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Spatial-Temporal Evolution and Cross-Industry Synergy of Carbon Emissions: Evidence from Key Industries in the City in Jiangsu Province, China

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Abstract: Cross-industry synergistic emission reduction has become a new strategy for achieving a carbon emissions peak and carbon neutrality. To explore the typical spatial distribution and cross-industry synergy effect of carbon emissions in key industries, this paper analyzes the carbon emissions of coal and power industries in Jiangsu Province from 2006 to 2020 using the empirical orthogonal function (EOF) and a panel vector autoregressive (PVAR) model. The results show that: (1) The distribution of coal resources determines the distribution of carbon emissions in the coal industry. Carbon emissions in the power industry have two typical distributions: consistent changes in cities and a "south-north" inverse phase, with a cumulative variance contribution rate of 86.74%. (2) The impulse response of carbon emissions from the coal industry to the power industry is >0 in the first period. There is a synergistic relationship of carbon emissions from the energy consumption side to the energy production side. (3) The shock effect of carbon emissions on economic development is >0. In resource-based cities, economic development explains about 2% of carbon emission fluctuations in the coal industry and 9.9% in the power industry, which is only 2% in non-resource-based cities. Carbon emissions would promote economic development. However, the impact of economic development on them varies significantly by industry and region. These findings can provide scientific support for developing differentiated measures to carbon emissions reduction and serve as an important reference role for other regions to promote collaborative carbon emission reduction in key industries.

Keywords: cross-industry; spatial-temporal evolution; carbon synergy

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1. Introduction

With the rapid growth of the global economy, the massive emissions of greenhouse gases have exacerbated climate warming, which has severely impacted human living environments [1]. Carbon emission reduction has become the global consensus. China, the world's largest developing country and the largest carbon emitter, has committed itself to a carbon peaking by 2030 and carbon neutrality by 2060 [2–4]. As the most intensive and active component of human activity, cities are also the primary source of energy consumption and greenhouse gas emissions such as carbon dioxide, contributing about 85% of direct carbon emissions. They are not only the main driver of the carbon cycle, but also an important subject to undertake the task of reducing emissions [5,6]. The scientific analysis of the spatial distribution and temporal evolution of urban carbon emissions serves as the foundation for rationally developing differentiated carbon-reduction policies.

The work of carbon emission reduction must be carried out gradually and orderly, and identifying key industries is critical. The resource endowment of "coal-rich, oil-poor, gas-poor" has made it difficult for China to wean itself off coal. The mining and washing process of coal consumes a significant amount of fossil energy, accounting for approximately 6% of the industry's energy consumption [7]. This has resulted in a large amount of carbon dioxide emission during coal production, putting great strain on the environment. We should pay more attention to the carbon emissions from coal production. The power industry is the largest carbon emitter in China, which is the first to be included in the national carbon trading market [8,9]. Its carbon emissions mainly come from thermal power generation, which is dominated by China's coal-based energy consumption structure. Although the supply capacity of clean electricity generation such as wind power and photovoltaic power generation is increasing, it is difficult to change the state of coal power as the primary power source in the short term to ensure a stable supply of electricity [10,11]. Therefore, as important supply and consumption sides of the coal supply chain, the coal industry and power industry should be the focus of carbon reduction efforts.

With the continuous development of society and economy, the awareness of green development has taken root among the people, resulting in a high demand for good environmental quality. It has prompted the government to implement carbon-cutting measures in key industries. Simultaneously, the continued decline of coal reserves has prompted cities to explore green transformation and propose new requirements for carbon emission reduction in key industries. It is worth noting that there is a coupling relationship between the carbon emissions of key industries, and the synergistic effect of carbon emission reduction across industries should not be overlooked. Giving full play to the synergistic effect of carbon emission reduction across industries can effectively reduce the cost of carbon emission reduction while expanding the carbon emission reduction space [12]. This will be a breakthrough point for future emission reduction efforts. Further exploring the dynamic interaction of carbon emissions between the coal industry and power industry and clarifying their synergistic effect may provide new directions for the development of carbon emissions' trading markets as well as the formulation and implementation of carbon emission reduction policies, and make a contribution to industry in the process of achieving carbon emissions peak and carbon neutrality.

In this context, this study selects 13 cities in Jiangsu province to investigate the dynamic evolution characteristics and the cross-industry synergistic relationship of carbon emissions in coal and power industries from 2006 to 2020. To summarize, Jiangsu province is a good example as it is a microcosm of China, similarly characterized by uneven energy distribution, environmental pollution, etc. [13]. As a result of rapid industrial development, Jiangsu province has experienced rapid economic development. However, industrial sector is an energy-intensive industry, and its rapid development brings a huge demand for electricity and coal, causing Jiangsu Province's carbon emissions to consistently rank among the highest in China [14]. The energy consumption structure in Jiangsu Province is representative of the country, with coal accounting for 55% of total energy consumption, which is roughly the same as the national level of 57%. Jiangsu Province currently ranks first in China in natural gas consumption and offshore wind power, which is a good foundation of low carbon practices ahead of other provinces and cities [15]. As the only pilot province in China for the modernization of ecological and environmental governance system and capacity, Jiangsu Province has proposed the development goal of "building a carbon peak pioneer area", which provides the realistic motivation and basic conditions for promoting low-carbon development in key industries. In general, Jiangsu Province, as a major energy-consuming and carbon-emitting province, is a key potential area for carbon emission reduction in China. Its energy saving and emission reduction work are urgent and feasible.

The marginal contributions of this paper include the following three aspects: (1) Extending the research perspective to key industries at the city level by calculating and analyzing carbon emissions' temporal evolution patterns of the coal industry and power industry at the city level, which will serve as a foundation for formulating differentiated carbon emission reduction strategies for cities as well as an extension of existing carbon emission studies. (2) The application of EOF to address the shortcomings of existing spatio-temporal evolution research methods, which can only study temporal cross-sectional data, so as to initially explore the spatial evolution of carbon emissions in key industries over a continuous long time series. (3) Effectively identifying the inter-industry transmission relationships of carbon emissions among key industries. The idea of cross-industry synergistic carbon emission reduction in key industries is proposed to further explore the potential and broaden the scope of carbon emission reduction. The findings of this paper will not only assist key industries scientifically develop differentiated carbon emission reduction measures, but also provide new ideas for carbon emission reduction policy formulation based on the synergistic effect of carbon emissions between industries, making cross-industry synergistic emission reduction a new path to achieve carbon emissions peak and carbon neutrality target. The findings are thus conducive to improving carbon emission reduction efficiency and expanding the emission reduction space, and have important reference effects for other industries and regions.

The rest of the paper is organized as follows. Section 2 provides a brief review of the relevant literature. Section 3 describes the study area overview, research methodology and data sources. Section 4 presents the results and discussion. Section 5 summarizes the research and makes policy recommendations.

2. Literature Review

Since the climate issue has gained international attention, scholars at home and abroad have conducted a large number of studies on carbon emissions. The existing studies have mainly focused on the measurement of carbon emissions, the spatial and temporal dynamics and the identification of influencing factors.

The main methods of accounting for carbon emissions are the IPCC method, the life-cycle approach and the input-output method. The IPCC method is to calculate the total carbon emissions of a region or industry by multiplying the consumption of various energy sources with carbon emission factors [16,17]. The life-cycle approach is to quantify the carbon emissions at different stages by following the principles of life-cycle assessment [18]. For example, Cao et al. [19] divided the life-cycle carbon emissions of machine tools into four stages: manufacturing, use, transportation, and recycling. Guo et al. [20] used the HLCA method to estimate carbon emissions from the production phase, use phase, disposal phase and fuel-cycle of the passenger car industry in China. Jordaan et al. [21] estimated the life cycle emissions from gas-fired electricity and the abatement potential of different mitigation options. The life-cycle approach is also widely used in the construction industry [22,23], agriculture [24], and the new energy sector [25]. The input-output method employs input-output tables to obtain the energy demand between regions or sectors through the transformation of the Leontief inverse matrix, and then accounts for the direct and indirect carbon emissions of regions or sectors based on carbon emission factors, which are mainly used to investigate the implicit carbon emissions and determine the carbon emission relationship between regions or sectors [26–28]. However, these methods may have statistical errors caused by inconsistencies in the statistical caliber of statistics and calculation methods, so with the development of remote sensing technology, some scholars have also applied remote sensing data products to the study of carbon emission estimation, using the DMSP/OLS nighttime light image data inversion simulation to obtain carbon dioxide emissions [29,30].

Based on carbon accounting, the dynamic evolution of carbon emissions is also an important part of carbon emissions research [31]. Exploratory spatial data analysis (ESDA) [32,33] and the Dagum Gini coefficient [34] are commonly used to analyze the spatiotemporal characteristics of carbon emissions differences. Non-parametric kernel density estimates [35] and Markov chains [36] are used to explore the dynamic evolution of carbon emissions and trends in long-term shifts. Standard deviational ellipse (SDE) [37,38], Thiel's index [39], and coefficients of variation [40] are also frequently used. However, as different methods have different analytical focuses, scholars often used multiple methods in their studies to explore the evolutionary characteristics of carbon emissions from various perspectives. For example, Han et al. [41] used ESDA and SDE to reveal the spatial characteristics of carbon emissions in four energy-rich regions of western China: Shaanxi, Gansu, Ningxia, and Inner Mongolia. Li, W. et al. [42] used kernel density estimation and ESDA to analyze the spatial and temporal evolution trends of carbon dioxide emissions in Chinese provinces and to determine the spatial autocorrelation of carbon dioxide emissions in each province. Ke et al. [43] explored the regional differences and evolutionary trends of urban-level carbon emission intensity in China from 2000–2017 with the Dagum Gini coefficient, ESDA, kernel density estimation, and the spatial Markov chain.

