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Dynamic relationships among energy structure, industrial structure, economic efficiency, and carbon emission efficiency in China: A panel vector autoregressive (PVAR) analysis

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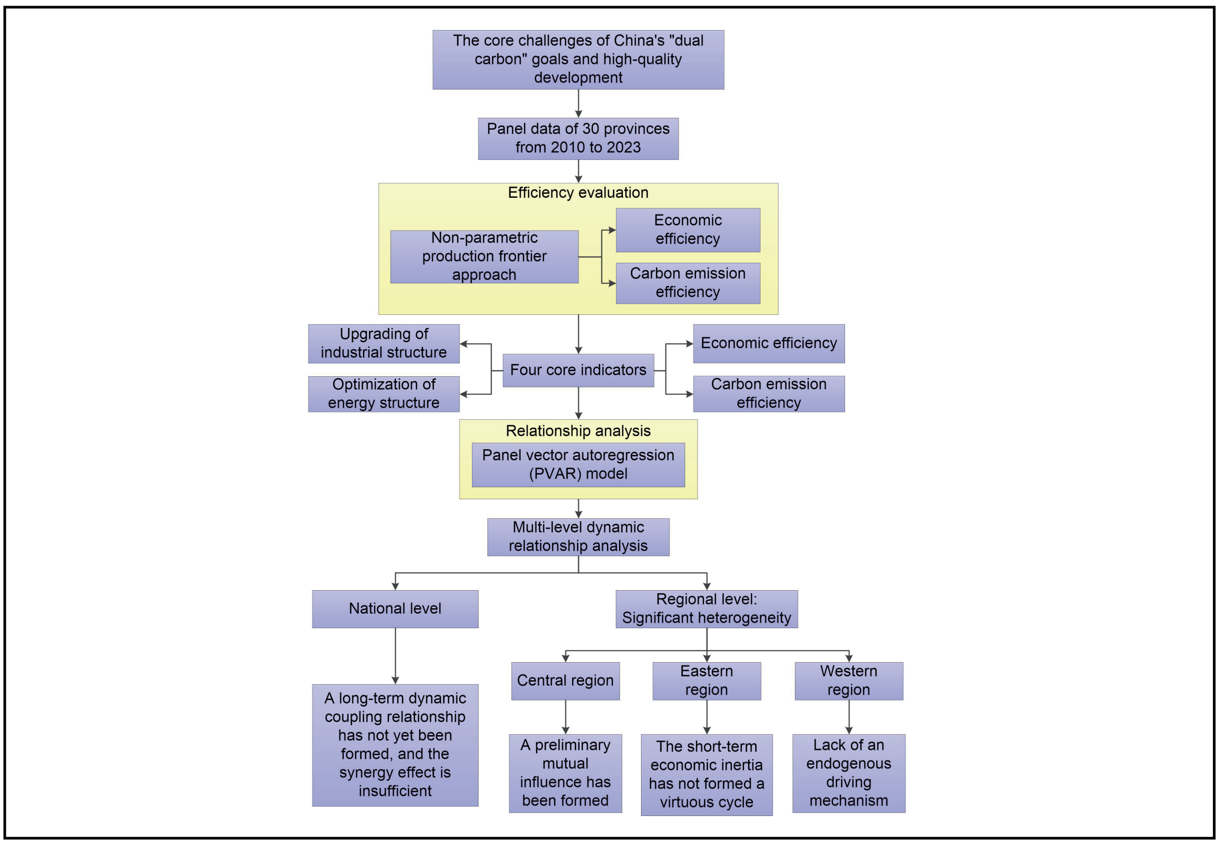
Graphical abstract



Research methods and conclusions on the core challenges of China's "dual carbon goals" and high-quality development.

Public summary

- A panel vector autoregressive (PVAR) framework is employed to unravel the dynamic interrelationships among the industrial structure, energy structure, economic efficiency, and carbon emission efficiency.
- A dual efficiency assessment is conducted via a nonparametric production frontier approach to objectively evaluate economic and carbon performance across 30 provinces in China.
- A multiregional comparative perspective reveals the heterogeneous nature of the green transition pathways across China.

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Abstract: As the world's largest greenhouse gas emitter, China announced its "dual carbon goals" in September 2020. Achieving these goals and advancing high-quality economic development require the coordinated advancement of energy structure optimization, industrial structure upgrading, economic efficiency improvement, and carbon emission efficiency enhancement. On the basis of panel data from 30 provinces in China (including municipalities and autonomous regions) from 2010 to 2023, this study first evaluates economic efficiency and carbon emission efficiency via a nonparametric production frontier approach. It then employs a panel vector autoregression (PVAR) model to examine the dynamic relationships among these four indicators—industrial structure upgrading, energy structure optimization, economic efficiency, and carbon emission efficiency—at both the national and regional levels. The findings reveal that: (ⅰ) At the national level, the four indicators have not yet established a long-term dynamic coupling relationship, indicating that synergies among these development factors in China's green transition remain insufficient; (ⅱ) significant regional heterogeneity exists. The central region shows preliminary mutual influences among the variables, although the strength and stability of these interactions require further enhancement. In contrast, the eastern region demonstrates short-term economic inertia, where economic efficiency and industrial structure upgrading have failed to form a virtuous cycle. The western region lacks an endogenous driving mechanism for effective coordination between industrial and economic efficiency.

Keywords: industrial structure; energy structure; economic efficiency; carbon emission efficiency; PVAR model

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1 Introduction

As the country with the world's highest greenhouse gas emissions, China has realized the importance of addressing climate change. To shoulder its due responsibilities, China put forward its "dual carbon goals" at the United Nations General Assembly on September 22, 2020, committing to carbon peaking by 2030 and carbon neutrality by 2060. The dual carbon goals reflect the importance of climate change and the Chinese government's ability to address this problem. China will intensify its efforts to reduce emissions, promote sustainable development, and contribute to the global response to climate change. At the same time, China will also strengthen international cooperation, actively participate in international climate negotiations and actions, and jointly address global climate challenges. Globally, countries are actively engaged in carbon emission reduction, promoting green economic transformation through pathways such as developing clean energy, improving energy efficiency, and optimizing industrial structures. In fact, the enhancement of carbon emission efficiency does not exist in isolation; instead, it has dynamic interactive relationships with energy structure optimization, industrial structure upgrading, and economic efficiency growth. Efficient carbon emission management can facilitate the rational allocation of energy resources, drive the green transformation of industrial structures, thereby enhancing overall economic efficiency. Conversely, the optimization of energy structures and the upgrading of industrial structures create favorable conditions for improving carbon emission efficiency.

