



Heterogeneous impacts of multi-energy power generation on carbon emissions: evidence from China's provincial data

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Abstract

The goals of carbon peak and carbon neutrality have put forward higher requirements for the low-carbon development of power supply. This paper discusses the impacts of multi-energy power generation on carbon emissions for 30 regions in China and proposes low-carbon development suggestions for the electric power industry. The research found that firstly there is a significant strong positive correlation between thermal power and carbon emissions in most regions of China, so the carbon emission reduction of power supply should still focus on thermal power. Secondly, wind power and photovoltaic power have positive effects or negative effects on carbon emissions in different regions. But combined with the analysis results in regions with the rapid development of wind power or photovoltaic power, it could be found that wind power and photovoltaic power contributed to reducing carbon emissions when they developed to a certain scale. It is proposed to speed up the construction of wind power and photovoltaic power in regions with rich wind resources or solar resources such as Inner Mongolia, Xinjiang, Liaoning, and Gansu. Thirdly, hydropower and nuclear power both have negative effects on carbon emissions. Considering the large demand for electricity in coastal regions where nuclear power is located, it is suggested that coastal regions should gradually promote the construction and application of nuclear power on the basis of safety.

Keywords Multi-energy power generation · Carbon emissions of production and supply of electric power, steam and hot water · Heterogeneous impacts · Panel data analysis

Introduction

Carbon emissions have caused climate warming on a global scale, which is closely related to energy consumption (Chishti et al. 2022; Murshed et al. 2021). How to coordinate energy consumption and environmental sustainability

has become an important issue worldwide (Ahmed et al. 2022; Khan et al. 2022; Murshed, 2020). As one of the main carbon emission countries, China has made great efforts in carbon emission reduction. To further respond to global climate change, the Chinese government has proposed the carbon peak and carbon neutrality goals which require reaching the peak of carbon emissions by 2030 and achieving carbon neutrality by 2060. The electric power industry is the main source of carbon emissions in China, accounting for more than 40% of the total carbon emissions (Wen and Yan, 2017; Zhang et al. 2019). Under the carbon peak and carbon neutrality goals, the electric power industry is stressed out in carbon emission reduction (Yu et al. 2020b). To further reduce the carbon emissions from the electric power industry, in June 2022, the goal of building a new power system with a gradually increasing proportion of new energy sources was proposed, which puts forward new requirements for the low-carbon adjustment of the power supply.

In recent years, according to the resource endowment, the Chinese government has actively promoted the low-carbon adjustment of the electric power supply in different regions.

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In the southwestern regions with rich water resources, such as Yunnan and Sichuan, hydropower has developed speedily; in the southeastern coastal regions, such as Zhejiang and Jiangsu, nuclear power has fast growth; and in the northern regions, such as Hebei and Inner Mongolia, wind power and photovoltaic power have rapid expansion. Different power generation forms and supply structures have formed in regions of China (Liu and Niu 2021; Yao et al. 2021). It is necessary to research the impacts of multiple energy on carbon emissions and further formulate the carbon emission reduction measures for the power industry based on the diverse development of regions.

China and the world have been striving to develop renewable energy power (Muntasir 2021; Murshed and Tanha 2021; Li et al. 2021a), but the impacts of renewable energy power generation on carbon emissions are not unified (Zheng et al. 2021). There are three views on the connection between renewable energy power generation and carbon emissions. The first view is that the development of renewable energy contributes to reducing carbon emissions (Aslan et al. 2021); the second opinion is that the effect of renewable energy on carbon emission reduction is not significant (Nathaniel et al. 2021), even the development of renewable energy increases carbon emissions (Magazzino et al. 2021); and the third view, comprehensively considering the above two views, is that the development of renewable energy needs to cross a certain threshold to inhibit carbon emissions (Nguyen and Kakinaka 2019). Based on the different power generation situations in regions of China, this paper discusses the nexus between wind power, photovoltaics, hydropower, and carbon emissions, which is helpful to clarify the impacts of renewable energy on carbon emissions and has strong practical significance.

Although the electric power industry is the main source of carbon emissions in China, the transportation industry, construction industry, and other industries also emit carbon emissions (Du et al. 2018; Liu et al. 2022; Song et al. 2021), which increases the error in the analysis of the relationship between electric power generation and the regional total carbon emissions. The carbon emissions of production and supply of electric power, steam, and hot water are the total carbon emissions from electricity production and supply, and heat production and supply. This paper uses the carbon emissions of production and supply of electric power, steam, and hot water replacing the regional total carbon emissions to analysis, which is effective to avoid the impacts of carbon emissions from other industries. In addition, carbon emission accounting in China is based on the volume of production in a region during a period. But the region of electricity production and the region of electricity consumption are often separated (Wang et al. 2021). In power consumption centers, such as Beijing and Shanghai, a large amount of power is supplied by other provinces. The transfer of electric

power between regions that has caused the consumption of electricity, which is often used in the previous study, cannot reflect the connection between the power supply and carbon emissions. Therefore, this paper according to the power generation forms classifies the 30 regions in China, and using the power generation and the carbon emissions of production and supply of electric power, steam, and hot water researches the impacts of multi-energy power generation on carbon emissions. In general, this paper proposes a method to overcome the influences of carbon emissions from other factors and the spatial difference in power production and consumption in the relationship analysis of multi-energy power generation between carbon emissions. The research idea of this paper is shown in Fig. 1.

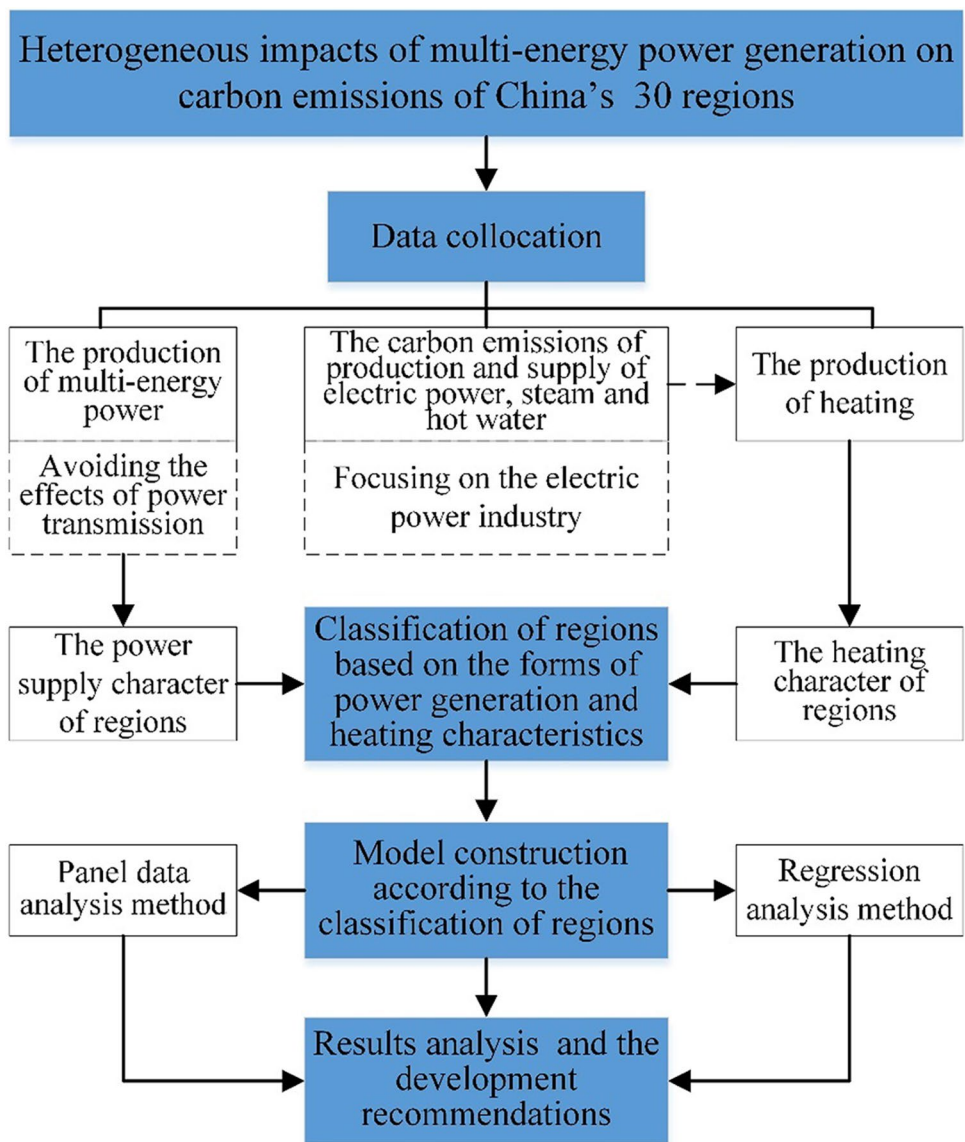
The remainder of the paper is organized as follows: the “Literature review” section reviews the views about power generation and carbon emissions and points out the significance of this study. The “Materials and methods” section presents the model construction and data sources. The “Results and discussions” section analyzes the nexus between multi-energy power generation and carbon emissions in different regions and proposes development strategies for the electric power industry. The “Conclusion” section is the conclusion of this paper.