The factors affecting carbon emissions are complex and diverse. Table 1 summarizes relevant studies on the factors that influence carbon emissions. In general, scholars mostly used index decomposition analysis (IDA) [44], structural decomposition analysis (SDA), and regression models [45,46] to quantitatively analyze the impact of micro or macro factors on carbon emissions, such as economic level, population size, energy structure, energy intensity, industrial structure, and so on [47–50]. In addition, Wei et al. [51] analyzed the GHG emissions caused by China's power transmission infrastructure construction during 1990–2017. However, there is significant industry heterogeneity in the direction and magnitude of each factor's effect on carbon emissions. For example, Dong et al. [52] discovered that the proportion of economic value added in agriculture, manufacturing and transportation was negatively correlated with carbon emissions, while the opposite is true for the construction, retail and accommodation sectors. Liu et al. [53] found significant synergistic effects among carbon emissions drivers in energy-intensive industries, manifesting themselves in long-term trends and short-term fluctuations, but the resulting impact effects varied considerably, and the six energy-intensive industries also demonstrated significant heterogeneity under the influence of the drivers. Gao et al. [54] discovered large differences in the efficiency of direct and implied carbon emissions across 28 industries by analyzing the carbon emission efficiency of China's industrial sectors. Shapiro found [55] that in most countries, import tariffs and nontariff barriers are substantially lower on dirty than on clean industries.

Table 1. Research on CO_2 emissions decomposition methods and influencing factors.

Literature	Region/Industry	Period	Method	Influencing Factors
Liu, Jian et al. [56]	The high-emission sectors in China's manufacturing industry	1995–2019	GDIM	Output scale, energy consumption scale, innovation input scale, output carbon intensity, energy consumption carbon intensity, innovation input carbon intensity, innovation input efficiency, energy intensity
Quan et al. [50]	The total carbon emissions of the logistics industry in China	2000–2016	LMDI	Carbon emission coefficient, energy intensity, energy structure, economic level, population size
Yan et al. [57]	Xinjiang industries' carbon emissions	1997–2017	SDA	The intensity of energy consumption, the structure of energy consumption, the structure of industrial linkages, the structure of demand industries, the structure of demand categories, the size of the economy, the size of the population
Wang, Y. et al. [58]	Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, Chengdu-Chongqing, middle reaches of Yangtze River, Central Plains region	2005–2019	GTWR	Spatial structure, per capita GDP, industrial structure, energy intensity
Zhu, C. et al. [59]	Carbon emissions of China's building sector	1996–2017	STIRPAT	Building construction area, value of the building unit area, Indirect emissions intensity, carbon emissions per unit energy consumed, energy intensity, total factor productivity

According to a review of the previous literature, the basic units of carbon emission-related research are national [26,60], provincial [11,61], and urban agglomerations [58]. Agriculture [62], the steel industry [63–65], transportation [66,67], the cement industry [68,69], and the power industry [26,70] are the primary research subjects. Existing research has developed mature methodologies for quantitatively assessing carbon emissions. They also offered ideas for clarifying the current situation of carbon emissions and implementing concrete and effective carbon-reduction measures. However, there are still the following shortcomings: (1) Due to the difficulty of data collection and statistical errors, most current studies focus on the carbon emissions of sub-industries at the national or provincial level or the industry-wide carbon emissions of smaller regions, and there is a lack of industry carbon emission at the city level. (2) Most studies on the spatial and temporal evolution of carbon emissions have focused on the characteristics of carbon emissions from a temporal cross-section, ignoring the time continuity. (3) Research from multiple industries has only revealed the differences, convergences, and influencing factors of carbon emissions, but have neglected the inter-industry transmission relationship of carbon emissions, and have failed to consider the synergy effect of carbon emissions between key industries.

3. Methodology and Data

3.1. Study Area

Located on the eastern coast of mainland China, Jiangsu Province contributes to more than 10% of China's economic growth. Figure 1 shows the geographical location and administrative division in Jiangsu Province. Industrial electricity consumption in Jiangsu Province has grown at an annual rate of 9% with economic development [71]. The carbon emissions from electricity generation have become an important part of the reduction of carbon emissions as a result of the purely thermal power grid [15]. Simultaneously, there are significant differences in the resource endowments of different cities in Jiangsu Province. Coal resources are mostly concentrated in Xuzhou in the northwest, with fewer in southern and central Jiangsu. Therefore, carbon emissions from coal industry vary greatly from city to city.

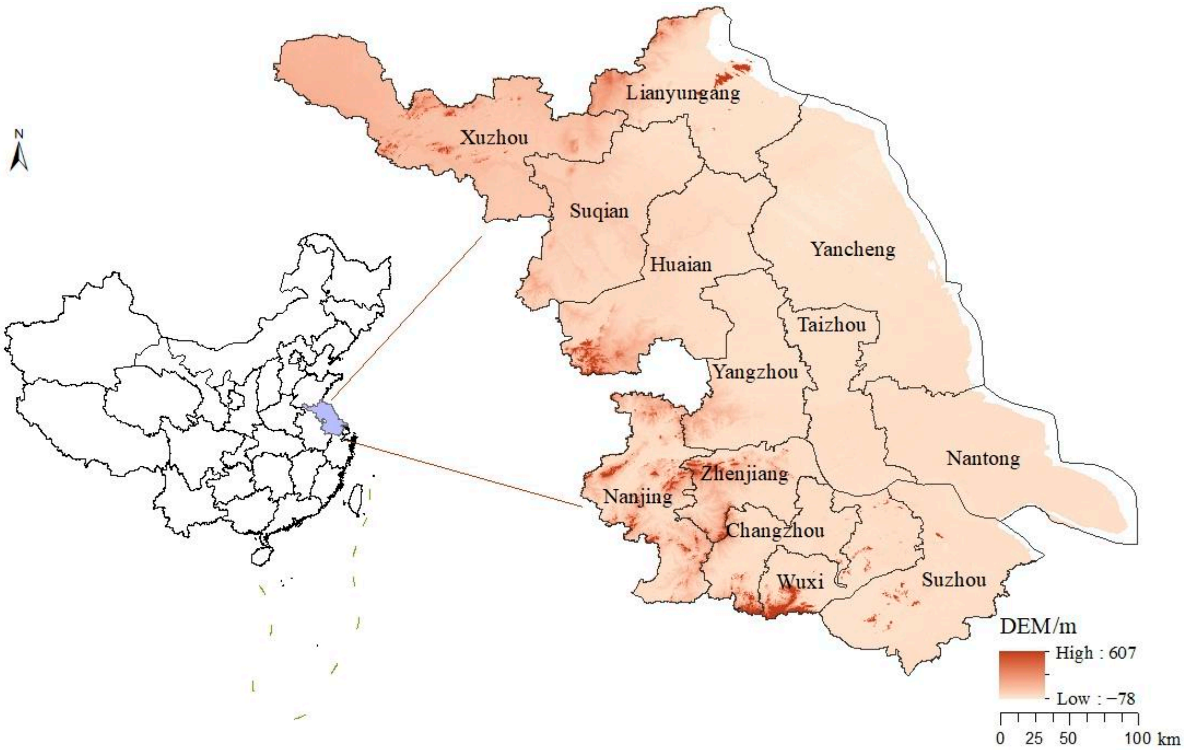


Figure 1. Geographical location and administrative division of the study area.

Overall, Jiangsu Province is a large province in terms of energy consumption and carbon emissions, in addition to being a large economic province [72]. It should play a role as a model and benchmark in China's efforts to reduce carbon emissions. Therefore, taking Jiangsu province as the research object, this paper examines the spatial and temporal evolution characteristics of carbon emissions from coal industry and power industry at the city level and the synergistic effect of carbon emissions between industries.

3.2. Method

3.2.1. Empirical Orthogonal Function

Empirical orthogonal function (EOF) is widely used in meteorological research [73]. This method converts the spatio-temporal data set of variables into a spatial model and its projection in time [74]. It is essentially a principal component analysis, which effectively identifies the spatial characteristics and evolutionary patterns of continuous-time events by focusing as much information as possible on a small number of independent spatial models and the corresponding time series [74,75]. It has the advantage of combining spatial and temporal evolutionary patterns [76]. Therefore, with the help of Matlab R2019a software, we employ EOF decomposition to analyze the typical spatial distribution of carbon emissions in the coal industry and power industry in Jiangsu Province.

$$X = EOF_{m\times m} \times PC_{m\times n} \tag{1}$$

In Equation (1), m represents the number of prefecture-level municipalities; n represents the length of the time series; EOF is the eigenvector, which represents the spatial modalities, reflecting the characteristics of the spatial distribution of carbon emissions that do not vary over time; PC represents the time coefficient, representing the model intensity over time.

3.2.2. PVAR Model

The PVAR model combines the advantages of time series and panel data to identify dynamic interactions among indicators in panel data and reveal bidirectional causal relationships between variables [77–79]. In this paper, with the help of Stata 16.0 software and PVAR2 program package developed by Lian Yujun [80], a PVAR model is constructed with the carbon emissions of coal industry and power industry and economic development, which are considered as endogenous variables. Then, we identify the dynamic relationship between carbon emissions from coal industry and power industry and explore the impact of economic development through generalized method of moments (GMM), impulse response, variance decomposition, and Granger causality. Furthermore, their stability and time lag also are analyzed.

$$Y_{i,t} = \alpha_{i,0} + \sum_{j=1}^{p} \alpha_{i,p} Y_{i,t-j} + \eta_i + \gamma_t + \mu_{it} \tag{2}$$

In Equation (2), i is the city, t is the length of the study period, p is the lagged order, $Y_{i,t}$ is the core variable, which in the case of resource-based cities is a three-dimensional column vector of endogenous variables including carbon emissions from the coal industry, carbon emissions from the power industry and the level of economic development, and in the case of non-resource-based cities is a two-dimensional column vector of endogenous variables including carbon emissions from the power industry and the level of economic development; $\alpha_{i,0}$ is the intercept vector, $\alpha_{i,p}$ are the regression coefficients for the lagged endogenous variables, η_i is the individual effect, γ_t is the time effect, and μ_{it} is the random disturbance term.