From the theoretical perspectives of economics and environmental science, there are close and complex logical connections among energy structure optimization, industrial structure upgrading, economic efficiency, and carbon emission efficiency. According to factor endowment theory and industrial lifecycle theory, when the energy factor structure transitions toward cleanliness, it forces high-energy-consuming industries to undergo technological innovation or gradually exit the market, thereby accelerating the upgrading of industrial structures toward higher-end sectors. Conversely, as industrial structures develop in high-tech and high-value-added directions, the demand for clean energy significantly increases, further promoting energy structure optimization. Between economic efficiency and carbon emission efficiency, there is a potential evolution law following the "environmental Kuznets curve". In the early stages of economic development, the improvement in carbon emission efficiency

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often coincides with economic growth, but with the continuous optimization of industrial and energy structures, the two are expected to achieve synergistic enhancement, leading to a win–win situation for economic development and environmental protection. Thus, energy structure optimization, industrial structure upgrading, economic efficiency, and carbon emission efficiency are closely and complexly interrelated. It is necessary to explore the underlying interaction mechanisms among them, providing theoretical support for global carbon emission reduction decision-making.

At present, China's energy structure still uses coal as the main energy source, but the government has been increasing its support for clean energy and promoting the optimization and transformation of the energy structure to achieve the goals of sustainable development and the construction of an ecological civilization. In addition, the industrial structure of China is developing in a more diversified and innovation-driven direction, but there are obvious differences between regions. In coastal areas, especially in the Yangtze River Delta and Pearl River Delta, manufacturing and service industries are relatively advanced, while the central and western regions still face the challenge of unbalanced development. The Chinese government is stepping up its reform and opening-up actions, promoting economic restructuring and transformation, and upgrading to achieve sustainable and high-quality development. As the world's largest developing country, China attaches great importance to improving economic efficiency. In 2015, the Chinese government proposed the strategy of "supply-side structural reform", aimed at improving supply-side efficiency and quality by accelerating industrial upgrading and promoting technological innovation. Moreover, the government actively promotes energy conservation and environmental protection and adopts a continuing series of measures to improve energy efficiency to achieve energy conservation and emission reduction, reduce enterprise costs, and improve economic benefits.

In this context, it is necessary to clarify the relationships among energy structure optimization, industrial structure upgrading, economic efficiency, and carbon emission efficiency, and explore this relationship's internal influence mechanisms. This knowledge has important practical guiding significance for realizing the dual carbon goals, promoting sustainable development, and ensuring the high-quality development of China's national economy.

The remainder of this paper is organized as follows. Section 2 reviews previous relevant literature. Section 3 constructs the PVAR model and discusses the selection of core variables. Section 4 conducts an empirical analysis based on the calculated data of the industrial structure upgrading level, energy structure optimization level, economic efficiency, and carbon emission efficiency, and identifies the relationships among these four variables for the whole country, eastern region, central region, and western region. The final section summarizes the conclusions drawn from the analysis results and provides relevant policy suggestions.

2 Literature review

The influence of adjusting the industrial structure and energy structure on carbon emissions has become a popular research topic in China and abroad. Research has shown that industrial structure upgrading and energy structure optimization constitute important ways to achieve carbon emission reduction targets[1]. Scholars have also reported that adjusting the industrial structure and energy structure is beneficial for reducing carbon emissions[2]; accelerating the realization of clean energy structure and strengthening the adjustment of the industrial structure can help achieve the dual carbon goals[3]; upgrading the industrial structure can significantly reduce carbon emissions; and adjusting the energy consumption structure can also significantly affect carbon emissions[4]. Reducing a province's energy intensity and accelerating the upgrading of its industrial structure and energy structure can reduce its carbon intensity, especially in provinces with high carbon emissions and slow economic growth[5].

In other sectors, the factors that greatly influence carbon intensity are different. In the economic sector, carbon intensity is affected mainly by energy intensity, followed by the industrial structure and energy structure, whereas in the residential sector, carbon intensity is affected mainly by per capita GDP and per capita energy consumption[6]. In addition, research shows that improving energy efficiency and upgrading the industrial structure are key measures for reducing carbon emissions[7]. Moreover, promoting industrial structure adjustment can also reduce carbon intensity and energy intensity[8]. Although both industrial structure upgrading and energy structure optimization affect carbon emissions, the contribution potential of industrial structure upgrading to reducing carbon emissions is greater than that of energy structure optimization[9]. Industrial structure upgrading can reduce carbon emissions by improving energy efficiency, whereas industrial structure optimization leads to an increase in carbon emissions because it hinders the improvement of energy efficiency[10]. In addition, in various energy-intensive industries, energy intensity, industrial structure, and energy structure have different influences on reducing carbon intensity, so the government should tailor policies specifically for different industries[11].

At present, research on the influence of the industrial structure and energy structure on economic efficiency is also increasing. Research has shown that establishing a clean energy structure and upgrading the industrial structure are conducive to the development of a low-carbon economy[12]. Additionally, the rationalization of the industrial structure has a greater effect on economic efficiency than does the upgrading of the industrial structure, and the impact of clean energy on improving economic efficiency is not as strong as that of coal and electricity[13]. Adjusting the industrial structure is an effective measure to alleviate the contradiction between energy conservation and the economy, but the scale and scope of industrial adjustment should also be rationally stipulated to achieve economic growth and reduce energy consumption[14].