Literature review

To alleviate climate warming, numerous studies focused on carbon emission-related issues in recent years (Sharma et al. 2021; Wang and Zheng 2021). The identification of carbon emission-related factors is one of the hotspots for carbon emission issues (Du et al. 2018; Liu et al. 2022; Song et al. 2021). Previous studies have found that energy intensity (Zheng et al. 2019) and electric power generation forms (Chen et al. 2018; Li et al. 2021b; Wen et al. 2018) are important factors affecting carbon emissions. After clarifying the factors related to carbon emissions, the effect intensity of economic growth (Khan 2021; Xie et al. 2020), urbanization level (Ali and Yi 2022; Siqin et al. 2022), foreign direct investment (Balsalobre-Lorente et al. 2021; Ghazouani 2021), financial development (Amin et al. 2022; Liu and Gong 2022), natural resources (Yu-Ke et al. 2021), and solar energy technology (Zhang et al. 2020) on carbon emissions have been explored.

The electric power generation form is an important factor affecting carbon emissions, and its influence on carbon emissions has been widely discussed (Wen and Yan 2017; Yu et al. 2020b). Renewable energy is an important part of electric power generation, but its impact on carbon emissions is still inconclusive. Some researchers hold the view that the development of renewable energy contributes to reducing carbon emissions (Aslan et al. 2021; Guney and Ustundag

Fig. 1 Research idea



2022). From location attribute, the relationship between carbon emissions and renewable energy power generation is discussed in Africa (Djellouli et al. 2022; Namahoro et al. 2021), Ethiopia (Usama et al. 2020), and Argentina (Yuping et al. 2021), and in these countries renewable energy power generation helps to reduce carbon emissions. In addition, some studies have focused on countries with outstanding characteristics, such as energy-consuming countries (Huang et al. 2021), highest-emitting countries (Usman et al. 2021b), and emerging economies (Appiah et al. 2019), and also found that the application of renewable energy decreases carbon emissions.

Some researchers hold the opinion that the influence of renewable energy on carbon emissions is insignificant, and even stimulative. Nathaniel et al. (2021) explored the connection between nuclear power, renewable energy, and

carbon emissions in G7 countries, and the impact of renewable energy on carbon emissions was found to be insignificant. Similarly, based on the data from 15 African countries, Nathaniel and Iheonu (2019) also pointed out that renewable energy has little effect on carbon emissions. And Magazzino et al. (2021) considered that in India from 1986 to 2017 wind power and photovoltaic power generation increased carbon emissions.

Based on the above two different views, the point that in the long run, the development of renewable energy will inhibit carbon emissions when its development crosses a certain threshold, has been proposed (Udeagha and Ngepah 2021; Usman et al. 2021a). As early as 2009, from the data of 30 member countries of the OECD from 1996 to 2005, Chiu and Chang (2009) discovered that renewable energy will decrease carbon emissions when the proportion

of renewable energy supply exceeded 8.3889% of the total energy supply. Considering that the application of renewable energy in developed countries is earlier than in developing countries, the nexus between renewable energy and carbon emissions in countries with different economic levels have been compared. It is found that in developed countries and high-income countries, the application of renewable energy has inhibited effect on carbon emissions; in developing countries and low-income countries, the application of renewable energy has promoted effect on carbon emissions (Khan and Ahmad 2021; Nguyen and Kakinaka 2019). In general, the relationship between renewable energy power generation and carbon emissions varies in regions. And analyzing the influence of power generation on carbon emissions in China has strong practical significance to the low-carbon development.

China is one of the main carbon emitters, for which the impact of the electric power industry on carbon emissions has attracted the attention of many scholars (Liu et al. 2021; Li et al. 2021c). From the national level, Yu et al. (2020a) and Zheng et al. (2021) discussed the connection between renewable energy and regional total carbon emissions, respectively, based on the data for 30 Chinese provinces from 2005 to 2016 and the data for 30 Chinese provinces from 2008 to 2017. And they both discovered that at the national level, improving the development of renewable energy is conducive to carbon emission reductions. But they did not further analyze the relationship in different regions in China. In addition, the above studies using renewable energy represent wind power, photovoltaic power, and hydropower and did not specifically analyze the impacts of wind power, photovoltaic power, and hydropower on carbon emissions.

Some researchers explored the effects of renewable energy and non-renewable energy on carbon emissions at the regional levels in China. According to the location of regions, Chen et al. (2019) divided 30 regions in China into the eastern region, western region, and central region, and found that in the eastern and western regions renewable energy had a negative impact on regional total carbon emissions, while in the central region the impact was statistically insignificant. Ma et al. (2021) further divided the 30 regions into 5 categories based on the regional distributions, and pointed out that renewable energy consumption had an inhibiting effect on regional total carbon emissions between 1995 and 2019. But it is limited to classify the regions according to the location before analyzing the nexus between renewable energy consumption, non-renewable energy consumption, and carbon emissions. The power generation forms of renewable energy in the provinces of China are significant differences (Zhu et al. 2019). For example, Shanghai and Fujian both belong to the eastern region in the above research (Chen et al. 2019; Ma et al. 2021), but Shanghai does not have hydropower and nuclear power, and the thermal power generation

accounts for 97% of the total electric power generation; while Fujian both has hydropower and nuclear power, and the thermal power generation only accounts for 57% of the total electric power generation. Therefore, this paper proposes a new classification method of regions based on the forms of power generation.

In summary, previous studies mostly use the regional total carbon emissions and power consumption to analyze. But economic development, industrial structure, urbanization, and other factors all affect the regional total carbon emissions (Du et al. 2018; Liu et al. 2022; Song et al. 2021). This makes the regional total carbon emissions unable to precisely reflect the effect of multiple-energy power generation on carbon emissions. To remove the impact of other factors, the carbon emissions of production and supply of electric power, steam, and hot water are used to replace the regional total carbon emissions. In addition, carbon emissions accounting for the electric power industry are based on the volume of production in the region. Electric power transmission makes power consumption and carbon emissions inconsistent in statistical regions (Wang et al. 2021). So, the regional power generation data are used to explore the impacts of multi-energy on carbon emissions for the electric power industry. Therefore, the main contributions are as follow:

- 1) The carbon emissions of the electric power industry are focused on. Previous studies mostly research the connection between multi-energy and carbon emissions by the regional total carbon emissions which are affected by many factors. In this paper, the regional total carbon emissions are replaced by the carbon emissions of production and supply of electric power, steam, and hot water, which can effectively eliminate the influence of other factors.
- 2) This paper uses the power production of multi-energy instead the power consumption to study the relationship between multi-energy and carbon emissions in regions. In China, the carbon emissions of the electric power industry are accounted for the volume of electric power production in regions. Previous studies explored the nexus between multi-energy and carbon emissions based on power consumption ignoring the carbon emissions transfer caused by power transmission. Therefore, it is more reasonable to research the connection between carbon emissions and multi-energy power generation.
- 3) Compared with the previous studies that classified regions according to their geographical location, the classification method of regions in this paper is different. According to the power generation forms, the 30 regions in China are divided into six categories, and the relationship between multi-energy power generation and carbon emissions in those regions is discussed.