3.3. Data Sources

The sample period for this research is 2006–2020, which was chosen after a thorough assessment of the availability and completeness of the data. Firstly, the IPCC method proposed by the Intergovernmental Panel on Climate Change was used to measure carbon emissions from the coal industry and power industry, with the following calculation formula:

$$CE = \sum e_i = \sum T_i \times \alpha_i \times \beta_i \quad (3)$$

where CE is the total carbon emissions, i is the type of energy, e_i is the carbon emissions from i, T_i is the raw consumption of i, α_i is the standard coal conversion factor for i, and β_i is the carbon emission factor for i.

The energy consumption data were collected from the statistical yearbooks of each city in Jiangsu, and the missing values were completed by using interpolation and multiplying the total carbon emissions of each city by the percentage of carbon emissions from the coal and power industries in Jiangsu Province, which come from China city emission data and China provincial CO_2 emission inventory in CEADs (https://www.ceads.net.cn/ (accessed on 10 October 2022)). Table 2 summarizes the standard coal conversion factors and carbon emission factors for various energy sources, referring to the IPCC Guidelines for National Greenhouse Gas Inventories and the China Energy Statistical Yearbook and existing research literature [41,81].

Table 2. Conversion factors and carbon emission factors for various energy sources of standard.

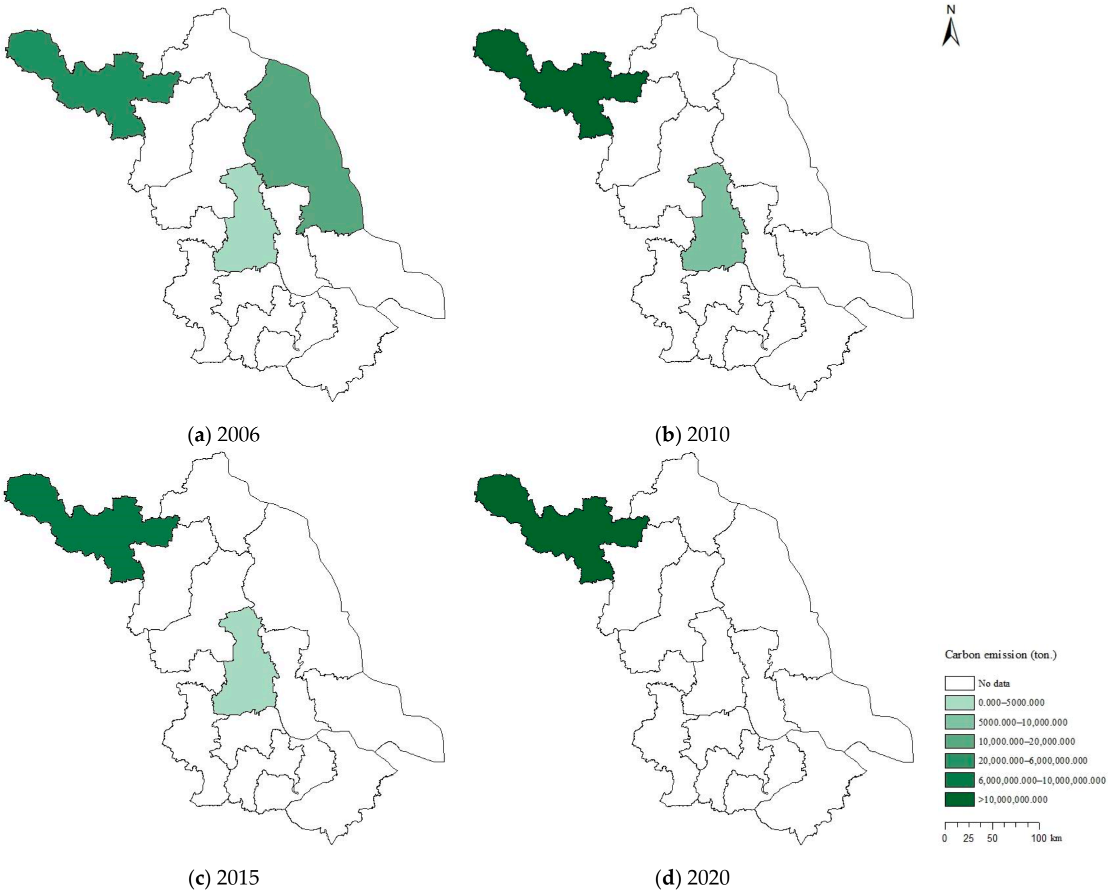
Types of Energy	Carbon Emission Factor	Standard Coal Conversion Factor	Unit of Measurement
Raw Coal	0.7559	0.7143	kg of standard coal/kg
Washing of refined coal	0.7559	0.9000	kg of standard coal/kg
Other coal washing	0.7559	0.2857	kg of standard coal/kg
Coke	0.855	0.9714	kg of standard coal/kg
Coke oven gas	0.3548	0.5714	kg standard coal/m^3
Blast furnace gas	0.4602	0.1286	kg standard coal/m^3
Other gas	0.3548	0.1786	kg standard coal/m^3
Other Coking Products	0.6449	1.1000	kg of standard coal/kg
Refinery dry gas	0.4602	1.5714	kg of standard coal/kg
Crude Oil	0.5857	1.4286	kg of standard coal/kg
Petrol	0.5538	1.4714	kg of standard coal/kg
Paraffin	0.5714	1.4714	kg of standard coal/kg
Diesel	0.5921	1.4571	kg of standard coal/kg
Fuel oil	0.6185	1.4286	kg of standard coal/kg
Liquefied Petroleum Gas	0.5042	1.7143	kg of standard coal/kg
Other petroleum products	0.586	1.4286	kg of standard coal/kg
Natural gas	0.4483	1.2143	kg standard coal/m^3
Heat	0.2600	0.0341	kg of standard coal/million joules
Electricity	2.5255	0.1229	kg of standard coal/kWh

In addition, the level of economic development is measured by regional GDP, which is obtained from the statistical yearbooks of each city. In order to ensure a consistent time series spanning 15 years, the GDP deflator is used to adjust the nominal GDP of different years to the real GDP based on 2006. The specific GDP deflator is converted by the gross regional product of each city from 2006 to 2020 and the gross regional product index (last year = 100). The vector administrative boundary data are obtained from the National Earth System Science Data Centre Shared Services Platform (http://www.geodata.cn/data/ (accessed on 1 November 2022)), and the topographic profile data are obtained from the SRTMDEM 90M resolution raw elevation data from the website of Geospatial Data Cloud (https://www.gscloud.cn/ (accessed on 5 November 2022)).

4. Results and Discussion

4.1. Results of Carbon Emission Measurement

Figure 2 shows the results of carbon emission measurement in the coal industry. Carbon emissions from the coal industry varied greatly between cities. Carbon emission in Xuzhou increased overall, but fell briefly from 2013 to 2015. Yangzhou's carbon emissions increased steadily from 2006 to 2012, then gradually declined from 2013 to 2016. From 2006 to 2008, Yancheng produced only a small amount of carbon emissions. Lianyungang only had a minor amount of carbon emissions in 2011. Carbon emissions from the coal industry were 0 in other cities during the study period. Overall, carbon emissions from the coal industry were concentrated in northern Jiangsu Province, which corresponded to the distribution of coal resources. This is mainly because of the fact that carbon emissions from the coal industry are emitted during the coal mining and washing process, and the coal industry is less developed in cities with limited coal resources. Furthermore, 2012 marked a clear turning point in the change of carbon emissions in the coal industry, most likely because cities in Jiangsu Province conscientiously implemented the State Council's instructions on further deepening the consolidation and closure of coal mines and strengthening coal mine safety during the 12th Five-Year Plan period, and carried out in-depth work to eliminate backward production capacity in the coal industry and reduce the number of small coal mines.



(**a**) 2006 (**b**) 2010

(**c**) 2015 (**d**) 2020

Figure 2. Calculation results of carbon emissions in the coal industry.

Figure 3 depicts the results of carbon emission measurement in the power industry. From 2006 to 2020, Suzhou, Wuxi and Changzhou showed a small fluctuating upward trend. Lianyungang, Zhenjiang, Nantong, Xuzhou, Nanjing, Taizhou, Suqian, and Yancheng had a faster growth rate and a larger rise; Huai'an and Yangzhou showed a trend of first rising, a small fluctuation, and then falling. In Jiangsu Province, carbon emissions from the power industry were higher in northern Jiangsu and the economically developed regions of southern Jiangsu. This could be because power plants in Jiangsu Province are mostly thermal, so factors such as fuel resource distribution and power demand planning affect the location of power plants.