However, some scholars have suggested that improving economic efficiency adversely inhibits the upgrading of the industrial structure and the optimization of the energy structure[15]. Under the current dual carbon goals, it is necessary to set the economic growth targets carefully and control the economic growth rate within a certain range to reduce carbon emission intensity by adjusting the industrial structure and

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energy structure[16]. At the same economic growth rate, the greater the adjustment of the energy structure is, the more carbon emissions will be reduced[17]. On the other hand, some research that does not account for the influence of energy structure suggests that industrial restructuring alone can facilitate the transition to a low-carbon economy[18]. Furthermore, a positive feedback mechanism exists between industrial structure and economic efficiency. Compared with the feedback effect of economic efficiency upgrading on industrial structure upgrading, industrial structure upgrading has a more significant positive driving force on economic efficiency[19].

Existing studies have examined the impacts of the industrial structure and energy structure on carbon emission efficiency, as well as their influences on economic performance. However, several issues deserve of further investigation. First, while most of the literature focuses on pairwise or triple relationships among industrial structure, energy structure, carbon emissions, and economic efficiency, no study has yet incorporated all four elements within a unified analytical framework. Second, although data envelopment analysis (DEA) has been widely used to evaluate carbon emission efficiency, conventional models often assess it in isolation. In contrast, a more appropriate approach should consider an integrated efficiency metric that simultaneously accounts for both economic and carbon emission performance. The model adopted in this study evaluates economic efficiency and carbon emission efficiency concurrently, thereby providing more accurate and reliable results. Finally, many existing studies rely on standard panel regression techniques without adequately addressing endogeneity concerns. To overcome these limitations, this study utilizes provincial panel data from 2010 to 2023 to reassess economic efficiency and carbon emission efficiency. It further investigates the dynamic relationships and regional heterogeneity among industrial structure upgrading, energy structure optimization, economic efficiency, and carbon emission efficiency vis a panel vector autoregression (PVAR) model, thereby deriving relevant conclusions.

3 Research methods and data sources

3.1 Model construction

According to previous research, there is a complex and dynamic interaction between energy structure optimization, industrial structure upgrading, economic efficiency, and carbon emission efficiency, and there may be a lag effect. To solve the problems of endogeneity and autocorrelation of variables, this paper adopts the PVAR model to explore the dynamic relationships among the four variables. The advantage of PVAR is that it does not need to assume any causal relationships among variables in advance; it treats all variables as endogenous variables and then analyzes the influence of each variable and its lagged variable on other variables in the model. Compared with the traditional vector autoregression (VAR) model, PVAR has the characteristic advantages of a large cross-section and short time series. In addition, PVAR fully considers the individual effect and time effect, and it can effectively solve the problem of individual heterogeneity by using panel data. Because of the above advantages, this study selects the PVAR model to study the dynamic relationships among the energy structure optimization (ESO), industrial structure upgrading (ISU), economic efficiency (ECE), and carbon emission efficiency (CEE). The formula of the model is as follows:

$$Y_{it} = b_0 + \sum_{k=1}^{m} a_k Y_{i,t-k} + \beta_i + \gamma_i + \varepsilon_{it}. \tag{1}$$

Here, Y_{it} is an 1×4 column vector representing the core variables. It includes four endogenous variables: ESO, ISU, ECE, and CEE. In Eq. (1), i represents sample i, t stands for the year, b_0 is the intercept term, k represents the order of lag, and a_k is a parameter matrix of order k lag. Additionally, β_i refers to the individual fixed effect of sample i, γ_i refers to the individual time effect of sample i, and ε_{it} is a random disturbance term.

3.2 Variable selection

This paper mainly includes four core variables: energy structure optimization, industrial structure upgrading, economic efficiency, and carbon emission efficiency.

(Ⅰ) Energy structure optimization (ESO).

As in Ref. [20], this paper uses the entropy weight method[21] and refers to the indicators of previous studies to measure the ESO level of each province from three aspects: the degree of social and economic development, the degree of rational energy planning, and the degree of environmental harmony[22]. As an objective weighting method, the entropy weight method can determine weights on the basis of discrete degree of the data itself, avoiding the bias caused by the subjective judgments of researchers in subjective weighting methods. This study involves multidimensional indicators such as ESO and ISU, whose importance is difficult to define accurately through subjective experiences. The entropy weight method, however, can objectively quantify the contribution of each indicator to the comprehensive evaluation according to the degree of variation of the indicator data, making the weight allocation more consistent with the actual data characteristics.

The degree of social and economic development provides both a demand foundation and capacity support for ESO. It facilitates the transition toward a cleaner and more efficient energy structure through four key indicators: GDP growth rate, urbanization process, employment rate, and education level. Rational energy planning serves as the direct pathway for ESO. It manifests structurally in energy production and consumption through three metrics: energy efficiency, the share of raw coal consumption, and clean energy consumption. This process is fundamentally guided by the principle of “reducing reliance on high-carbon energy and improving energy utilization efficiency”. Environmental harmony determines whether ESO can align with a sustainable development trajectory. By acting as both a constraint and a feedback mechanism, it ensures that energy structure transformation adheres to sustainability goals. This is assessed through three indicators: carbon emission intensity, sulfur dioxide emissions, and soot emissions. Consequently, environmental harmony also serves as a criterion for evaluating the success

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of ESO. The carbon emission intensity is calculated via a common method[23,24], defined as total carbon emissions divided by gross domestic product (GDP). Table 1 illustrates the comprehensive evaluation index system of China's provincial ESO level.

(Ⅱ) Industrial structure upgrading (ISU).