Materials and methods

This paper aims to analyze the nexus between multi-energy power generation and carbon emissions and put forward suggestions for low-carbon development of the electric power industry in different regions of China. Therefore, firstly, the data of multiple-energy power generation and the carbon emissions of production and supply of electric power, steam, and hot water for 30 regions in China are collected; secondly, the 30 regions are classified based on the power generation forms; and finally, the appropriate modeling methods are selected according to the characteristics of the region classification, and the relationship between carbon emissions and thermal power generation, wind power generation, photovoltaic power generation, hydropower generation, and nuclear power generation are analyzed.

Data collection and classification of regions

Data collection and descriptive statistics

In China, the carbon emissions from the electric power industry account for more than 40% of total carbon emissions, but about 60% of carbon emissions come from other industries. To exclude the impact of carbon emissions from other industries, this paper uses the carbon emissions of production and supply of electric power, steam, and hot water for 30 regions from the China Emission Accounts & Dataset. “Industrial classification for national economic activities (GB/T 4754–2017)” stipulates that the sector of production and supply of electric power, steam, and hot water mainly includes electricity production and supply, and heat production and supply. As the supply of electricity and heat is mainly through the grid and heating pipe network, its carbon emissions are extremely small. Therefore, the carbon emissions of the production and supply of electric power, steam, and hot water mainly come from the carbon emissions from electricity production, and the carbon emissions from heat production.

There are five main forms of electricity production in China, thermal power (TG), photovoltaic power (PG), wind power (WG), hydropower (HG), and nuclear power (NG). Taking the carbon emission regional production accounting methods and the electric power transmission between regions into account, this paper selects the electric power production of the five forms as the explanatory variables for carbon emissions of the production and supply of electric power, steam, and hot water. The annual power generation of the five forms of 30 regions in China is obtained from the China Electricity Council. The data

shows that since 2010, wind power and photovoltaic power have rapidly developed; hence, the power generation data from 2010 to 2019 can be used.

The carbon emissions from heating also are the component of the carbon emissions of the production and supply of electric power, steam, and hot water. In northern China, such as Heilongjiang, Liaoning, and Jilin, heating is required for about half of 1 year, which generated a large amount of carbon emissions. Therefore, for heating regions, the amount of heating is an explanatory variable for carbon emissions that cannot be ignored. There are 15 provinces and cities that are heating in winter in China, which are shown in Fig. 2. But it should be noted that not all cities in Henan Province are heated in winter. The amount of heating is closely related to the number of heating days and the heating area (Mi et al. 2021), so this paper uses the product of the number of heating days and the heating area to reflect the heating situation (H). The number of heating days and heating areas from 2010 to 2019 in 15 regions are collected. The number of heating days comes from local government websites, and the heating areas come from the National Bureau of Statistics. The data sources are shown in Table 1.

The statistical results of the carbon emissions of production and supply of electric power, steam and hot water, thermal power generation, wind power generation, photovoltaic power generation, hydropower generation, and nuclear power generation for 30 regions from 2010 to 2019 in China are shown in Table 2. The lowest carbon emissions of production and supply of electric power, steam, and hot water are 9.970 tons in Qinghai in 2010, and the largest are 604.180 tons in Inner Mongolia in 2019, which indicated that there are significant differences in carbon emissions for different regions. The maximum production of thermal power is 482.4 billion kWh in Shandong in 2019, and the minimum production is 10.4 billion kWh in Qinghai in 2010. The maximum production of thermal power generation is 48 times of the minimum. The maximum production of wind power, photovoltaic power, hydropower, and nuclear power, respectively, are 666, 176, 3316, and 110.6 billion kWh, and the minimum production all is 0. Some regions do not have wind power and photovoltaic power in 2010, and some regions do not have hydropower and nuclear power, which resulted in their minimum production being 0. The statistical results show that the differences in the power generation forms for different regions are significant. Therefore, it is scientific and reasonable to divide regions according to the form of power generation.

Classification of regions based on the forms of power generation and heating characteristics

Affected by resource endowment, the forms of power generation in regions are quite different in China. For example,

Fig. 2 The distribution of heating regions in winter for China



Table 1 Data sources

Variable	Time	Data sources
The carbon emissions of production and supply of electric power, steam, and hot water	2010–2019	China Emission Accounts & Dataset
The production of thermal power	2010–2019	China Electricity Council
The production of hydropower	2010–2019	China Electricity Council
The production of wind power	2010–2019	China Electricity Council
The production of photovoltaic power	2010–2019	China Electricity Council
The production of nuclear power	2010–2019	China Electricity Council
The number of heating days	2010–2019	The local government websites
The heating areas	2010–2019	National Bureau of Statistics

Table 2 The statistical results

	CE (ton)	TG (billion kWh)	WG (billion kWh)	PG (billion kWh)	HG (billion kWh)	NG (billion kWh)
Mean	162.370	1416.300	67.455	21.874	338.865	59.168
Maximum	604.180	4824.000	666.000	176.000	3316.000	1106.000
Minimum	9.970	104.000	0.000	0.000	0.000	0.000
Standard deviation	124.658	1119.131	98.813	38.101	600.519	160.516
Skewness	1.176	1.128	2.874	2.047	3.008	3.336
Probability	0.000	0.000	0.000	0.000	0.000	0.000

nuclear power is mainly located in coastal provinces, such as Fujian and Guangdong, while in other inland provinces, they do not have nuclear power generation. The distribution

of nuclear power in China is shown in Fig. 3. The water resources are enriched in the southwestern region, such as Sichuan, Yunnan, Guizhou, and Qinghai, which have

Fig. 3 The distribution of nuclear power in China



achieved remarkable results in hydropower generation. But in Shanghai, they do not have hydropower generation. In Tianjin, the hydropower generation is too small, and from 2012 to 2015 the production of hydropower is 0, so Tianjin is considered to be the region without hydropower generation. Wind resources, solar resources, and coal resources are easily obtained; therefore, there are wind power generation, photovoltaic power generation, and thermal power generation in 30 regions.

The heating regions have been identified in data collection. Based on the forms of power generation and heating characteristics, the 30 regions are divided into 6 classes. And the regions included in each class are shown in Fig. 4.

The Class I mainly includes Shandong and Liaoning, which has thermal power generation, photovoltaic power generation, wind power generation, hydropower generation, nuclear power generation, and heating in winter.

The Class II is the regions that have thermal power generation, photovoltaic power generation, wind power generation, hydropower generation, and heating in winter. They are Jilin, Heilongjiang, Inner Mongolia, Beijing, Hebei, Henan, Shanxi, Shaanxi, Ningxia, Qinghai, Gansu, and Xinjiang.

The Class III only contains Tianjin, which has thermal power generation, photovoltaic power generation, wind power generation, and heating in winter.

The Class IV is the regions that have thermal power generation, photovoltaic power generation, wind power

generation, hydropower generation, nuclear power generation, and does not have heating in winter. They are Jiangsu, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan.

The Class V is the regions that have thermal power generation, photovoltaic power generation, wind power generation, hydropower generation, and do not have heating in winter. They are Sichuan, Yunnan, Guizhou, Chongqing, Hubei, Hunan, Jiangxi, and Anhui.