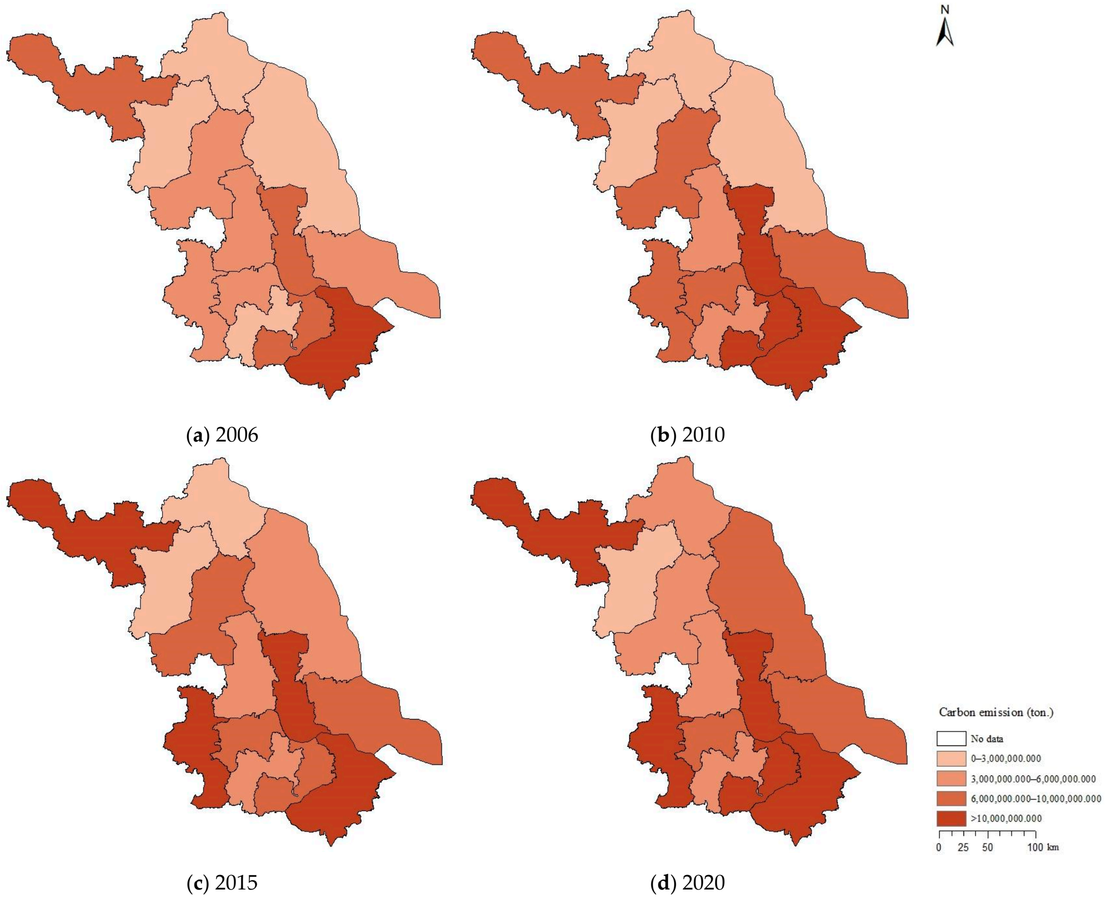


Figure 3. Results of carbon emission measurement in the power industry.

4.2. The Evolution of the Spatial-Temporal Pattern

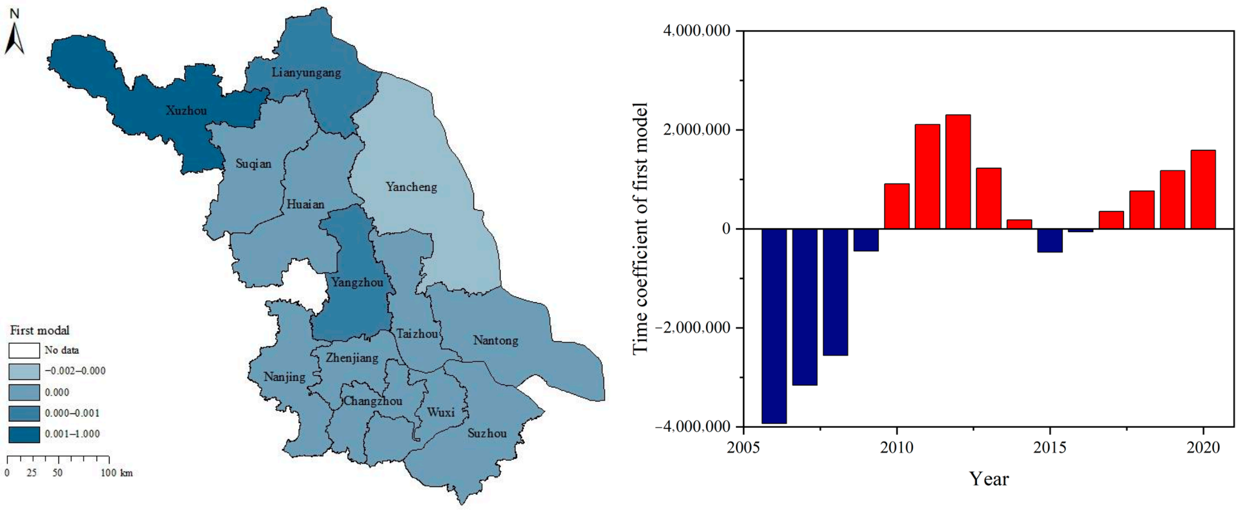
To investigate the spatial and temporal evolution of carbon emissions in the coal industry and power industry in Jiangsu Province during the study period, the carbon emission annual anomalies of the coal industry and power industry in each city from 2006 to 2020 were first obtained with the help of matlab2021b, and then EOF decomposition was used to identify the eigenvectors with significant differences and their corresponding time coefficients. The first eigenvector reflects the average state of the carbon emission annually anomalies. The remaining eigenvectors represent the variation state of the carbon emission annual anomalies at different scales. The time coefficients, as the weights of the eigenvectors, reflect the contribution of different years to this spatial distribution.

As shown in Table 3, the first model variance contribution rate of the coal industry reaches 100%, which is the main form of the spatial distribution of carbon emissions in the coal industry. The corresponding variance contribution rates of model 1 and model 2 of the power industry are 75.64% and 11.09%, and the cumulative variance contribution rate reaches 86.74%, which can fully reveal the typical spatial distribution and temporal evolution of carbon emissions in the power industry. Therefore, this section analyses the first model of carbon emissions in the coal industry and the first and second models in the power industry, respectively.

Table 3. Contribution of variance and cumulative variance of typical models (%).

Industry	Model	Variance Contribution Rate	Cumulative Variance Contribution Rate
The coal industry	1	100	100
The power industry	1 2	75.6443 11.0931	75.6443 86.7374

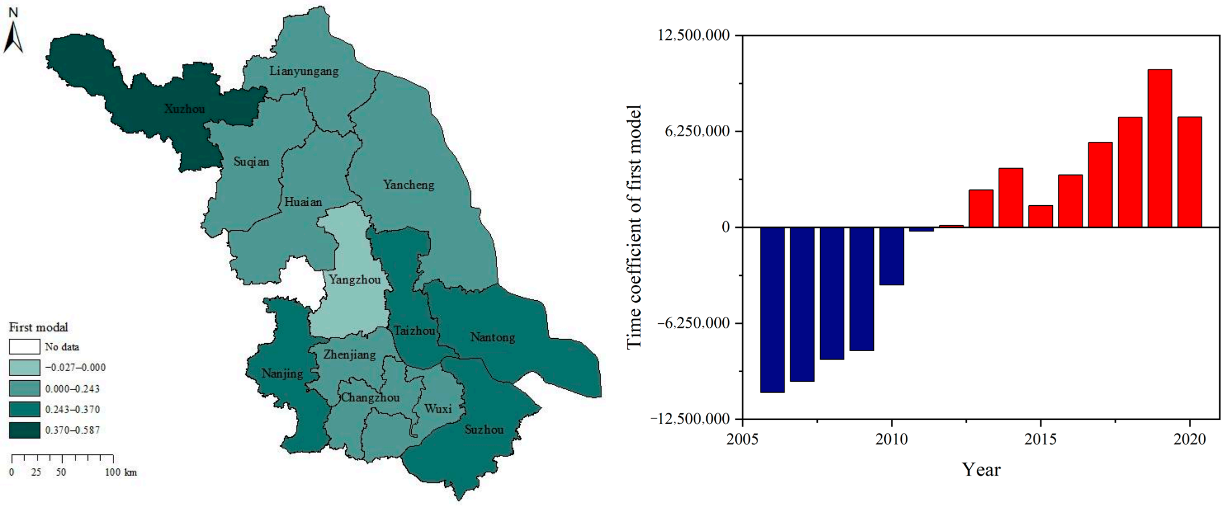
For the coal industry, the EOF first model reflects the overall spatial distribution of carbon emissions (Figure 4a). Xuzhou, Lianyungang, and Yangzhou have positive eigenvalues. Yancheng has negative values, while the eigenvalues of all other cities are 0 due to the absence of carbon emissions from the coal industry. The distribution of model eigenvalues matches that of the coal resource. The time coefficients of the first model (Figure 4b) show clear inter-annual variation with an "N" pattern. The time coefficient was negative from 2006 to 2009. The absolute value of the time coefficient was the largest in 2006, which indicates that this type of spatial distribution was most typical for 2006, with Xuzhou, Lianyungang, and Yangzhou slowing down the growth of carbon emissions from the coal industry but Yancheng accelerating the growth. From 2010 to 2014, the time coefficient was positive. The absolute value of the time coefficient was the highest in 2012, indicating that this type of spatial distribution was typical in 2012 and that the growth rate of carbon emissions from the coal industry accelerated in Xuzhou, Lianyungang, and Yangzhou, while it slowed in Yancheng. Then, it was negative in 2015–2016, and turned positive and continued to rise in 2017, as carbon emissions from the coal industry entered a new round of spatial cycle development period.



(**a**) The spatial distribution of first model (**b**) The change of the first model time coefficient

Figure 4. The spatial distribution of the EOF first model in the coal industry and the change of its time coefficients.