To measure the level of industrial structure in each province, this paper improves upon previous research results[25] by means of the entropy weight method to comprehensively evaluate that level from three aspects: industrial efficiency, industrial structure upgrading, and industrial structure rationalization. Industrial efficiency serves as the core driver of ISU. The increase in labor productivity fundamentally reflects an improvement in industrial quality, constituting both the foundation and a central manifestation of ISU. The advancement of the industrial structure represents the formal characteristic of ISU, guided by the core principle of "transitioning from an industry-dominated to a service-dominated structure". A more prominent leading role of the service sector signifies a greater distance from industrial reliance on high energy consumption, aligning more closely with green and efficient development goals as well as the general patterns of economic development. The rationalization of the industrial structure acts as a coordinating mechanism for ISU, centered on the "balanced allocation of resources and demand–supply matching across sectors", thereby providing a stable structural foundation for upgrading. Here, industrial efficiency is measured by the labor productivity of the three major industries. The upgrading of the industrial structure is expressed as the ratio of tertiary industry added value to that of secondary industry. Regarding industrial structure rationalization, this study adopts the reciprocal of the Theil index to quantify its level; the resulting metric is a positive indicator that simplifies calculation. Table 2 shows the evaluation index system of China's provincial ISU level.

(Ⅲ) Economic efficiency (ECE) and carbon emission efficiency (CEE).

Most previous studies used the radial DEA model to calculate classical carbon emission efficiency (e.g., Refs. [26, 27]). With capital, labor, and energy as inputs; GDP as the desired output; and carbon emissions as the undesired output, the classical CEE of each region can be calculated. The efficiency calculated in this way is a comprehensive efficiency that includes this study's ECE and CEE indices. The calculation of this classical efficiency via the radial model indicates that the ECE and classical CEE indices are the same. Therefore, to achieve effective goals, the desired and undesired outputs are adjusted in equal proportions, which may allow the level of efficiency favored by decision makers. Therefore, this paper uses the nonradial efficiency evaluation model. This model allows for independent adjustment of all desirable and undesirable outputs, more realistically reflecting the characteristics of nonproportional changes in actual production processes. It can accurately capture the differences between

Table 1. Evaluation index system of the ESO level.

Primary index	Secondary index	Tertiary index (unit)	Index direction	Index weight
The degree of ESO	Degree of social and economic development	GDP growth rate (%)	Positive	0.0451
		Urbanization process (%)	Positive	0.1610
		Employment rate (%)	Positive	0.0543
		Education level (%)	Positive	0.0431
	Rational degree of energy planning	Energy efficiency (tce/10 thousand CNY)	Negative	0.0801
		Raw coal consumption (%)	Negative	0.2005
		Clean energy consumption (%)	Positive	0.2511
	Environmental harmony	Carbon emission intensity (ton/ten thousand CNY)	Negative	0.0651
		Sulfur dioxide emission (ten thousand tons)	Negative	0.0621
		Soot emission (ten thousand tons)	Negative	0.0374

The tce in the units of energy efficiency in the table is the abbreviation for tons of standard coal equivalent.

Table 2. Evaluation index system of the ISU level.

Primary index	Secondary index	Tertiary index (unit)	Index direction	Index weight
Level of ISU	Industrial efficiency	Labor productivity in the primary industry (100 million CNY/10000 people)	Positive	0.4084
		Labor productivity in the secondary industry (100 million CNY/10000 people)	Positive	0.1866
		Labor productivity in the tertiary industry (100 million CNY/10000 people)	Positive	0.1339
	Advanced level of industrial structure	Added value of the tertiary industry/ Added value of the secondary industry	Positive	0.1346
	Rationalization of industrial structure	1/Thiel index	Positive	0.1365

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improvements in economic efficiency and carbon emission efficiency when energy inputs are reduced, avoiding the efficiency measurement bias caused by the proportional assumption of radial models. Traditional radial models assume that all inputs or outputs change in the same proportion, ignoring the disequilibrium between factor inputs and output efficiency in actual production. Therefore, the nonradial model used in this paper has greater discriminative power than the radial model does and can decompose classical comprehensive efficiency to measure the CEE part of that efficiency.

Suppose there are n DMUs (decision-making units), denoted as DMU_j $(j=1,\cdots,n)$. Each DMU has p inputs $x_{ij}(i=1,\cdots,p)$ and can produce s desired outputs $y_{rj}(r=1,\cdots,s)$ and t undesired outputs $b_{fj}(f=1,\cdots,t)$. λ_j $(\lambda_j\geq 0)$ represents the weight. The formula of the model is as follows:

$$\min TE=\frac{s}{\sum_{r=1}^{s}(1+\phi_{ro})}\times\frac{\sum_{f=1}^{t}(1-\varphi_{fo})}{t}$$
$$\text{s.t.}\begin{cases}\sum_{j=1}^{n}\lambda_j x_{ij}\leq x_{io},\ i=1,\cdots,p;\\ \sum_{j=1}^{n}\lambda_j y_{rj}\geq(1+\phi_{ro})y_{ro},\ r=1,\cdots,s;\\ \sum_{j=1}^{n}\lambda_j b_{fj}\leq(1-\varphi_{fo})b_{fo},\ f=1,\cdots,t;\\ \lambda_j\geq 0,\ j=1,\cdots,n.\end{cases}\tag{2}$$

Here, TE represents the total efficiency of the entity being evaluated. The variable $\phi_{r0}(r=1,\cdots,s)$ represents the percentage by which each desired output can be increased, and the variable $\varphi_{f0}(f=1,\cdots,t)$ represents the percentage by which each undesired output can be decreased. The indices for ECE and CEE adopted in this study are defined by the following formula:

$$\mathrm{ECE}=\frac{s}{\sum_{r=1}^{s}(1+\phi_{ro}^{*})},\tag{3}$$

$$\mathrm{CEE}=\frac{\sum_{f=1}^{t}(1-\varphi_{fo}^{*})}{t}.\tag{4}$$

Model (2) is a fractional programming and can be transformed into a linear one through the following steps: Let

$$\frac{1}{\sum_{r=1}^{s}(1+\phi_{r0})}\times\frac{1}{t}=\beta_o,$$

then Model (2) becomes:

$$\min TE=\beta_o s\sum_{f=1}^{t}(1-\varphi_{fo})$$
$$\text{s.t.}\begin{cases}\beta_o t\sum_{r=1}^{s}(1+\phi_{ro})=1;\\ \sum_{j=1}^{n}\lambda_j x_{ij}\leq x_{io},\ i=1,\cdots,p;\\ \sum_{j=1}^{n}\lambda_j y_{rj}\geq(1+\phi_{ro})y_{ro},\ r=1,\cdots,s;\\ \sum_{j=1}^{n}\lambda_j b_{fj}\leq(1-\varphi_{fo})b_{fo},\ f=1,\cdots,t;\\ \lambda_j\geq 0,\ j=1,\cdots,n.\end{cases}\tag{5}$$