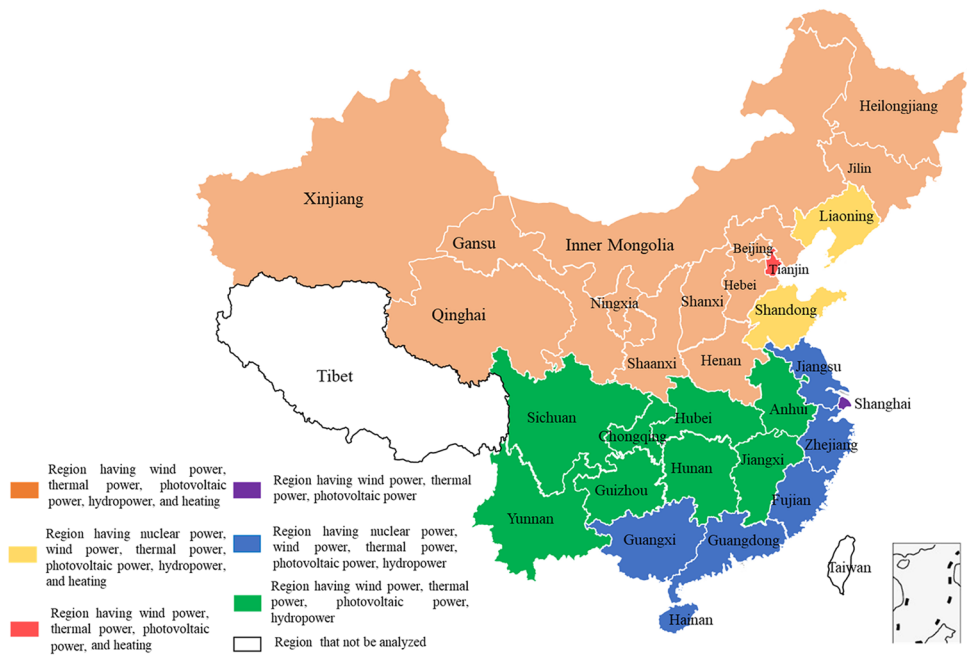
The Class VI only includes Shanghai, which has thermal power generation, photovoltaic power generation, wind power generation, and does not have heating in winter.

Model construction

This paper applies the transformed Cobb–Douglas function to explore the nexus between multi-energy power generation and carbon emissions. To eliminate the influence of heteroscedasticity, the logarithm of variables is used. Due to the different forms of power generation in regions, this paper conducts models for the 6 classes of regions, respectively. Taking the Class I regions as an example, the equation of carbon emissions and multiple energy is shown in formula (1).

$$\log(CE_{it}) = c_{it} + \beta_{1it}\log(TG_{it}) + \beta_{2it}\log(HG_{it}) + \beta_{3it}\log(WG_{it}) + \beta_{4it}\log(PG_{it}) + \beta_{5it}\log(NG_{it}) + \beta_{6it}\log(H_{it}) + \varepsilon_{it} \quad (1)$$

Fig. 4 The classification of 30 regions



Based on formula (1), combining the forms of power generation and heating situation for each class of region, the explanatory variables should be adjusted, respectively. For Class II regions, which are without nuclear power generation compared to Class I regions, the explanatory variable of nuclear power production should be excluded. And for Class IV regions, which are without heating compared to Class I regions, the explanatory variable of heating should be excluded. Due to the strong similarity of the formula for each class, the introduction will not be repeated.

It should be noted that the provinces and cities in Class II regions, Class IV regions, and Class V regions are more than 3. So the basic data in the three classes fulfill the requirements of panel data that multi-dimensional time-series data for cross-sectional individuals at continuous times. Compared with the pooled time-series and cross-section data, panel data carry more information, which can reflect the change rules in time series and cross section at the same time. Based on the assumption of the Cobb–Douglas function, the panel data modeling method can be used in the three classes.

There are Liaoning and Shandong in Class I regions, Tianjin in Class III regions, and Shanghai in Class VI regions. The number of individuals in the above three categories is not more than two, which does not fulfill the panel data requirements. Therefore, for the above regions, this paper uses regression analysis to research the connection between multiple-energy power generation and carbon emissions. The regression analysis process is simple and will not be introduced in detail. The following process for panel data analysis does not apply to the above 4 regions.

Cross-sectional dependence test

The cross-sectional dependence test is one of the important processes for panel data analysis. Cross-sectional correlation of panel data can lead to biased, inconsistent, and inefficient results in the estimated coefficients. Hence, it is necessary to test whether the cross-sectional is dependent. The method for the cross-sectional dependence test mainly contains the Pesaran test (Pesaran et al. 2004) and the Breusch and Pagan test (Breusch and Pagan 1980). In the cross-sectional dependence test, the null hypothesis is that there is no cross-sectional correlation in panel data. When the null hypothesis is accepted, the panel data does not have cross-sectional correlation. Since the Pesaran test is more suitable for panel data with relatively large individuals and short time, this paper uses the Pesaran test to explore cross-sectional correlation. The calculation formula of the Pesaran test is shown in formula (2).

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \right) \tag{2}$$

where N is the number of individuals, $i, j \in N$; T is the time period; and $\hat{\rho}_{ij}$ is the correlation coefficient, which calculation formula is as follows:

$$\hat{\rho}_{ij} = \left(\sum_{t=1}^T \hat{\mu}_{it}^2 \right)^{-1/2} \left(\sum_{t=1}^T \hat{\mu}_{jt}^2 \right)^{-1/2} \sum_{t=1}^T \hat{\mu}_{it} \hat{\mu}_{jt} \tag{3}$$

where $\hat{\mu}_{it}$ and $\hat{\mu}_{jt}$ are the residuals of i and j .

Panel unit root test

The aim of the panel unit root test is to ensure the stability of the panel data. The non-stationary series may result in false regression. To protect the credibility of the estimation, it is necessary to do the panel unit root test. The methods for the panel unit root test mainly contain Levin, Lin, and Chut test (LLC) (Levin et al. 2002); Im Pesaran and Shin test (IPS) (Im et al. 2003); and augmented Dickey-Fuller test (*ADF*-Fisher) (Maddala and Wu 1999). The null hypothesis of these tests is the panel data series have a unit root, and the data is unstable. When the unit root test rejects the null hypothesis, the data is stationary.

It should be noted that the alternative hypothesis of the LLC test is different from other tests. The null hypothesis and the alternative hypothesis of the LCC test are as follow. H_0 represents that the panel data contains the unit root; H_1 represents that the panel data is stationary, and the autoregressive coefficient for each individual is the same. To ensure the reliability of the test, the LLC test and the *ADF*-Fisher test are both used.

$$\begin{aligned} H_0 : \eta_1 = \eta_2 = \eta_3 = \dots \eta_n = 0, \text{for } i = 1, 2, 3 \dots N \\ H_1 : \eta_1 = \eta_2 = \eta_3 = \dots \eta_n < 0, \text{for } i = 1, 2, 3 \dots N \end{aligned} \quad (4)$$

The LCC test method is as follows:

$$\Delta y_{it} = \eta y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-1} + x'_{it} + u_{it} \quad (5)$$

where η is the autoregressive coefficient, p_i is the lag order for individual i , x'_{it} are the exogenous variables including individual fixed effects and time, and u_{it} is the random error.

The alternative hypothesis of the *ADF*-Fisher test also is the panel data is stationary, but the autoregressive coefficient for each individual is different, which is different from the LLC test. The null hypothesis and the alternative hypothesis of the *ADF*-Fisher test are as follow:

$$\begin{aligned} H_0 : \eta_1 = \eta_2 = \eta_3 = \dots \eta_n = 0, \text{for } i = 1, 2, 3 \dots N \\ H_1 : \eta_1 = 0, \text{for } i = 1, 2, 3 \dots N_1 \text{ and } \eta_i < 0, \text{for } i = N_1 + 1, N_1 + 2, \dots N \end{aligned} \quad (6)$$

The *ADF*-Fisher test method is as follows:

$$-2 \sum_{i=1}^N \log(\pi_i) \rightarrow \chi^2(2N) \quad (7)$$

where π_i is the p statistic of the unit root test for individual i , which obeys the chi-square distribution with $2N$ degrees of freedom.