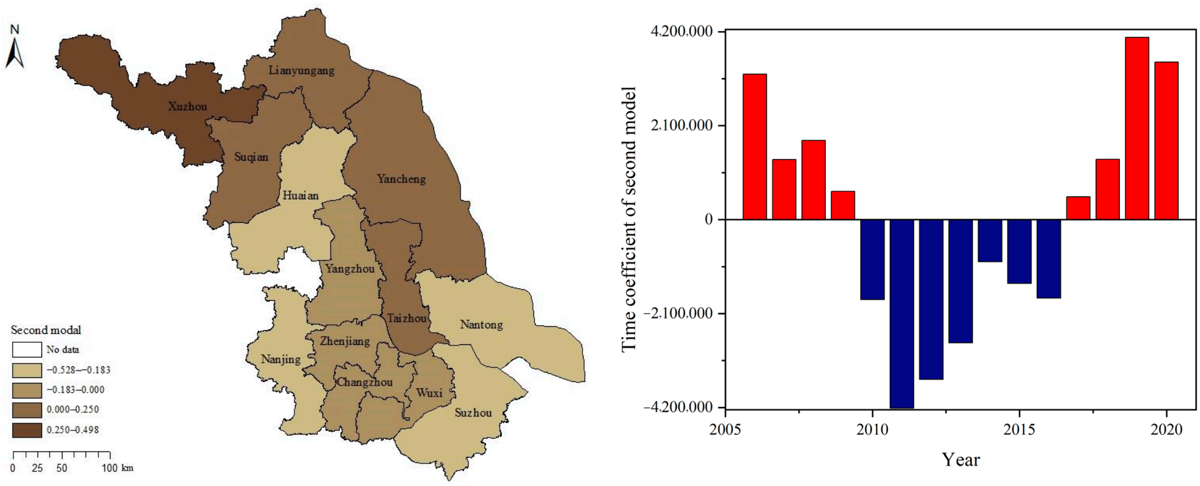
The variance contribution of the first model of carbon emissions in the power industry is 75.64%, far exceeding that of the second model. It reflects the overall spatial distribution of carbon emissions (Figure 5a). Except for Yangzhou, all other regions have positive eigenvalues, indicating that the trend of carbon emission changes in the power industry from 2006 to 2020 is essentially consistent in space, i.e., the carbon emission level is consistently increasing or decreasing. The time coefficients for the first model show a consistent upward trend (Figure 5b). The negative values and decreasing absolute values from 2006 to 2011 indicate that the spatial distribution of such carbon emissions was most typical in 2006, and its typicality gradually decreased, during which the growth rate of carbon emissions in the power industry slowed down, except for Yangzhou. From 2012 to 2020, they all showed positive values and increasing absolute values, and the typicality of this spatial distribution tended to strengthen as the growth rate of carbon emissions in the power industry increased, except in Yangzhou.



(**a**) The spatial distribution of first model (**b**) The change of the first model time coefficient

Figure 5. The spatial distribution of the EOF first model in the power industry and the change of its time coefficients.

The variance contribution of the second model of carbon emissions in the power industry is 11.09%, showing a north-south opposing pattern of development (Figure 6a). The time coefficient of the second model has more inter-annual variation characteristics than the first model (Figure 6b), with 2011 as the inflection point showing a U-shaped trend. The time coefficient was positive until 2009, negative from 2010 to 2016, and turned positive from 2017 to 2020, representing the inter-annual anomalies in carbon emissions. While the growth rate of carbon emissions accelerated in the north during 2006–2009 and 2017–2020, it slowed down in the south. The characteristics of spatial distribution became less typical in the former period and more typical in the latter period. While the growth rate of carbon emissions slowed down in the north during 2010–2016, it accelerated in the south.



(**a**) The spatial distribution of second model (**b**) The change of the second model time coefficient

Figure 6. The spatial distribution of the EOF second model in the power industry and the change of its time coefficients.

4.3. Analysis of Carbon Emission Synergies

In this part, 13 cities in Jiangsu Province are classified as resource-based or non-resource-based cities based on their coal resource endowment, and a PVAR model is constructed to examine the dynamic synergistic relationship between carbon emissions from key industries and the impact of economic development. Table 4 shows the classification results of resource-based and non-resource-based cities. Since Lianyungang only had carbon emissions from the coal industry in 2011 and Yancheng only had carbon emissions from the coal industry from 2006 to 2008, they are classified as non-resource-based cities.

Table 4. Results of cities classification.

Area Name	Coverage
Resource-based cities	Xuzhou, Yangzhou
Non-resource-based cities	Taizhou, Nantong, Nanjing, Suzhou, Wuxi, Changzhou, Zhenjiang, Lianyungang, Suqian, Huai'an, Yancheng

4.3.1. Panel Data Stationarity and Co-Integration Test

To avoid pseudo-regressions caused by unsteady data in the variables, this part logarithms the raw data to obtain LnCCE (carbon emissions from the coal industry), LnPCE (carbon emissions from the power industry), and LnGDP (economic development), and then uses LLC, IPS, and PP-Fisher unit root tests to conduct the stationarity test for each variable and its corresponding first-order difference series d.LnCCE, d.LnPCE, and d.LnGDP. As shown in Table 5, LnCCE, LnPCE, and LnGDP cannot reject the hypothesis that the variables are non-stationary, and the corresponding first-order difference series are all significantly stationary at the 10% level, implying that the original data series are homogeneous single integer series, and further cointegration tests are performed. Table 6 shows that several statistics, including the Kao test, Pedroni test, and Westerlund test, cannot reject the original hypothesis of "no cointegration relationship" between the original series of variables, indicating that there is no long-term equilibrium relationship between the original series of variables. Therefore, the PVAR model is developed using the logarithmically processed first-order difference series of carbon emissions from the coal industry and power industry, as well as economic development data [82].

Table 5. Results of unit root test.

Region	Variables	LLC Statistics	IPS Statistic	PP-Fisher Test Statistics				Conclusion
				P	Z	L *	Pm	
Non-resource-based cities	LnGDP	−1.0521 (0.1464)	0.8841 (0.8117)	13.7713 (0.9094)	1.3684 (0.9144)	1.5128 (0.9322)	−1.2405 (0.8926)	Unstable
	LnPCE	−5.1595 *** (0.0000)	−2.4004 *** (0.0082)	15.4110 (0.8440)	1.1599 (0.8769)	1.1122 (0.8647)	−0.9933 (0.8397)	Unstable
	d.LnGDP	−4.9516 *** (0.0000)	−3.4454 *** (0.0003)	93.5328 *** (0.0000)	−6.6462 *** (0.0000)	−7.7216 *** (0.0000)	10.7840 *** (0.0000)	Stable
	d.LnPCE	−8.9316 *** (0.0000)	−6.1930 *** (0.0000)	214.1378 *** (0.0000)	−10.9395 *** (0.0000)	−17.8714 *** (0.0000)	28.9659 *** (0.0000)	Stable
Resource-based cities	LnGDP	0.5935 (0.7236)	2.4454 (0.9928)	0.7203 (0.9488)	1.3788 (0.9160)	1.3171 (0.8955)	−1.1596 (0.8769)	Unstable
	LnPCE	−5.0582 *** (0.0000)	−4.0616 *** (0.0000)	0.3900 (0.9833)	1.8712 (0.9693)	1.8494 (0.9572)	−1.2763 (0.8991)	Unstable
	LnCCE	−1.2845 * (0.0995)	0.7122 (0.7618)	0.3733 (0.9846)	1.9040 (0.9715)	1.8866 (0.9599)	−1.2822 (0.9001)	Unstable
	d.LnGDP	−3.0639 *** (0.0011)	−1.6644 ** (0.0480)	8.6517 * (0.0704)	−1.6977 ** (0.0448)	−1.6562 * (0.0600)	1.6446 ** (0.0500)	Stable
	d.LnPCE	−6.6418 *** (0.0000)	−4.9239 *** (0.0000)	94.6602 *** (0.0000)	−9.1341 *** (0.0000)	−19.2050 *** (0.0000)	32.0532 *** (0.0000)	Stable
	d.LnCCE	−3.8637 *** (0.0001)	−2.1646 ** (0.0152)	20.0436 *** (0.0005)	−3.4999 *** (0.0002)	−4.0611 *** (0.0006)	5.6723 *** (0.0000)	Stable

Notes: ***, ** and * represent significance at the levels of 1%, 5% and 10%, respectively.

Table 6. Results of the Co-integration test.

Inspection Standards		Non-Resource-Based Cities	Resource-Based Cities
Kao test	Modified Dickey-Fuller t	0.3373 (0.3679)	−0.9774 (0.1642)
	Dickey-Fuller t	−0.8716 (0.1917)	−2.8257 *** (0.0024)
	Augmented Dickey-Fuller t	−0.9519 (0.1706)	−2.3679 *** (0.0089)
	Unadjusted modified Dickey-Fuller t	0.3980 (0.3453)	−0.9774 (0.1642)
	Unadjusted Dickey-Fuller t	−0.8259 (0.2044)	−2.8257 *** (0.0024)
Pedroni test	Modified Phillips-Perron t	2.2186 ** (0.0133)	1.3543 * (0.0878)
	Phillips-Perron t	0.0889 (0.4646)	0.6321 (0.2637)
	Augmented Dickey-Fuller t	−0.4215 (0.3367)	0.5963 (0.2755)
Westerlund test	Variance ratio	0.6786 (0.2487)	−0.2179 (0.4138)

Notes: ***, ** and * represent significance at the levels of 1%, 5% and 10% respectively.

4.3.2. Estimation Results of the PVAR Model

In order to accurately reflect the dynamic relationship between variables and maintain the validity of parameter estimation, this study uses Akaike information criteria (AIC), Bayesian information criteria (BIC), and the Hannan-Quinn information criteria (HQIC) to determine the optimal lag order of the model. According to Table 7, the optimal lag order of the PVAR model is 1 for both resource-based and non-resource-based cities, and the PVAR models with first-order lags are constructed for resource-based and non-resource-based cities, respectively.

Table 7. Optimal lag order selection.

Region	Lag	AIC	BIC	HQIC
Non-resource-based cities	1	−4.2956	−3.7278 *	−4.0649 *
	2	−4.3412 *	−3.6480	−4.0597
	3	−4.2279	−3.3932	−3.8893
Resource-based cities	1	−0.4591 *	0.2772 *	−0.2638 *
	2	0.0126	1.2029	0.2930
	3	17.1257	18.7687	17.4464

Notes: * represents the optimal lag order corresponding to each information criteria.