Nevertheless, Model (5) is still nonlinear since it contains the nonlinear terms $\beta_o\varphi_{fo}$ in the objective function and $\beta_o\phi_{ro}$ in the constraints. Let $\beta_o\varphi_{fo}=\rho_{fo}$, $\beta_o\phi_{ro}=\delta_{ro}$, and $\beta_o\lambda_j=\gamma_j$. Model (5) can then be transformed into the following linear form:

$$\min TE=s\left(\beta_o t-\sum_{f=1}^{t}\rho_{fo}\right)$$
$$\text{s.t.}\begin{cases}t\left(\beta_o s+\sum_{r=1}^{s}\delta_{ro}\right)=1;\\ \sum_{j=1}^{n}\gamma_j x_{ij}\leq\beta_o x_{io},\ i=1,\cdots,p;\\ \sum_{j=1}^{n}\gamma_j y_{rj}\geq(\beta_o+\delta_{ro})y_{ro},\ r=1,\cdots,s;\\ \sum_{j=1}^{n}\gamma_j b_{fj}\leq(\beta_o-\rho_{fo})b_{fo},\ f=1,\cdots,t;\\ \lambda_j\geq 0,\ j=1,\cdots,n.\end{cases}\tag{6}$$

By solving Model (6), we can obtain the solution $(\gamma_j^*,\rho_{fo}^*,\delta_{ro}^*,\beta_o^*)$ and TE. Using $\beta_o\varphi_{fo}=\rho_{fo}$, $\beta_o\phi_{ro}=\delta_{ro}$, and $\beta_o\lambda_j=\gamma_j$, φ_{fo}^* and ϕ_{ro}^* can be obtained. By further applying Eqs. (3) and (4), we can then calculate the ECE and CEE.

3.3 Data sources and descriptive statistics

This paper selects data for 30 provinces (including 4 municipalities and 4 autonomous regions) in China from 2010 to 2023, and divides them into the eastern, central, and western regions according to the division method of the National Bureau of Statistics of China. Because the data for Xizang Autonomous Region are not available, it is not considered. The selected data are from the China Statistical Yearbook, China Energy Statistical Yearbook, China Labor Statistics Yearbook, and the National Bureau of Statistics of China. The descriptive statistics of each variable are shown in Table 3. To reduce the absolute difference between the data and mitigate the impact of heteroscedasticity, this study uses the logarithm of each index for ESO, ISU, ECE, and CEE.

As shown in Table 3, the averages of ESO, ISU, ECE, and CEE in the eastern region are all the highest, and all are higher than the respective national averages. By contrast, averages of the four variables in the central and western regions are lower than the corresponding national averages. In terms of ESO, ISU, and ECE, the eastern region is the best, followed by the western region, and the worst is the central

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Table 3. Descriptive statistics of the variables.

Region	Variables	Number of samples/PCS	Mean value	Standard deviation	Minimum value	Maximum value
National	ESO	420	0.5171	0.1261	0.2558	0.9692
	ISU	420	0.1647	0.1126	0.0233	0.8060
	ECE	420	0.7094	0.2251	0.2405	1.0000
	CEE	420	0.3933	0.2579	0.0329	1.0000
Eastern	ESO	154	0.5708	0.1449	0.2660	0.9692
	ISU	154	0.2438	0.1400	0.0530	0.8060
	ECE	154	0.8183	0.2047	0.3257	1.0000
	CEE	154	0.4731	0.2767	0.0839	1.0000
Central	ESO	112	0.4630	0.0750	0.2713	0.6357
	ISU	112	0.1159	0.0582	0.0233	0.2381
	ECE	112	0.6100	0.1917	0.2688	0.9997
	CEE	112	0.3734	0.1780	0.0340	0.8243
Western	ESO	154	0.5029	0.1142	0.2558	0.7080
	ISU	154	0.1211	0.0513	0.0278	0.2766
	ECE	154	0.6728	0.2219	0.2405	1.0000
	CEE	154	0.3281	0.2663	0.0329	1.0000

region. For CEE, from east to west, CEE gradually decreases.

4 Empirical results and analysis

4.1 Unit root check of panel data

As a dynamic analysis tool for panel data, the PVAR model can simultaneously consider the interactions among multiple variables. It not only captures the current effects between variables but also reveals lag effects, which is highly consistent with the core need of this study to explore the dynamic feedback mechanisms of variables. Additionally, compared with traditional panel regression models, the PVAR model effectively addresses potential endogeneity issues among variables through its specification of endogenous variable systems, avoiding estimation biases caused by reverse causality. Therefore, it is particularly suitable for exploring the dynamic relationships among the four variables: ESO, ISU, ECE, and CEE. To avoid pseudoregression, the unit root test was first carried out on four variables. To ensure the accuracy of the test results, this paper adopted four test methods: the LLC test, IPS test, Fisher-ADF test, and Fisher-PP test. The results show that the ESO, ISU, ECE, and CEE do not all pass the four tests in any region. However, after performing first-order differencing on the time series values of all the variables, all four variables in all the regions pass all the unit root tests. This result reveals that the logarithmic forms of energy structure optimization (lnESO), industrial structure upgrading (lnISU), economic efficiency (lnECE), and carbon emission efficiency (lnCEE) all exhibit I(1) characteristics. This indicates that these series become stationary after undergoing first-order differencing, thus satisfying the prerequisites for constructing PVAR models.