Panel co-integration test

The co-integration test is used to test the long-term relationship among the variables. If the explanatory variable and

explained variable are co-integrated, there is a long-term stable relationship between the variables. The method for the panel co-integration test mainly uses the Kao test (Kao 1999). The null hypothesis of the co-integration test is that there is no long-term co-integration relationship between the variables. When the co-integration test rejects the null hypothesis, it means that there is a long-term co-integration relationship between the variables. The Kao test includes two stages. In the first stage, it is assumed that each individual has different intercept terms and the same coefficient, and the corresponding regression equation in the Kao test is as follows:

$$y_{it} = \alpha_i + \delta_i t + x'_{it} \beta + u_{it} \quad (8)$$

where, according to the assumption for different individual i , the α_i is different and the β is the same. And the δ_i is the estimated error term and represents deviances from the long-term relationship, which is set to be equal to zero according to the assumption.

In the second stage, conducts the unit root test of u_{it} in the first stage, and the *ADF* statistic of u_{it} for the Kao test is as follows:

$$ADF = \frac{t_p + \sqrt{6N} \hat{\sigma}_v / 2 \hat{\sigma}_{0v}}{\sqrt{\frac{\hat{\sigma}_{0v}^2}{2 \hat{\sigma}_v^2} + \frac{3 \hat{\sigma}_v^2}{10 \hat{\sigma}_{0v}^2}}} \quad (9)$$

where t_p is the t-statistic in *ADF* regression for co-integration, $\hat{\sigma}_v^2 = \hat{\Sigma}_{yy} - \hat{\Sigma}_{yx} \hat{\Sigma}_{xx}^{-1}$, and $\hat{\sigma}_{0v}^2 = \hat{\Omega}_{yy} - \hat{\Omega}_{yx} \hat{\Omega}_{xx}^{-1}$.

Model specification test

After the unit root test and the co-integration test, the model form for panel data should be tested. Model specification test can improve the validity of the model. The models for panel data mainly include three types: variable coefficient model, variable intercept model, and constant coefficient model. Usually, the F test is used to determine the model specification. Based on formula (1), the hypothesis is as follows.

$$H_1 : \beta_1 = \beta_2 = \beta_3 = \dots \beta_n \quad (10)$$

$$H_2 : C_1 = C_2 = C_3 = \dots C_N, \text{ and } \beta_1 = \beta_2 = \beta_3 = \dots = \beta_N \quad (11)$$

The hypothesis of H_2 means that for each individual, the constant and coefficient are the same. When the hypothesis H_2 is accepted, the constant coefficient model should be established. The hypothesis of H_1 means that for each individual, the coefficient is the same, but the constant is different. When the hypothesis H_1 is accepted, the variable intercept model should be established. When the hypotheses H_1 and H_2 are both rejected, the variable coefficient model should be established,

which means that for each individual, the constant and coefficient is different.

Firstly, based on the F test, hypothesis H_2 is tested. The formula for the F statistic of H_2 is as follows:

$$F_2 = \frac{(S_3 - S_1) / [(N - 1)(K + 1)]}{S_1 / [N(T - K - 1)]} \tag{12}$$

where S_1 is the residual sum of squares for the variable coefficient model, S_3 is the residual sum of squares for the constant coefficient model, N is the number of cross-section individual, K is the number of indicators, and T is the length of time.

Compare F_2 with the critical value F_α in a given significant level, which usually is 5%. The formula for F_α is as in formula (13). If $F_2 < F_\alpha$, the hypothesis H_2 should be accepted, and the constant coefficient model be constructed. If $F_2 > F_\alpha$, the hypothesis H_2 should be rejected, and it is necessary to continue to test hypothesis H_1 .

$$F_\alpha = F_{0.05}[(N - 1)(K + 1), N(T - K - 1)] \tag{13}$$

Secondly, testing the hypothesis H_1 , the formula for the F statistic of H_1 is as follows:

$$F_1 = \frac{(S_2 - S_1) / [(N - 1)K]}{S_1 / [N(T - K - 1)]} \tag{14}$$

where S_2 is the residual sum of squares for the variable intercept model. Compare F_1 with the critical value $F_{1\alpha}$ in 5% significant level. The formula for $F_{1\alpha}$ is as follows.

$$F_{1\alpha} = F_{0.05}[(N - 1)K, N(T - K - 1)] \tag{15}$$

If $F_1 < F_{1\alpha}$, the hypothesis H_1 should be accepted, and the variable intercept model be constructed. If $F_1 > F_{1\alpha}$, the hypothesis H_1 should be rejected, and the variable coefficient model be constructed.

And it should be noted that the variable coefficient model and the variable intercept model can be divided into fixed effect or random effect, which are different in the correlation between individual and explanatory variables. The Hausman test is the common method for testing the fixed effect or the random effect of models. The null hypothesis of the Hausman test is that the random effect is irrelevant to explanatory variables. The statistics of the Hausman test is as follows:

$$W = (\hat{b}_{CV} - \hat{b}_{GLS})' [\text{var}(\hat{b}_{CV}) - \text{var}(\hat{b}_{GLS})]^{-1} (\hat{b}_{CV} - \hat{b}_{GLS}) \tag{16}$$

where \hat{b}_{CV} is the estimated parameters of the fixed-effect model and \hat{b}_{GLS} are the estimated parameters of the random-effect model. W obeys the χ^2 distribution with degree of freedom K , which is the number of explanatory variables, and $\chi^2_\alpha(k)$ is the critical value at a given significant level. If $W > \chi^2_\alpha(k)$, the null hypothesis should be rejected, and the fixed-effect model is constructed. Otherwise, the null hypothesis should be accepted, and the random-effect model is constructed. The modeling process is shown in Fig. 5.

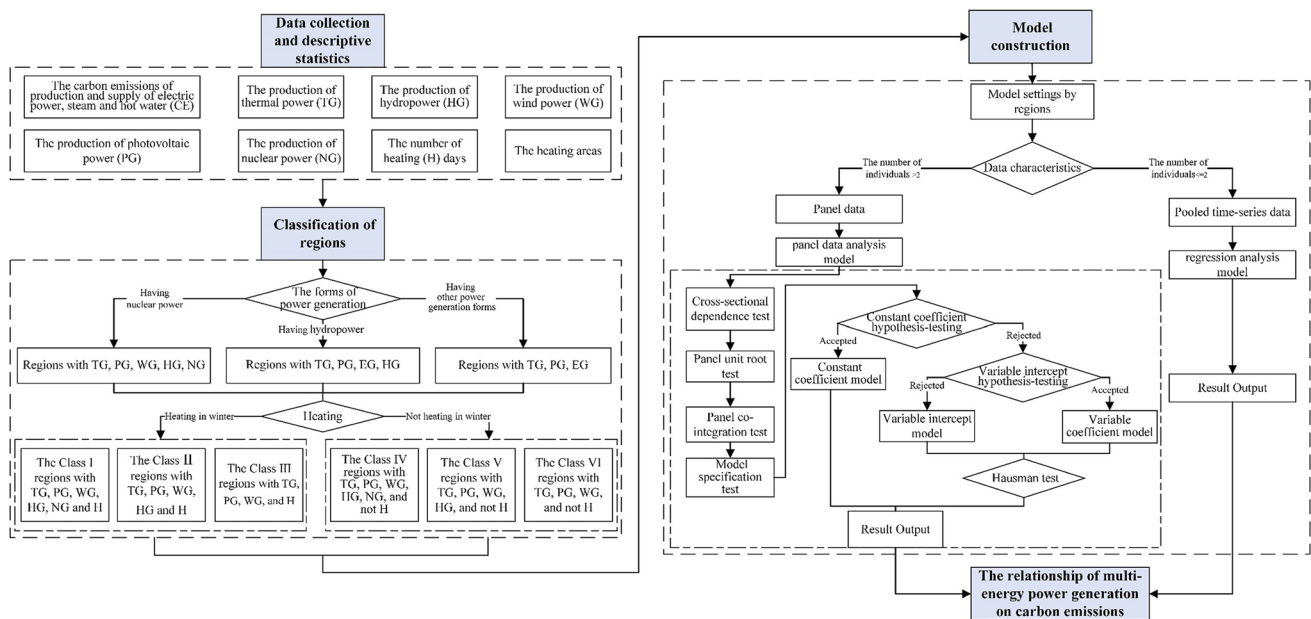


Fig. 5 The modeling process

Results and discussions

Under the carbon peak and carbon neutrality goals, the electric power industry, which is the main source of carbon emissions, is under enormous pressure. To promote the low-carbon development of the electric power industry, this paper analyzes the influences of multi-energy power generation on carbon emissions in different regions in China and proposes the low-carbon development advices for different regions.