Next, the Hermert transformation is applied to the first-order difference series of the variables to eliminate individual fixed effects of the model and ensure that the transformed variables and their lags can be orthogonal to form valid instrumental variables. The transformed variables are h_ d.LnGDP, h_ d.LnPCE, and h_ d.LnCCE. The model parameters are estimated using GMM, and the influence relationship between variables and lagged terms is presented in Table 8 as a preliminary result. A summary of the GMM estimation results follows.

1. The first-period lag of economic development has a significant positive effect on itself in both non-resource-based cities and resource-based cities, with elasticity coefficients of 0.6378 and 0.5962, respectively. The first-period lag of carbon emissions from the coal industry has a significant positive effect on itself, with elasticity coefficients of 0.0504. These findings imply that there is a general cumulative effect of time on economic development and carbon emissions from the coal industry. Therefore, cities

with a stronger economic foundation and development will continue to be more resilient to external economic shocks, so economic development planning should be long-term in order to maximize the positive cumulative effect. In terms of carbon emissions, the work of reducing them will take time. It is necessary to pay close attention to the trend of carbon emission changes, break the cumulative effect of carbon emissions, and be wary of the potential rebound effect in the process of carbon emission reduction.

2. The first-period lags of carbon emissions from the coal industry in resource-based cities will have a significant positive effect on economic development, with an elasticity coefficient of 0.0024, indicating that the economic development of resource-based cities has resource characteristics and their coal resource endowment is conducive to the formation of an energy-dependent industrial structure [83]. Carbon emission reduction policies will have a negative impact on economic development. However, resource-based economic development is unsustainable, so it is crucial for cities to transform their development strategies. The government should encourage the development of diverse industries in order to optimize the industrial structure and gradually reduce the reliance of economic development on energy source.

Table 8. Estimation results of the PVAR model.

Region	Impulse Variables	Response Variables		
		h_ d.LnGDP	h_ d.LnPCE	h_ d.LnCCE
Non-resource-based cities	L1. H_ d.LnPCE	0.0027 (0.789)	−0.0217 (0.883)	–
	L1. H_ d.LnGDP	0.6378 *** (0.000)	0.0537 (0.940)	–
Resource-based cities	L1. H_d.LnCCE	0.0024 * (0.053)	0.0051 (0.284)	0.0504 * (0.084)
	L1. H_ d.LnPCE	−0.0265 (0.509)	−0.0624 (0.667)	−0.7628 (0.388)
	L1. H_ d.LnGDP	0.5962 *** (0.004)	0.3350 (0.647)	7.9199 (0.198)

Notes: *** and * represent significance at the levels of 1% and 10%, respectively.

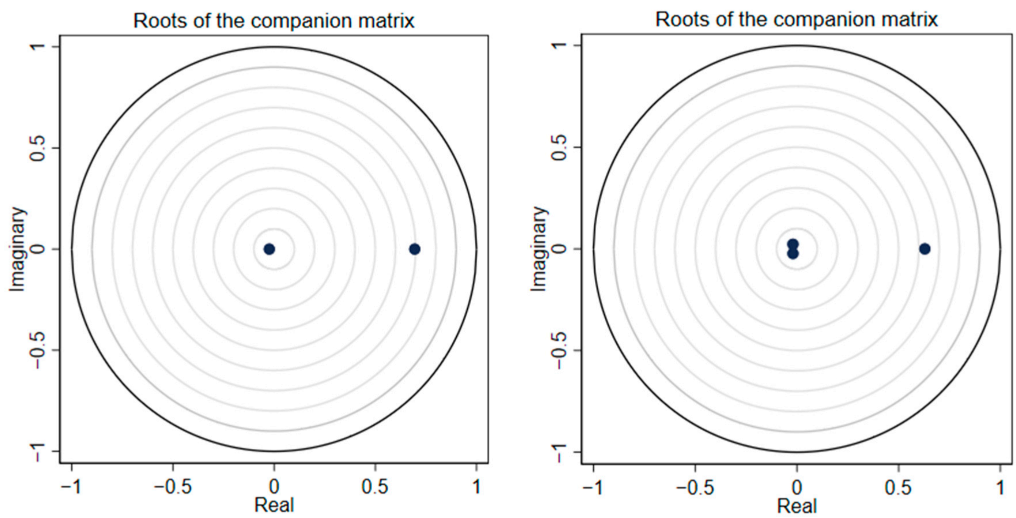
It should be noted that the application of VAR-type models in economic forecasting and policy evaluation is conditional. VAR-type models can only successfully forecast systems that operate according to the laws of the market without government intervention. Conversely, for systems with government intervention, it is difficult to make successful forecasts. Structurally, the PVAR model is a dynamic model that does not focus on the interpretation of the coefficients of the parameters to be estimated, and it is also difficult to confirm the significance of individual variables. Considering the above limitations of the PVAR model and the fact that both planned and market prices are implemented in the Chinese energy market during the sample period, this paper does not conduct in-depth economic analysis and policy evaluation of the PVAR model parameter estimation results, but focuses on the dynamic effects of the exogenous perturbations of each variable on itself and other variables using impulse response function and variance decomposition based on the PVAR model.

4.3.3. Impulse Response Analysis

The impulse response function can further measure the change in variables caused by a random perturbation of a variable, reflecting the dynamic interaction between variables as well as predicting the degree of lag and influence between the variables. However, the PVAR model's stability should be tested before performing the impulse response function analysis. As shown in Table 9 and Figure 7, the inverse of all unit roots is distributed within the unit circle, indicating that the first-order PVAR model constructed in this part based on the panel data of economic development and carbon emissions in the coal and power industries is robust. It is eligible to continue the impulse response shock and variance decomposition analysis.

Table 9. Eigenvalue stability condition.

Region	Eigenvalue		Modulus
	Real	Imaginary	
Non-resource-based cities	0.6945 −0.0238	0 0	0.6945 0.0238
Resource-based cities	0.6289 −0.0195 −0.0195	0 0.0228 −0.0228	0.6289 0.0300 0.0300



(**a**) Non-resource-based cities (**b**) Resource-based cities

Figure 7. Test of PVAR model stability.

In this section, the time span of the simulation was set to 10 periods, and 200 Monte-Carlo simulations were run to obtain the non-resource-based cities' impulse response diagrams (Figure 8) and resource-based cities' impulse response diagrams (Figure 9), where the horizontal coordinates indicate the number of periods of response to the effect of the shock and the vertical coordinates indicate the degree of response to shocks. There are three lines in the impulse response plots: the middle line represents the actual impulse response effect of each endogenous variable in the face of a shock, and the top and bottom lines form a 95% confidence interval. The impulse response results show that the impulse responses between the variables all have a good convergence trend. We discovered the following:

1. Carbon emissions from the power industry respond negatively to shocks in the coal industry, with the highest response in the first period, and then gradually converge to 0 after several periods. Although coal is the primary energy source and electricity is the secondary energy source, there is a certain energy substitution between coal and electricity as energy supply sources [84]. When deciding on an energy supply method, the energy consumption side of the equation will consider the cost of supplying coal versus electricity and adjust the demand for different energy types [85]. Carbon emissions from the coal industry are primarily caused by the mining and washing of coal, so an increase in carbon emissions from the coal industry implies an increase in the scale of coal production. The increase in coal supply will cause the price of coal to fall, and energy consumers may choose coal to supply energy to pursue higher

corporate interests and reduce the electricity demand. In brief, because of energy substitution, the increase in carbon emissions from the coal industry may reduce carbon emissions from the electricity industry. Some studies have shown that the increase of coal price can more effectively convey the negative externalities associated with coal consumption and indirectly influence the energy consumption patterns of downstream enterprises through the industrial chain [86,87]. The production and consumption cost of coal can be raised through the regulating effect of taxes such as resource tax and environmental tax, which is an effective way to reduce coal consumption in the short term. It will promote the enterprises to actively alter the development strategies and decrease their consumption and production of coal in order to lessen the carbon emissions released throughout the coal production process.

2. The impulse response of carbon emissions from the coal industry to carbon emissions from the power industry is a negative feedback in the current period and shifts to a positive direction in the first period. However, the degree of the impulse response is low. The main reason for this shift is a lag in the coal industry's reflection of coal demand in the power industry. Coal production is not a fully market-based behavior but rather is more influenced by pre-planning and macro-regulation. In addition, the coal industry and the power industry are in the upstream and downstream of the coal supply chain, respectively, so the energy demand is not transmitted in real-time. In addition, because coal for power generation can be imported and transferred from other provinces [15], the impact of carbon emissions from the power industry on local carbon emissions from coal industry is relatively weak. In the long term, there is a positive synergy between carbon emissions from the power industry and the coal industry, which means an increase in carbon emissions from the power industry will boost carbon emissions from the coal industry. It is primarily due to the advancement of electrification in the transportation, construction, and industrial industries, which has increased the demand for electricity in each industry, and the continued development of the economy also necessitates adequate electricity supply. To meet society's electricity demand, the coal-based electricity mix must consume more coal [88]. Therefore, lowering coal consumption and providing alternatives should be the main priorities for reducing carbon emissions from the coal production process [87]. Electrification of energy use becomes an important path to decarbonization, resulting in a large demand for electricity [89]. If the structure of the electricity supply is not changed, it will promote an increase in carbon emissions from the power industry and the coal industry. We must recognize that investment in renewable energy is a fundamental way to replace coal consumption in thermal power grids [89,90]. While promoting the electrification of the industries, it is necessary to accelerate the development of a new type of power system based primarily on clean energy and to promote the low-carbon transformation of the power structure. However, many studies show that renewable energy substitution is a long-term and slow process [87,91]. In the initial stage, a large capital investment is required, and the emission reduction and substitution effect is relatively limited, which needs time to accumulate before showing a sufficient effect. However, using renewable energy to replace coal is beneficial to the economy in the long run [90]. It is necessary to have a long-term plan for promoting clean power substitution for coal, and to provide guarantee measures for stable energy substitution through financial subsidies and R&D investment.
3. The shock effect of carbon emissions from the power industry on economic development is positive. The effect of the shock caused by carbon emissions from the coal industry on economic development is positive in the first period. The results support the findings of Acheampong [92] and Menyah and Wolde-Rufael [93]: that carbon emissions promote economic growth. However, they contradict the findings of Lu [94]. They indicate that carbon emissions in key industries have not yet decoupled from economic development. The coal and power industries are characterized by extensive development, and we should pay attention to the critical role of fossil energy

in economic growth. It is important to be wary of the deregulation of carbon emissions in some regions in pursuit of rapid economic growth and to rein the behavior of some enterprises in creating higher economic benefits by sacrificing the environment. Currently, we need to develop advanced energy conversion and production technologies to improve energy utilization efficiency and the level of economic growth per unit of carbon emissions [95]. Then, in order to promote the decoupling of economic development from carbon emissions, we should focus on the development of clean energy. Upgrading industrial structure through green technological innovation and increasing the proportion of tertiary industries are good ways to promote lighter and cleaner industry, which not only promote an energy-driven economy into a technology-driven and innovation-driven economy, but also facilitate the decoupling of the economy from carbon emissions [96].