4.2 The optimal lag order of the model

Before the PVAR model is used to analyze the results, it is necessary to determine the optimal lag order of the model. The minimum value corresponding to each criterion is generally considered the best lag order selected by this criterion. The results of selecting the best lag period are shown in Table 4. The optimal lag order in each region was analyzed comprehensively under the three information criteria: AIC, BIC and HQIC (Akaike, Bayesian, and Hannan–Quinn information criteria, respectively), and results show that the optimal lag order for the whole country, as well as the eastern, central, and western regions is the first order. Therefore, the PVAR (1) model is constructed for all regions.

4.3 Robustness test of the model

It is necessary to test the robustness of the model to ensure the validity of generalized method of moments (GMM) estimation, impulse response analysis, and variance decomposition. The index of the robustness test is whether the modulus of the

Table 4. Determination of the optimal lag order.

Region	Lag	AIC	BIC	HQIC
National	1	−24.52*	−191.59*	−91.84*
	2	−15.46	−126.84	−60.34
	3	−7.60	−48.09	−14.84
Eastern	1	−43.84*	−162.75*	−91.75*
	2	−32.25	−111.52	−64.19
	3	−13.63	−53.27	−29.60
Central	1	−42.31*	−145.94*	−83.13*
	2	−29.94	−99.02	−57.15
	3	−12.35	−46.89	−25.96
Western	1	−45.04*	−163.95*	−92.94*
	2	−31.72	−110.99	−63.65
	3	−7.89	−47.53	−23.86

* indicates the optimal lag order under this criterion.

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dynamic matrix eigenvalue is less than 1, that is, within the unit circle. Fig. 1 shows the PVAR robustness test results for the whole country and the eastern, central, and western regions. All the PVAR models pass the robustness test and have good robustness, validating the subsequent empirical analysis.

4.4 GMM estimation of the PVAR model

Before performing GMM parameter estimation via the PVAR model, the data were first transformed via the Helmert transformation. This can eliminate the individual fixed effects and time fixed effects of samples, thereby mitigating potential biases in parameter estimation. Table 5 shows the GMM estimation results of the PVAR models for China and the regions.

To make the GMM estimation result more concise, the estimation result is drawn with a more intuitive graphic method, as shown in Fig. 2. In the subfigures, the red arrow indicates that the explanatory variables that lag one period have a significant positive effect on the explained variables, and the blue arrow indicates that the explanatory variables that lag one period have a significant negative effect on the explained variables.

From a national perspective, ESO has significant mutual inhibitory effects on ISU. ECE has a significant inhibitory effect on itself. The optimization of the energy structure can promote improvement in economic efficiency, and improvement in efficiency can enhance carbon emission efficiency. In addition, CEE also has a positive role in promoting itself. This conclusion is consistent with the findings of existing research[3], which enhances its persuasiveness.

From an intraregional perspective, ESO in the eastern region is significantly influenced by ISU and CEE, whereas ECE only has a significant impact on itself. This indicates that the direct influence of ECE on other variables in the eastern region is relatively limited, and a benign interactive cycle among core elements has not yet been formed, requiring further enhancement of the coordination of the regional economic system. In the central region, there is strong coordination among the four variables of ESO, ISU, ECE, and CEE, with significant unidirectional or bidirectional influence relationships between each pair. These close interactive connections demonstrate that the central region has initially formed a pattern of mutual promotion and collaborative development among various elements, providing a good foundation for development. In the western region, there is a significant promotional effect between ESO and ISU, as well as a significant positive promotional relationship between ECE and CEE. However, no significant interactive relationship is formed between the above two groups of variables. This suggests that