Results of cross-sectional dependence test

For the three classes of regions, which contain 26 provinces, the cross-sectional correlation test is carried out. Considering the data characteristic of the three classes of regions, this paper uses the Pesaran test to research the cross-sectional correlation, which result is shown in Table 3. The statistical results show that the *p* values of Class II regions, Class IV regions, and Class V regions are 0.166, 0.133, and 0.060, respectively, which all accept the null hypothesis with no cross-sectional dependence at the 5% significant level.

Results of panel unit root test

To ensure the reliability of the unit root test, the LLC test and the *ADF* test are used to research the stability of the panel data for the three classes of regions. The statistical results and the *p* values of the LLC test and the *ADF* test

for the three classes of regions are shown in Table 4. The smaller the *p* value is, the higher the reliability of the results is. For Class II regions, the *p* value indicates that all variables reject the null hypothesis with unit root in level at the 10% significance level, so the panel data are stationary. For Class IV regions and Class V regions, all variables reject the null hypothesis with unit root in the first difference at the 5% significance level, so the panel data are stationary. Generally, the panel data of the three classes of regions are stationary.

Results of panel co-integration test

To ensure the co-integration relationship among the variables, the Kao test is employed. The results of the Kao test for the three classes of regions are shown in Table 5. For Class II regions and Class IV regions, the null hypothesis of no co-integration can be rejected at the 1% significance level. For Class V regions, the null hypothesis of no co-integration is rejected at the 5% significance level. And the results of the panel co-integration test for the three classes of regions all support the conclusion that there is a co-integration relationship among the variables.

Results of model specification test

To determine the model specification of the three classes of regions, the residuals are calculated. According to formulae

Table 3 Pesaran cross-sectional dependence test results

Classification	Pesaran’s test of cross-sectional independence	<i>p</i> value
Class II regions	− 1.386	0.166
Class IV regions	− 1.503	0.133
Class V regions	1.878	0.060

Table 5 The results of panel co-integration test (Kao panel co-integration test)

Classification	Statistic	<i>p</i> -value
Class II regions	− 6.896	0.000***
Class IV regions	− 4.809	0.000***
Class V regions	− 2.159	0.016**

* denotes 10% level of significance, ** denotes 5% level of significance, and *** denotes 1% level of significance

Table 4 Panel data unit root test results (*p* values in parentheses)

Variables	Class II regions (level)		Class IV regions (first difference)		Class V regions (first difference)	
	LLC	<i>ADF</i>	LLC	<i>ADF</i>	LLC	<i>ADF</i>
Log CE	− 7.099 (0.000***)	31.832 (0.001***)	− 6.045 (0.000***)	41.652(0.004***)	− 10.914 (0.000***)	88.773 (0.000***)
Log TG	− 6.010 (0.000***)	27.116 (0.007***)	− 9.479 (0.000***)	58.786 (0.000***)	− 11.307 (0.000***)	72.291 (0.000***)
Log WG	− 4.383 (0.000***)	29.295 (0.004***)	− 19.986 (0.000***)	65.505 (0.000***)	− 16.833 (0.000***)	80.512 (0.000***)
Log PG	− 5.810 (0.000***)	19.225 (0.083*)	− 7.644 (0.000***)	37.380 (0.019**)	− 4.776 (0.000***)	81.648 (0.000***)
Log HG	− 4.217 (0.000***)	24.419 (0.019**)	− 7.799 (0.000***)	51.995 (0.000***)	− 10.764 (0.000***)	69.446 (0.000***)
Log NG	− 12.904 (0.000***)	44.675 (0.000***)	−	−	−	−
Log H	−	−	−	−	− 4.867 (0.000***)	45.969 (0.004***)

* denotes 10% level of significance, ** denotes 5% level of significance, and *** denotes 1% level of significance

(12) and (14), the F statistic is calculated. The specific calculation data is shown in Table 6.

Comparing the F statistic value with the critical values at 5% significance level, it is found that for the three classes of regions, the F_2 statistic and the F_1 statistic are all greater than the critical values at the 5% significant level, which means that the variable coefficient model should be established. The results of the model specification test illustrate that even in provinces with the same power generation forms, the connection between carbon emissions and multiple energy power generation is significantly different between provinces.

In addition, the results of the Hausman test are shown in Table 7. For Class II regions and Class IV regions, the null hypothesis that the random-effect model should be constructed is rejected at the 1% significance level. And for Class V regions, the null hypothesis is rejected at the 10% significance level. In summary, for the three classes of regions the model should be a fixed-effect variable coefficient model. And the R -squared for the three classes of regions, respectively, are 0.998, 0.996, and 0.981, which means that the model has high goodness of fit.

Estimation results and development suggestions

According to the electric power generation forms and heating situation, the 30 regions in China are classified into 6 classes. For the 26 provinces and cities in Class II regions, Class IV regions, and Class V regions, the variable coefficient model is established. And for the 4 provinces and cities in Class I regions, Class III regions, and Class VI regions, the regression analysis model is built. The estimated results of the relationship between carbon emissions and multi-energy power generation for 30 regions in China are shown in Table 8.

To promote the low-carbon development of the power industry, according to the nexus between carbon emissions and power generation, and the resource endowment in regions, the future development suggestions of the electric power industry are explored. To fully reflect the resource endowment in different regions, based on the data released by the China Meteorological Administration and the National Energy Administration, the distribution map of wind resources, water resources, solar resources, and coal

Table 7 The results of Hausman test

Classification	W	K	p-value
Class II regions	30.885	5	0.000***
Class IV regions	269.880	5	0.000***
Class V regions	8.449	4	0.094*

* denotes 10% level of significance, ** denotes 5% level of significance, and *** denotes 1% level of significance

resources have been drawn (Fig. 6). It can be found that in China, coal resources are mainly concentrated in Shanxi, Inner Mongolia, Shaanxi, and Xinjiang; wind resources and solar resources are mainly concentrated in Heilongjiang, Jilin, Liaoning, Hebei, Inner Mongolia, Gansu, Qinghai, Ningxia, and other places; and water resources are mainly concentrated in Sichuan, Guizhou, Yunnan, Hubei, and other places in the southwest region. Based on the resource distribution and the connection between power generation and carbon emissions, the development suggestions of different provinces in the electric power supply are discussed.

- (1) The impact of thermal power generation on carbon emissions and the development suggestions

The result shows that thermal power significantly increases carbon emissions in China. But the effect intensity of thermal power generation on carbon emissions is various in regions. In Anhui, thermal power generation has the greatest impact on carbon emissions, and a 1% increase in thermal power generation increases carbon emissions by 1.498%. In Beijing, thermal power generation has the least impact on carbon emissions, and a 1% increase in thermal power generation only increases carbon emissions by 0.282%.