4. In resource-based cities, economic development has a negative shock effect on carbon emissions from the coal industry and power industry. Because people's demand for environmental quality rises as their income rises and coal resources become scarcer, resource-based cities are actively seeking the path to green transformation, so economic development represents a suppressive effect on carbon emissions. If economic development is considered as an intrinsic motivation in the process of carbon emission reduction, it will greatly improve the efficiency of carbon emission reduction. In non-resource-based cities, the effect of the shock caused by economic development on carbon emissions from the power industry is positive in the first period. This is mainly because the increase in demand for electricity caused by economic development has resulted in an increase in the power industry capacity, which in turn has led to an increase in carbon emissions in the power generation process. This is consistent with the findings of He et al. [97]: that economic growth is the dominant driver of increased carbon emissions in the power industry. Therefore, we should continue to explore mechanisms for the coordinated and healthy development of clean energy generation and coal-fired power, and improve clean energy supply technologies to reduce the increase in carbon emissions in the power industry caused by economic development.

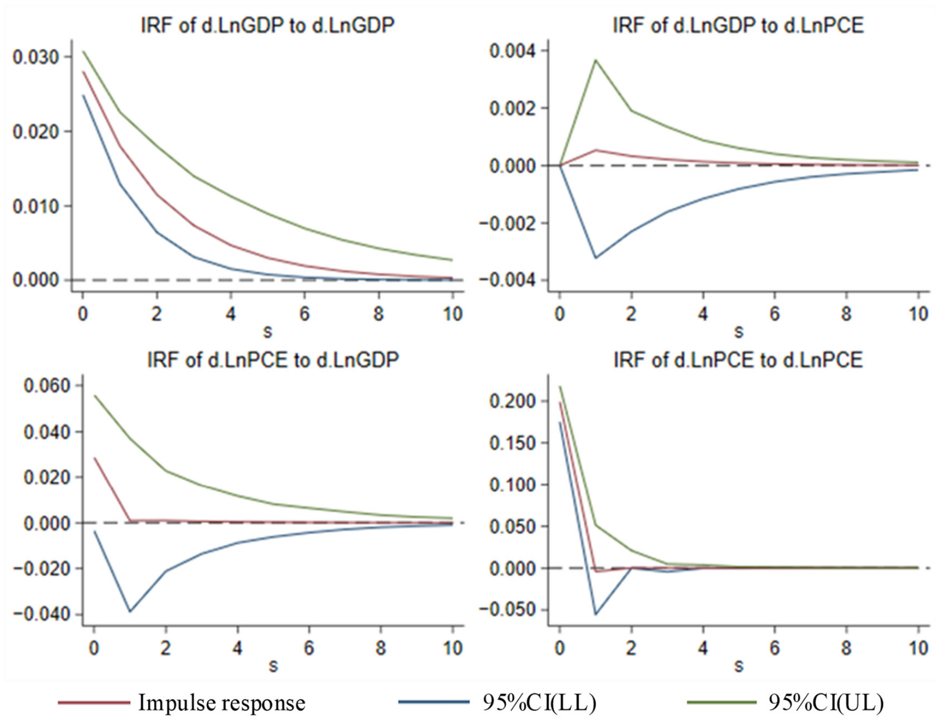


Figure 8. Results of impulse response functions for non-resource-based cities.

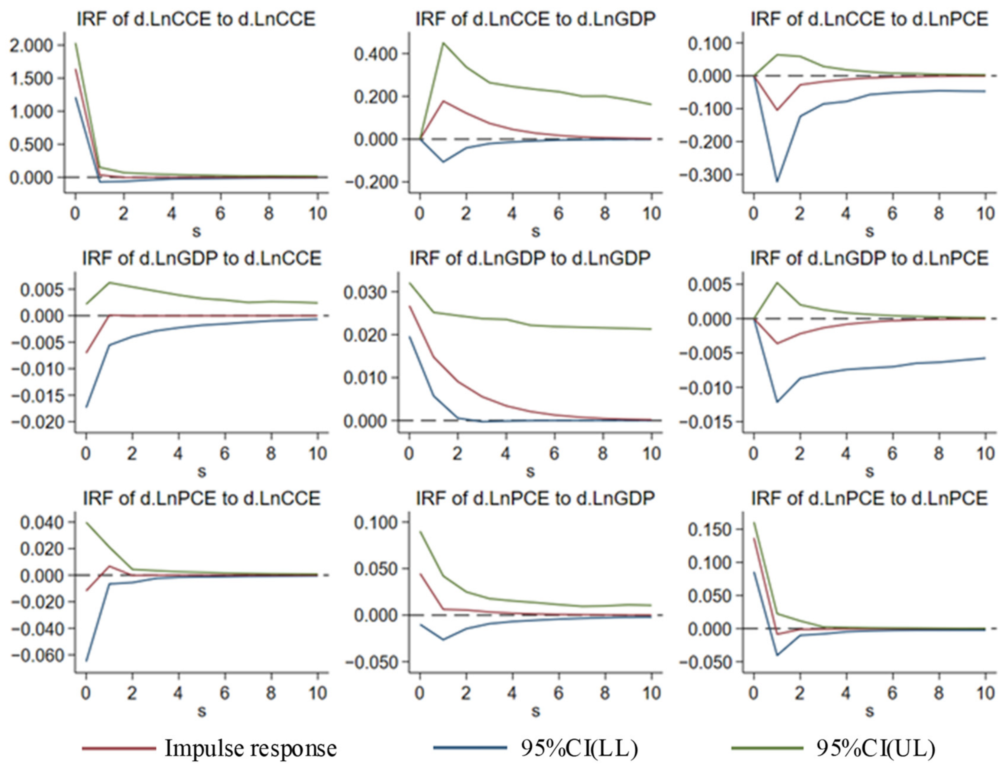


Figure 9. Results of impulse response functions for resource-based cities.

4.3.4. Variance Decomposition

To further understand the long-term dynamic impact relationship between carbon emissions from the coal industry and the power industry, this section conducts a 20-period variance decomposition of the error term, using the variance contribution ratio to indicate the degree to which shocks to the random disturbance term explain variables prediction errors.

As shown in Table 10, for non-resource-based cities, the variance decomposition results are consistent over the forecast period. Future changes in economic development are entirely the result of their own shocks. Economic development accounts for about 2% variation in carbon emissions from the power industry, and the remaining 98% is due to the power industry's shocks.

Table 10. Variance decomposition for non-resource-based cities.

Response Variables	Forecast Horizon	Impulse Variables	
		d.LnGDP	d.LnPCE
d.LnGDP	1.000	1.000	0.000
	2.000	1.000	0.000
	3.000	1.000	0.000
	4.000	1.000	0.000
	5.000	1.000	0.000
	10.000	1.000	0.000
	20.000	1.000	0.000
d.LnPCE	1.000	0.020	0.980
	2.000	0.020	0.980
	3.000	0.020	0.980
	4.000	0.020	0.980
	5.000	0.020	0.980
	10.000	0.020	0.980
	20.000	0.020	0.980

According to Table 11, for resource-based cities, economic development and carbon emissions from the power industry and carbon emissions from the coal industry all have some mutual explanatory power. The explanation ceases to change after five years, indicating that the fluctuations of each variable all reach a steady state in the fifth year. Economic development explains about 9.9% variation in carbon emissions from the power industry and 2% variation in carbon emissions from the coal industry, while carbon emissions from the power industry account for only 1.8% variation in economic development and 0.4% variation in carbon emissions from the coal industry. Carbon emissions from the coal industry explain 4.4% of the change in economic development and 0.9% variation in carbon emissions from the power industry.

Table 11. Variance decomposition for resource-based cities.