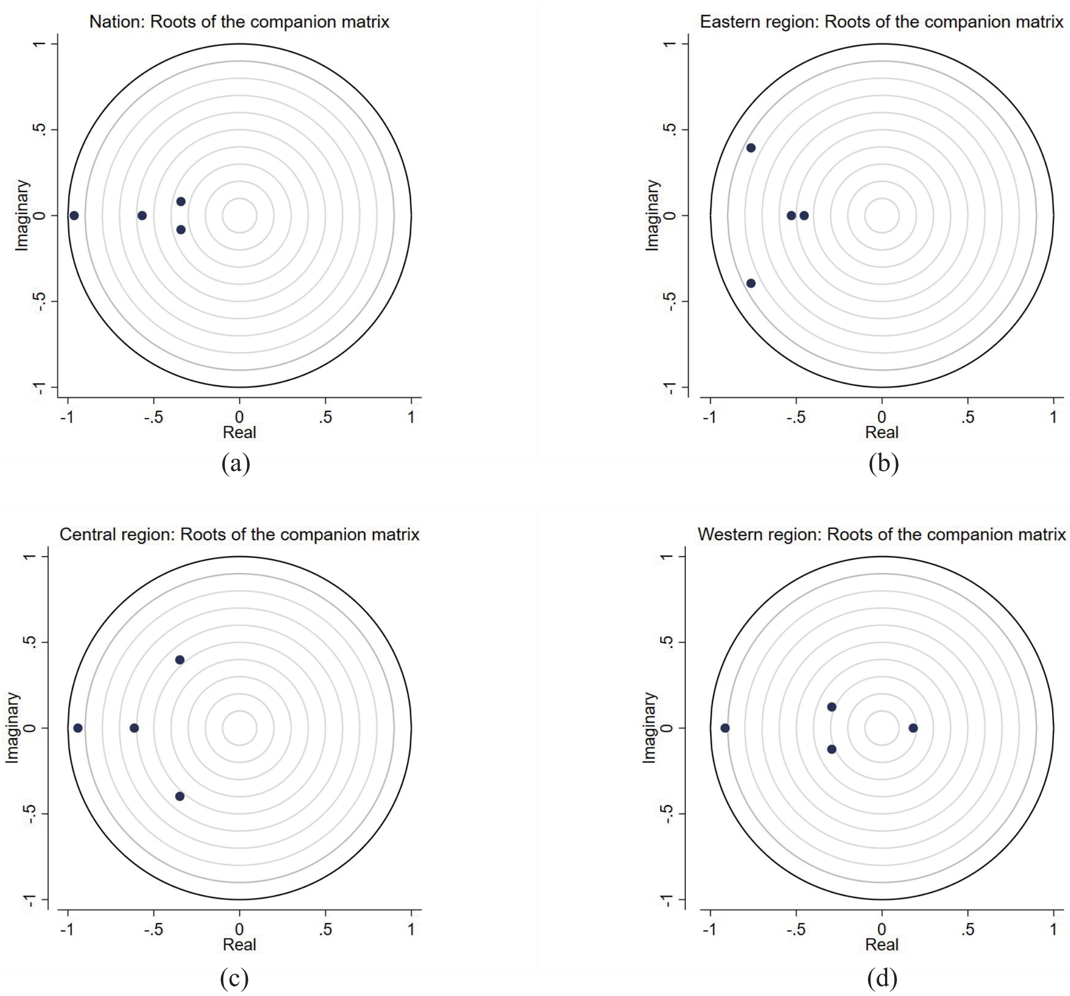

Fig. 1. Robustness tests of the PVAR models in various regions.

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Table 5. Results of the GMM estimation.

Region	Variables	h_dlnESO	h_dlnISU	h_dlnECE	h_dlnCEE
National	L. h_dlnESO	0.1303* (1.89)	0.4564*** (3.04)	0.8342* (1.73)	−0.8746 (−1.48)
	L. h_dlnISU	0.1252*** (4.41)	0.2811*** (2.49)	−0.1666 (−1.22)	−0.2591 (1.26)
	L. h_dlnECE	0.0012 (0.11)	0.0036 (0.16)	−0.3184*** (−3.50)	0.4204*** (4.04)
	L. h_dlnCEE	−0.0093 (−1.26)	−0.0083 (−0.50)	−0.0266 (−0.61)	0.1377** (2.40)
Eastern	L. h_dlnESO	0.1529 (1.51)	0.4278 (1.62)	−0.1205 (−0.21)	−0.335 (−0.04)
	L. h_dlnISU	0.1022** (2.58)	0.0286 (0.14)	0.0423 (0.23)	−0.2327 (−0.74)
	L. h_dlnECE	−0.0060 (−0.29)	−0.0108 (−0.35)	−0.4150** (−2.10)	0.3490 (1.23)
	L. h_dlnCEE	−0.0256* (−1.70)	−0.0100 (−0.49)	−0.0766 (−1.06)	0.1454 (1.53)
Central	L. h_dlnESO	−0.0816 (−0.60)	0.4601*** (3.06)	1.8006* (1.69)	−2.2401* (−1.78)
	L. h_dlnISU	0.1465*** (2.85)	0.4535*** (4.43)	−0.5699* (−1.91)	1.0400*** (3.26)
	L. h_dlnECE	0.0126 (0.84)	−0.0496 (1.42)	−0.2764** (−2.08)	0.4717*** (3.14)
	L. h_dlnCEE	−0.067 (−0.47)	−0.0207 (0.93)	−0.0570 (−0.59)	0.1750* (1.71)
Western	L. h_dlnESO	0.2338** (2.03)	0.2631 (1.03)	1.1417 (1.53)	−0.8650 (−0.89)
	L. h_dlnISU	0.1294** (2.46)	0.4453** (2.52)	−0.1225 (−0.54)	0.2104 (0.63)
	L. h_dlnECE	−0.0015 (−0.10)	−0.0187 (0.63)	−0.3408** (−2.41)	0.4613*** (2.89)
	L. h_dlnCEE	−0.0006 (−0.06)	−0.0128 (0.59)	−0.0311 (−0.52)	0.1636* (1.83)

The values in parentheses are Z statistics. *, **, and *** denote significance at the confidence levels of 10%, 5%, and 1%, respectively.

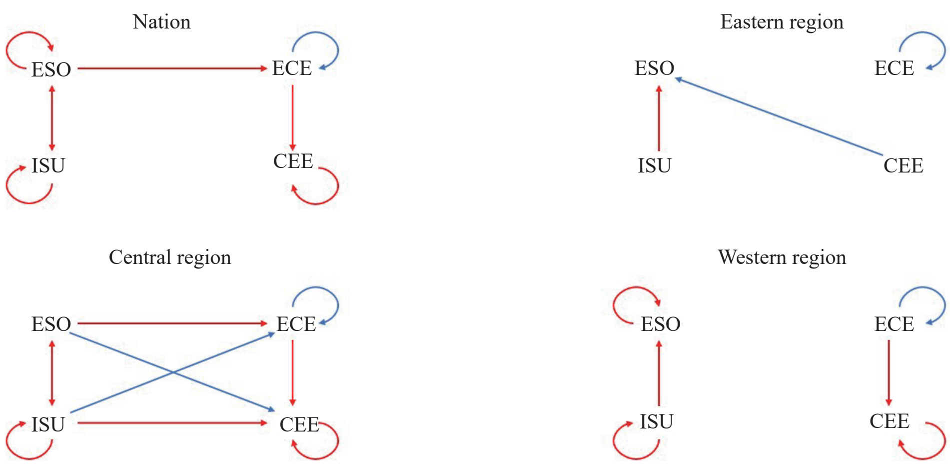

Fig. 2. Graphical representation of the GMM estimation results.

the degree of matching between industrial and energy structures, as well as the degree of coordination between economic development and the ecological environment in the western region, needs further adjustment and improvement. In response, governments should strengthen top-level design and introduce targeted policies to promote the integrated development of these two systems. The above results also indicate that there is regional heterogeneity in the influence mechanism of variables among different regions, which is consistent with the conclusions of existing studies[28].