Further analyzing the different effect intensities, it is found that in 2019, in Anhui the proportion of thermal power generation on total power generation is extremely high, the thermal power generation accounting for 92.26% of the total power generation. This reflects that in Anhui electric power production heavily relies on thermal power, which makes the great impact of thermal power generation on carbon emissions. Although the proportion of thermal power generation in Beijing also is relatively high, Beijing has made great efforts to promote the turnoff of coal-fired power plants. The

Table 6 The results of model specification test

Classification	S_1	S_2	S_3	N	T	K	F_2	F_1	The critical values of F_2 (5%)	The critical values of F_1 (5%)
Class II regions	0.145	0.871	2.848	12	10	5	13.563	4.373	1.60	1.60
Class IV regions	0.003	0.014	0.139	6	10	5	34.876	3.450	2.25	2.25
Class V regions	0.207	0.499	0.927	8	10	4	3.969	2.017	1.84	1.84

Table 8 The relationship between carbon emissions and multi-energy power generation for 30 regions in China

Classification	Regions	Log TG	Log WG	Log PG	Log HG	Log NG	Log <i>H</i>	<i>C</i>
Class VI regions	Shanghai	0.838***	−0.005*	0.002	−	−	−	−0.576
Class V regions	Anhui	1.498**	0.001	−0.063	0.265	−	−	−7.087
	Jiangxi	0.653*	0.035	−0.029	−0.049*	−	−	0.181
	Hubei	0.545**	−0.021***	0.028**	−0.031*	−	−	1.383
	Hunan	1.197***	−0.016*	0.005	−0.217*	−	−	−5.684
	Chongqing	0.526	0.031	0.025	−0.194	−	−	4.739
	Sichuan	0.589***	−0.037	−0.034	−0.508*	−	−	−3.406
	Guizhou	0.740*	−0.002	0.039**	−0.22*	−	−	7.219
	Yunnan	1.064***	−0.009	−0.006	−0.463*	−	−	−2.725
Class IV regions	Jiangsu	1.070**	−0.118	0.011	0.083	0.085	−	−1.353
	Zhejiang	0.867**	0.163	0.080	0.041	−0.194*	−	−0.979
	Fujian	0.740***	0.064	0.007	−0.006*	−0.110**	−	−0.304
	Guangdong	1.134***	−0.131	0.054	−0.002*	0.471	−	−0.297
	Guangxi	0.650***	0.023**	−0.013	−0.189**	0.001	−	0.569
	Hainan	1.082**	−0.019	−0.024	−0.025*	−0.11*	−	−1.337
Class III regions	Tianjin	0.782*	0.003	−0.025	−	−	0.177	−0.841
Class II regions	Beijing	0.282*	0.088	−0.008	−0.105	−	−0.693*	6.486
	Hebei	1.491***	−0.135**	0.002	−0.076	−	0.289*	−6.824
	Shanxi	0.976***	−0.044	0.012	0.169	−	0.114*	−2.517
	Inner Meng	1.485***	−0.059*	−0.0003	−0.022	−	−0.240	−3.942
	Jilin	0.421*	−0.254*	0.011	0.203	−	0.382	0.063
	Heilongjiang	0.706*	−0.232*	0.020	−0.127	−	0.543*	2.959
	Henan	1.432***	−0.195	0.029	0.046	−	0.224	−8.088
	Shaanxi	0.430*	−0.018	0.036	−0.179	−	0.029*	2.792
	Gansu	0.646*	−0.130*	0.017	−0.268*	−	0.341**	−0.703
	Qinghai	0.691*	0.014	−0.043**	−0.371**	−	0.051**	3.765
	Ningxia	0.862***	−0.106*	0.026	0.285	−	0.340**	−3.408
	Xinjiang	1.198***	−0.151*	0.011	−0.085*	−	0.669	−2.896
	Class I regions	Liaoning	1.106*	0.078	0.015	0.007	−0.013	0.258
Shandong		0.711*	−0.145	0.065	0.034	0.023	−0.100	3.025

* denotes 10% level of significance, ** denotes 5% level of significance, and *** denotes 1% level of significance

thermal power generation in Beijing has changed the situation that coal-based power generation, which results in the impact of thermal power generation on carbon emissions in Beijing, is less than in other regions.

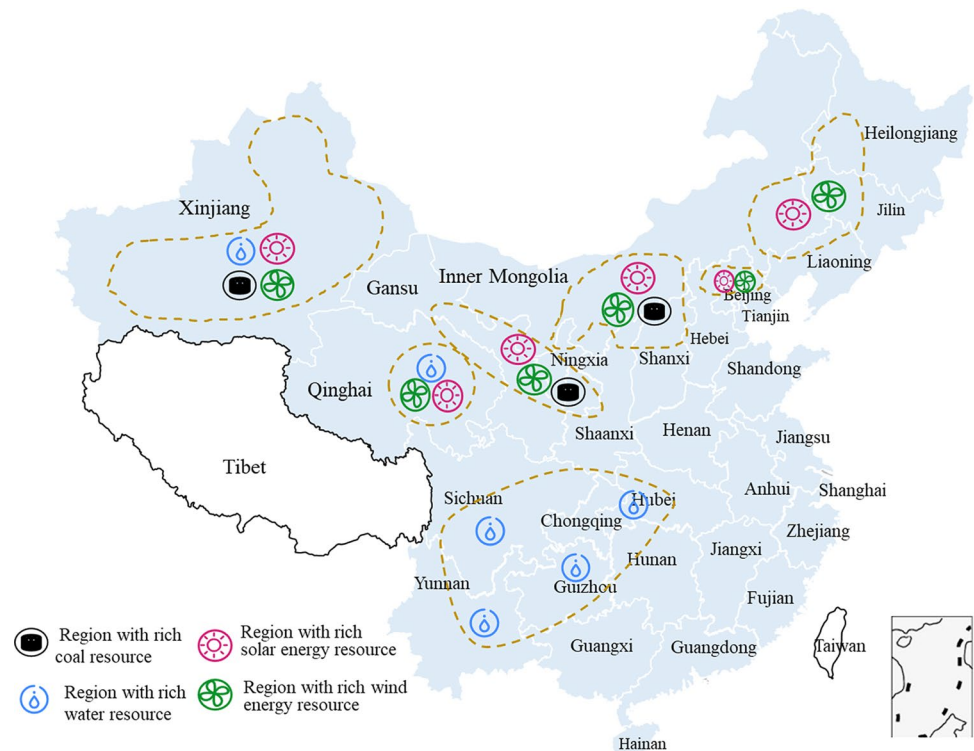
Based on the results that thermal power has a significantly strong positive effect on carbon emissions, at this stage, the carbon emission reduction in the electric power industry still needs to focus on thermal power. It cannot be ignored that the Chinese government has made a great effort to reduce the carbon emissions of thermal power, and the efficiency of thermal power has been greatly improved. The data from the China Electricity Council show that the consumption of coal to generate 1 kWh of electricity for thermal power dropped from 311 g in 2010 to 289 g in 2019. But according to the significantly strong positive effect of thermal power on carbon emissions, the Chinese government should continue to promote the clean

and efficient utilization of coal, such as energy-saving and carbon-reducing transformation, flexibility transformation, and explore measures to reduce the carbon emissions of thermal power further.

In addition, it should be noted that in China the electric power supply will be dominated by thermal power for a long time, which is highly dependent on coal-burning power plants. Taking the carbon emissions from production, transportation, and use of coal into account, this paper suggests that the thermal power bases should construct in coal-rich regions to reduce the carbon emissions in coal transportation. The coal resources are mainly concentrated in Shanxi, Inner Mongolia, Shaanxi, and Xinjiang, so the thermal power development should also focus on those regions.

