central government should focus on supporting areas with long-term low carbon emission efficiency in the type B1 and C1 regions, especially Guizhou, Qinghai, and Shanxi provinces. The government should take measures to improve the emission efficiency to further improve the coordination level of the "carbon emission efficiency–industrial structure upgrading" system in these regions. In addition, since the improvement of carbon emission efficiency can promote the improvement of the system development level, the coupling promotion path of $C_1 \rightarrow A$ or $B_1 \rightarrow A$ can be realized in these areas. This strategy has two aspects: first, it can alleviate the solidification problem of carbon emission efficiency among regions help regions with a low level of carbon emission efficiency avoid falling into "low-level traps," and realize a dynamic coordination development of the carbon emission efficiency and industrial structure. Second, it can stimulate the provinces in the D type regions, especially in Ningxia, Shaanxi, the Inner Mongolia Autonomous Region, Jiangxi, Sichuan, and other provinces, by urging them to change the state of coordination and improve the coupling degree in steps and stages under the current coordination situation. Specifically, they can take a $D \rightarrow B_1 \rightarrow A$ or $D \rightarrow C_1 \rightarrow A$ path to boost their coupling by improving the level of industrial structure, entering the type B_1 or type C_1 classification, and then by obtaining government support and ultimately, becoming a type A region with higher degrees of development and coordination.

In addition, provinces in other regions can also take targeted measures to improve their coupling levels of carbon emission efficiency and industrial structure upgrading according to their own conditions. For example, the type B_2 provinces with high carbon emission efficiency and poor coordination should start by improving their industrial structure, so that they can become type A regions by improving the quality of economic development and the degree of coordination between carbon emission efficiency and their industrial structures.

Main conclusions and policy suggestions

This paper explores the coupling degree and coupling path of carbon emission efficiency and industrial structure upgrading in China. The super-efficiency SBM model was used to calculate the carbon emission efficiency of 29 provinces in China from 1997 to 2016, and the industrial structure level of each province was calculated by the industrial structure layer index. On this basis, we use the coupling degree model to analyze the coupling degree of carbon emission efficiency and industrial structure in each province, especially on the analysis of the coupling type and specific coupling characteristics, and propose the coupling degree improvement path in the dynamic coordination of industry. Through the research and analysis, the following conclusions are drawn:

(1) China's regional carbon emission efficiency is not high in general and shows a downward trend. In the spatial pattern, it is higher in the southwest and lower in the northwest by Heihe-Tengchong Line. The spatial differentiation of the level of industrial structure upgrading is clear, and there is no gradient characteristic of carbon emission efficiency. In terms of time, it is also different from carbon emission efficiency with a rising trend. Therefore, there is quite a difference between China's carbon emission efficiency and its industrial structure upgrading over a period of time and in its spatial distribution pattern.

(2) China's carbon emission efficiency has a low degree of coupling with industrial structure upgrading. Except for Shanghai, Tianjin, Beijing, and those provinces with high qualities and intermediate and primary coordinated development, most of the provinces are in a state of dysregulation with light or mildly dysfunctional decline. In addition, in terms of specific coupling characteristics, nearly half of the provinces belong to the coupling type D with lower development but higher coordination, except for Shanghai, Tianjin, Zhejiang, Jiangsu, Fujian, and Chongqing, which have high development and degree of coordination. These regions should take measures to change the current situation of "low-level coordination" and achieve an increased level in coupling.

(3) No matter what kind of discretization method is adopted, the degree of carbon emission efficiency solidification between regions in China is far greater than the upgrading of industrial structure, and this difference tends to increase with the accumulation of time. This shows that, from a dynamic perspective, there is an obvious disharmony between the carbon emission efficiency and the upgrading of industrial structure between regions. The former shows the characteristics of high- and low-level solidification, while the latter has relatively high mobility. In other words, with the change of time, some "vulnerable regions" may perform better in industrial structure upgrading and show a certain catch-up trend, but these regions may face the problem of "low efficiency trap" of carbon emissions. It can be seen that the effect of national coordination on inter-regional industrial upgrading is obviously better than that of regional carbon emission efficiency.

Based on the research conclusions, the policy recommendations are as follows:

(1) When improving the coupling degree of each province, the central government should support the efficiency of regions with long-term low carbon emission efficiency, especially those regions (B_1, C_1) with low coordination degree due to low carbon emission efficiency. This cannot only improve the coupling degree of the region but also have two aspects of benefits. First, it can alleviate the problem of the solidification of China's regional carbon emission efficiency, especially the problem of "low efficiency trap", and realize the dynamic coordination between the carbon emission efficiency and industrial structure upgrading in the region. Second, it can stimulate the regions with the same low carbon emission efficiency but the low industrial structure (D type regions) to take a step-by-step and phased path to improve the coupling degree.

(2) According to the specific types of coupling characteristics of the carbon emission efficiency and industrial structure upgrading, specific improvement strategies should be taken in different regions. For example, regions with high carbon emission efficiency but low industrial structure level (C_2) should attach importance to the coordination degree of the two, and take unilateral measures to improve the coupling degree.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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