Response Variables	Forecast Horizon	Impulse Variables		
		d.LnCCE	**d.LnGDP**	**d.LnPCE**
d.LnGDP	1.000	0.065	0.935	0.000
	2.000	0.050	0.937	0.013
	3.000	0.046	0.938	0.017
	4.000	0.044	0.938	0.018
	5.000	0.044	0.938	0.018
	10.000	0.044	0.938	0.018
	20.000	0.044	0.938	0.018
d.LnPCE	1.000	0.007	0.096	0.897
	2.000	0.009	0.097	0.894
	3.000	0.009	0.098	0.893
	4.000	0.009	0.099	0.892
	5.000	0.009	0.099	0.892
	10.000	0.009	0.099	0.892
	20.000	0.009	0.099	0.892
d.LnCCE	1.000	1.000	0.000	0.000
	2.000	0.985	0.012	0.004
	3.000	0.979	0.017	0.004
	4.000	0.977	0.019	0.004
	5.000	0.976	0.019	0.004
	10.000	0.976	0.020	0.004
	20.000	0.976	0.020	0.004

Overall, economic development and carbon emissions from the coal industry and power industry have the strongest explanatory power for their respective changes. We also discovered:

1. In resource-based cities, the contribution of carbon emissions from the coal industry to the change in carbon emissions from the power industry is greater than the contribution of carbon emissions from the power industry to the change in carbon emissions from the coal industry. This could be because local coal resources are mainly used to meet local coal demand, while the coal demand of the power industry can also be met by resources from outside the province.
2. Economic development contributes more to variation in carbon emissions from the power sector than it does to carbon emissions from the coal industry. This is probably because economic growth is more likely to be reflected in an increase in electricity demand. In comparison to the coal industry, the power industry has stronger and more extensive links with other industries, as electricity is the main mode of energy supply for many industries. Economic development is the main driver of increased electricity consumption, which also provides financial security for the transformation of the electricity structure. It is essential to actively promote the development of a low-carbon economy. By increasing the demand for clean electricity, the low-carbon economy can facilitate a shift in the electricity structure from thermal generation to clean energy

generation [98]. The low-carbon economy could also provide sufficient funds for the transformation of green power generation technologies. It is not only conducive to increasing investment in renewable energy generation, but it also supports the research and development of core technologies for carbon reduction [99].

3. I contribution of carbon emissions from the coal industry to changes in economic development is decreasing, while the contribution of the power industry is gradually increasing, but the former is always higher than the latter. This indicates that although the green transformation of cities has gradually reduced the reliance on coal resources for economic growth, coal resources remain the main driver of economic growth. As electrification has strengthened the linkages between the power industry and other industries, which increases the importance of the power industry, the power industry has a growing impact on economic development. Resource-based cities should improve the urban industrial system and plan the regional industrial layout in an integrated manner. By extending the coal industry chain and developing coal substitution industries, they can transform traditional industries and develop new leading industries, which is beneficial to reducing the over-dependence of regional economic and industrial development on resources and accelerating the transformation of old and new dynamics of economic development [100]. The construction of new electric power systems in non-resource-based cities should take the economic development goals as constraints while ensuring energy supply security. To realize deep decarbonization of economic development, non-resource-based cities should strictly control new coal power projects, enhance the capacity of renewable energy consumption, and establish a green power trading market [101].

4.3.5. Granger Causality Test

This section uses the Granger causality test to further clarify the causal relationship between the variables. Table 12 shows the results of the Granger causality test. There is only a unidirectional causality from carbon emissions in the coal industry to economic development, which is significant at the 10% level, i.e., the growth of carbon emissions in the coal industry will promote economic development, but economic growth will not promote an increase in carbon emissions from the coal industry. There is no two-way Granger causality between all variables, especially between carbon emissions from the coal industry and carbon emissions from the power industry, which is the focus of this paper.

Table 12. Results of the Granger causality test.

Region	Explained Variables	Explanatory Variables	chi2	df	Prob > chi2
Non-resource-based cities	h_ d.LnGDP	h_ d.LnPCE	0.0716	1	0.789
		ALL	0.0716	1	0.789
	h_ d.LnPCE	h_ d.LnGDP	0.00576	1	0.940
		ALL	0.00576	1	0.940
Resource-based cities	h_ d.LnGDP	h_ d.LnPCE	0.43566	1	0.509
		h_ d.LnCCE	3.7456	1	0.053 *
		ALL	3.8003	2	0.150
	h_ d.LnPCE	h_ d.LnGDP	0.21012	1	0.647
		h_ d.LnCCE	1.1502	1	0.284
		ALL	1.5149	2	0.469
	h_ d.LnCCE	h_ d.LnGDP	1.6605	1	0.198
		h_ d.LnPCE	0.74643	1	0.388
		ALL	1.6606	2	0.436

Notes: * represents significance at the level of 10%, respectively.

5. Conclusions and Recommendations

This paper calculates the carbon emissions of the coal industry and power industry by the IPCC method in 13 cities in Jiangsu Province from 2006 to 2020, then it adopts the EOF decomposition to explore the spatial and temporal evolution characteristics of carbon emissions in key industries, and finally employs the PVAR model to systematically evaluate the interaction between the carbon emissions of coal industry and power industry, as well as the effect of economic development. The following are the main conclusions of this study:

1. From the perspective of spatial distribution, there is a close relationship between carbon emissions and coal resource distribution in the coal industry, and the time coefficients of EOF decomposition show an "N"-shaped variation, with the type of spatial distribution varying with the positive and negative values of temporal coefficients. In the power industry, the first model of the EOF shows a consistent trend of carbon emissions across the entire region, with the time coefficients showing a continuous upward trend and the typicality of the spatial distribution showing weakening firstly and then strengthening in the opposite direction. The second model of the EOF is characterized by a "south-north" inverse phase distribution, with a "U-shaped" change in time coefficients, which is characterized by interannual variability, and the typicality of spatial distribution undergoes three changes.
2. In terms of long-term development, there is a synergistic effect from carbon emissions of the power industry to carbon emissions of the coal industry, which is closely related to the supply and demand of coal. However, the results of the variance decomposition and causality test indicate that the synergistic relationship between the carbon emissions of the coal industry and power industry is relatively weak. We should improve the degree of synergy between carbon emissions of key industries through technological innovation and cross-industry materials development. It is essential to start from the energy consumption side to reduce emissions, which can reduce coal production by reducing the demand for coal, thereby reducing carbon emissions on the production side.
3. The increase in carbon emissions will promote economic development; the economic development of resource-based cities in particular has resource characteristics. There is a unidirectional causal relationship between carbon emissions from the coal industry to economic development. However, the improvement of economic development in resource-based cities will suppress carbon emissions from the coal and power industries. Thus, resource-based cities should use economic development as an internal impetus to promote urban green transformation, and non-resource-based cities should focus on promoting the decoupling of the economy from carbon emissions.

This paper makes the following policy recommendations based on the research findings discussed above:

1. Promote differentiated carbon emission reduction efforts, taking into account the characteristics of urban development. The typical spatial distribution of carbon emissions in the coal industry and power industry side-by-side reflects some irrationality in dividing regions and implementing carbon emission reduction policies based on traditional geographical locations. Therefore, when developing carbon-reduction strategies, we should adhere to formulating and implementing policies in accordance with local conditions, taking into account the local economic development and resource endowment. For example, non-resource-based cities should prioritize the quality of economic development and adjust the supply structure of power industry. They could mitigate the impact of economic development on the promotion of carbon emissions from the power industry by pursuing a clean energy supply aggressively. The energy-rich regions are constrained by resource endowment and industrial base. Natural resources underpin their economic development. In order to accelerate the transition between old and new economic dynamics and break the "lock-in effect" of

energy-driven economic development, they should optimize their industrial structure by encouraging energy-saving technological innovation and increasing the proportion of tertiary industries.

2. Identify ideas to reduce carbon emissions through cross-industry synergies. The results of the study show that there is a synergistic effect of carbon emissions between key industries, from the energy consumption side to the energy production side. Therefore, it is important to start from the energy consumption side when formulating cross-industry synergistic carbon emission reduction policies. First of all, we must reduce the reliance on fossil energy on the consumption side. Then, we must reduce the production of fossil energy at the production side by lowering demand, thereby promoting the green and low-carbon transformation of the entire energy supply chain. For example, enhance the substitution of electricity for fossil energy by increasing the electrification of the energy consumption side of the industry. Next, develop clean energy vigorously and establish a new power system with new energy as the mainstay to promote the low-carbon transformation of the energy and power structure, which will help to reduce the overall demand for fossil energy for social development.
3. Strengthen the synergy of carbon emissions reduction among key industries. To promote the expansion of energy conservation and emission reduction policies from individual industries to multiple industries, it is crucial to thoroughly comprehend the synergistic effect of carbon emissions among key industries and establish a coordinated and complementary mechanism for reducing pollution and carbon emissions in key industries first. Secondly, an innovation system of energy-saving and carbon-reducing should be built. In order to fully exploit and improve the synergistic effect between industries, it will help to break down industry barriers through research and development and the promotion of low-carbon and green technologies such as energy substitution, energy gradient utilization and optimization, and resource recycling.
4. Facilitate the harmonious development of environmental protection and economy. Stable economic development is a prerequisite for carbon emission reduction; it is essential to consider economic development as an endogenous driving force for carbon emission reduction. With the construction of the carbon emission trading market, the market-based mechanism will mobilize the enthusiasm of enterprises to save energy and reduce carbon emissions, lowering the cost of emission reduction and achieving both economic and social benefits. Furthermore, in order to break the cumulative effect of carbon emissions, a monitoring and verification platform of carbon emissions based on the carbon emission trading market can be established to grasp the carbon emission dynamics in real-time, allowing problems to be detected and carbon emission reduction policies to be optimized and adjusted in time.

There are still several limitations in this paper. First, due to the limitations of the PVAR model and the non-disclosure of industry data for more variables at the city level, this paper developed a study of carbon emissions from standpoint of the coal and power industries and economic development, which inevitably has the shortcomings of omitting variables and simplifying the complexity of reality. It is necessary to consider more complex realistic connections. Therefore, further studies can be carried out by broadening the research perspective and exploring more advanced research methods. It is suggested that future studies can achieve significant results by comprehensively considering various influencing factors of carbon emissions and the spatial effects between them. Moreover, the negative externalities of carbon emissions should not be overlooked. They will make the research more closely related to real economic and social activities. Second, the present study only took the coal and power industries in 13 cities in Jiangsu Province as samples. However, the level and mode of development of different economic agents vary greatly. In the future, the sample scope should be expanded to include more industries, more cities, and even more countries. It is suggested that the mechanism of the synergistic effect of carbon emissions can be investigated further by comparing multiple agents. Exploring the path of synergistic carbon emission reduction of multiple agents will help to improve carbon emission reduction efficiency and enhance carbon emission reduction space.

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