(2) The impact of wind power, photovoltaic power on carbon emissions, and the development suggestions

Fig. 6 The distribution of wind resources, water resources, solar resources, and coal resources in China



The result shows that in the 30 regions, wind power generation both has positive effect and negative effect on carbon emissions. But the effect intensity of wind power on carbon emissions generally is small, and the absolute value of the coefficient does not exceed 0.254. In Hebei, Jilin, Heilongjiang, Gansu, and Ningxia, the production of wind power has a significant inhibitory effect on carbon emissions. In Jilin, a 1% increase in wind power generation reduces carbon emissions by 0.254%. While, in Guangxi, wind power has positive effects on carbon emissions, and a 1% increase in wind power generation increases carbon emissions by 0.023%.

The relationship between photovoltaic power and carbon emissions is similar to the connection between wind power and carbon emissions. Photovoltaic power both has positive impact and negative impact on carbon emissions, but the impact only in three regions has statistical significance. In Qinghai, photovoltaic power generation contributed to reducing carbon emissions, and a 1% increase in photovoltaic power generation reduces carbon emissions by 0.043%. However, in Hubei and Guizhou, photovoltaic power generation increased carbon emissions.

Further exploring the relationship between wind power, photovoltaic power, and carbon emissions, it is found that in the regions where wind power or photovoltaic power has significant negative effects on carbon emissions, the production of wind power or photovoltaic power has occupied an important proportion of the total electric power generation. For example, in Hebei, Jilin, Heilongjiang, Gansu,

and Ningxia, in 2019, the proportion of wind power generation to the total electric power generation all has exceeded 10%. Similarly, in 2019, the proportion of photovoltaic power generation to the total power generation in Qinghai reached 17.89%. Therefore, this paper considers that the reason for the insignificant impact of wind power generation and photovoltaic power generation on carbon emissions in some regions is the low proportion of wind power generation or photovoltaic power generation on the total power generation. Combined with the research results in Hebei, Jilin, Qinghai, and other regions, it is reasonable to believe that wind power and photovoltaic power contributed to reducing carbon emissions when they develop to a certain scale (Nguyen and Kakinaka 2019).

It should be noted that in some regions where wind resources or solar resources are rich, the effect of wind power or photovoltaic power on carbon emission is insignificant, such as Inner Mongolia, Xinjiang, and Liaoning. Based on the effect of wind power on carbon emissions in Jilin, Heilongjiang, Hebei, Gansu, and Ningxia, it is recommended to speed up the construction of wind power in the regions with rich wind resources, such as Inner Mongolia, Xinjiang, and Liaoning. Based on the effect of photovoltaic power on carbon emissions in Qinghai, it is recommended to speed up the construction of photovoltaic power in the regions where photovoltaic resources are rich, such as Inner Mongolia, Xinjiang, and Gansu.

(3) The impact of hydropower on carbon emissions and the development suggestions

The results show that hydropower both has positive effects and negative effects on carbon emissions, but there is statistically insignificant when hydropower generation increase carbon emissions. Therefore, there is a negative correlation between hydropower generation and carbon emissions in China. The effect intensity of hydropower generation on carbon emissions also is various in regions. In Sichuan, hydropower generation has the greatest impact on carbon emissions, and a 1% increase in hydropower generation reduces carbon emissions by 0.508%. In Guangdong, hydropower generation has the least impact on carbon emissions, and a 1% increase in hydropower generation only reduces carbon emissions by 0.002%.

Further analyzing the proportion of hydropower generation on the electric power supply in regions, it is found that in 2019 in Sichuan, the proportion of hydropower in total power generation is 84.96%, while in Guangdong, the proportion of hydropower on total power generation only is 8.06%, which leads to the different effects of hydropower. Compared with thermal power, the development of hydropower is significantly affected by resource endowments. Therefore, the effect intensity of hydropower generation on carbon emissions and the proportion of hydropower generation on total electric power are various in regions. It should be noted that even in regions with rich water resources, the effect intensity is also different. The distribution of water resources shows that there are abundant water resources in Qinghai, Sichuan, Yunnan, and Hubei. However, the carbon emission reduction coefficient of hydropower in Hubei only is 0.031, which is significantly different from 0.508 in Sichuan. Therefore, the suggestion is the water resource-rich regions should focus on exploring ways to improve the effect of hydropower, and achieving maximum utilization of water resources by means such as water resources cascade dispatch.

(4) The impact of nuclear power on carbon emissions and the development suggestions

In China, there are only 8 regions that have nuclear power. Nuclear power also has positive effects and negative effects on carbon emissions, but only when nuclear power generation reduces carbon emissions has statistical significance. Therefore, it is reasonable to believe that nuclear power has a significant negative effect on carbon emissions. In Zhejiang, a 1% increase in nuclear power generation reduces carbon emissions by 0.194%; in Fujian and Hainan, a 1% increase in nuclear power generation both reduces carbon emissions by 0.110%.

Generally, in China, nuclear power is mainly located in developed coastal regions, such as Zhejiang, Jiangsu, and Guangdong, which have the characteristics of large population density, high-speed economic development, and large demand for electricity. Considering the characteristics of those regions, nuclear power should be avoided in a one-size-fits-all abandon approach. It is suggested that those regions should gradually promote the construction and application of nuclear power on the basis of safety.

(5) The impact of heating on carbon emissions and the development suggestions for other regions

Heating is an important source of the carbon emissions of production and supply of electric power, steam, and hot water in some regions; therefore, it is reasonable to use the heating situation as an explanatory variable in the model. There are 15 regions heating in winter in China. The result shows that in most regions, heating has a statistically significant positive impact on carbon emissions. In Heilongjiang, a 1% increase in heating increases carbon emissions by 0.543%. But only in Beijing, there is a significant negative correlation between heating and carbon emissions, which is closely related to the clean heating renovation in recent years, such as replacing coal heating with natural gas heating and electric heating. The results for Beijing prove the effect of clean heating implementation.

In China, some provinces and regions have prominent environmental and ecological development goals, such as Qinghai. Compared with other regions, Qinghai Province should pay more attention to the low-carbon development of electric power supply. Based on the research results, Qinghai should focus on the development of wind power, photovoltaics, and hydropower, which inhibit carbon emissions, and prohibit the construction of large-scale thermal power, which is positively correlated with carbon emissions.

Conclusion

As the main source of carbon emissions, the electric power industry has enormous pressure on carbon emission reduction under the carbon peak and carbon neutrality goals. Based on the significantly different forms of power generation, this paper discusses the influences of multi-energy power generation on carbon emissions in 30 regions of China. There are four important findings. Firstly, in China, thermal power has a significant positive impact on carbon emissions, which should shoulder the main task of carbon emission reduction in the electric power industry. Secondly, wind power and photovoltaic power contributed to reducing carbon emissions, if they are developed to a certain scale. And it is proposed to speed up the construction of wind

power and photovoltaic power in regions with rich wind resources and solar resources such as Inner Mongolia, Xinjiang, Liaoning, and Gansu. Thirdly, the inhibited effect of hydropower on carbon emissions varies in different regions. It is recommended to focus on improving the efficiency of hydropower in regions with rich water resources and to maximize the utilization of water resources by cascade dispatch of water resources. Fourth, nuclear power has a significant negative effect on carbon emissions. It is suggested that the coastal regions should gradually promote the construction and application of nuclear power on the basis of safety.

This paper using the panel data analysis method effectively analyzed the heterogeneous impacts of multi-energy power generation on carbon emissions in different regions of China. However, the panel data analysis method has high requirements for data which should be a large number of continuous data with consistent statistical caliber. If the amount of data is small or the data is discontinuous, the panel data analysis method is not suitable. Therefore, this method is usually used in fields or industries with continuous data, such as the electric power industry. However, the traditional panel data analysis method has limitations in studying issues with high spatial dependence. Therefore, future studies can collect the spatial data and discuss the joint prevention and treatment of carbon emissions.

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Xiaopeng Guo: methodology, investigation, writing—review and editing, funding acquisition;

Yun Li: methodology, investigation, writing—review and editing;

Kun Yang: supervision, writing—review and editing.

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Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

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