4.5 Impulse response analysis

The GMM estimation is a static analysis of the model. For further insights, we performed a dynamic analysis of the interactions among ESO, ISU, ECE, and CEE. An impulse response function can model one variable impacting another

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variable while keeping other variables unchanged, thus allowing analysis of the dynamic relationship between the two variables in a certain period in the future. In this paper, with the help of the Monte Carlo method, the impulse response diagrams of the whole country and the eastern, central, and western regions with a lag of ten periods are obtained through 200 simulations, as shown in Figs. 3–6. In the figures, the horizontal axis represents the number of lagging periods, the red curve represents the impulse response value of the response variable after being impacted by a standard deviation of the impact variable, the green curve represents the upper limit of the 95% confidence interval, and the blue curve represents the lower limit of the 95% confidence interval.

In the whole country and all three regions, when ESO, ISU, ECE, and CEE face the impact of one standard deviation from themselves, they all have a positive impact, and the impact tends to zero in the short term. This result indicates that all four variables respond quickly to their own information shocks. The previous effects are all positive promotions, indicating that the four variables have strong economic inertia in the short term and a good self-enhancement effect.

When ESO is subjected to a one-standard-deviation shock from ISU, ESO exhibits a significant positive response in the national, eastern, central, and western regions, after which the impact gradually decays to zero over time. This result indicates that at the national level, ISU can effectively drive ESO in the short term, confirming the leading role of industrial transformation in promoting cleaner and more efficient energy development. However, in the long term, this impact fails to have a sustained effect, suggesting that the collaborative development mechanism between industrial and energy structures has not yet fully matured. It is necessary to build a long-term linkage mechanism through policy guidance, technological innovation, and other means.

When CEE faces an ECE impact one standard deviation away, the impact is negative in the whole country and in the eastern, central, and western regions, and then tends to 0. This may be because all regions pay too much attention to improving ECE and choosing a reasonable degree of energy planning and environmental harmony, thus inhibiting the optimization of the energy structure and CEE.

When ECE is confronted with a standard deviation of ESO impact, a positive impact is initially observed in the national, eastern, and central regions, and then the impact tends to 0. In the western region, a negative impact is observed which gradually tends to 0. This may be due to insufficient investment in the optimization of the energy structure in the western region, resulting in ECE that cannot be improved.

When CEE is confronted with a standard deviation of ESO impact, it first has a negative effect on in the whole country and the eastern and central regions, and then, the impact tends to 0. However, in the western region, the initial influence is small and positive, and it then gradually tends to 0. This result shows that the optimization of the energy structure in the western region may have little impact on CEE improvement in the short term. However, in the long run, it can improve CEE and bring greater benefits to the western region.

Figs. 3–6 show that from a long-term perspective, the interaction between those pairs of figures weakens gradually after the second period until it becomes zero. The findings indicate

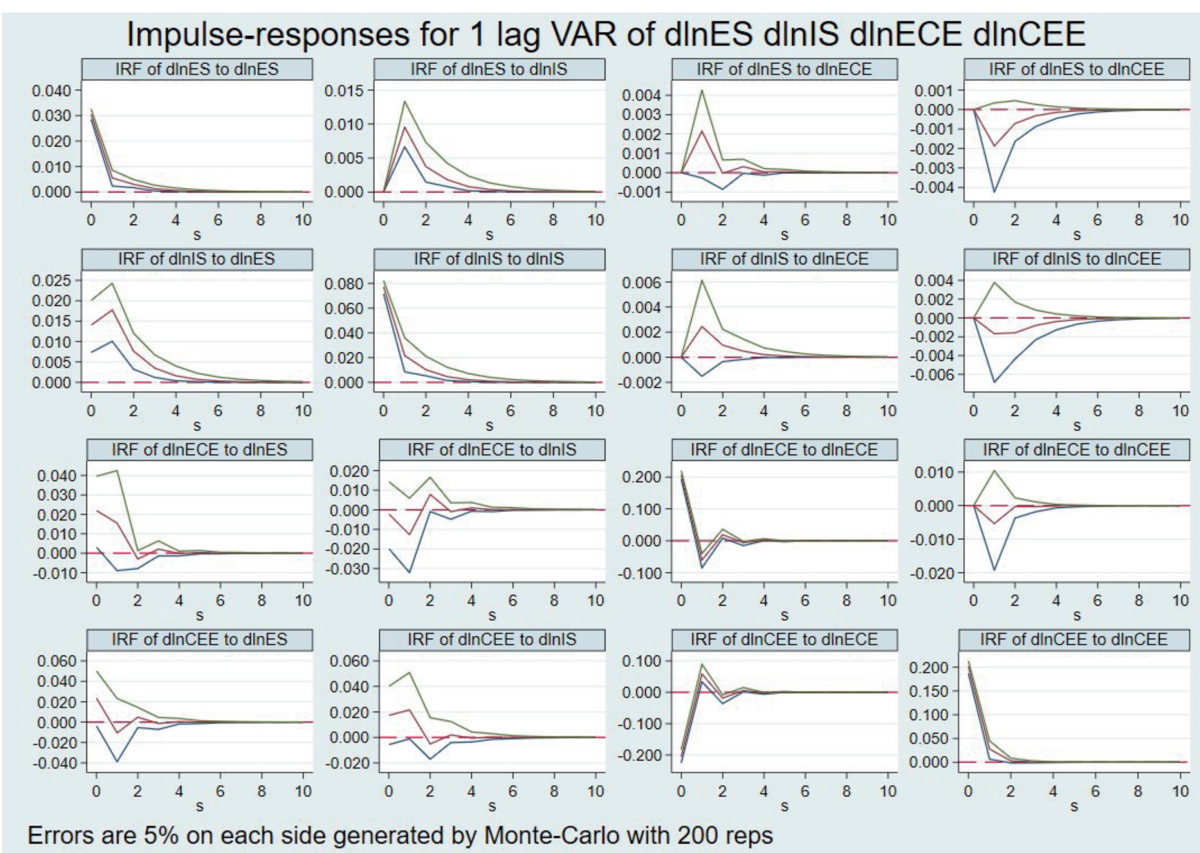

Fig. 3. Impulse response diagrams for the whole country.

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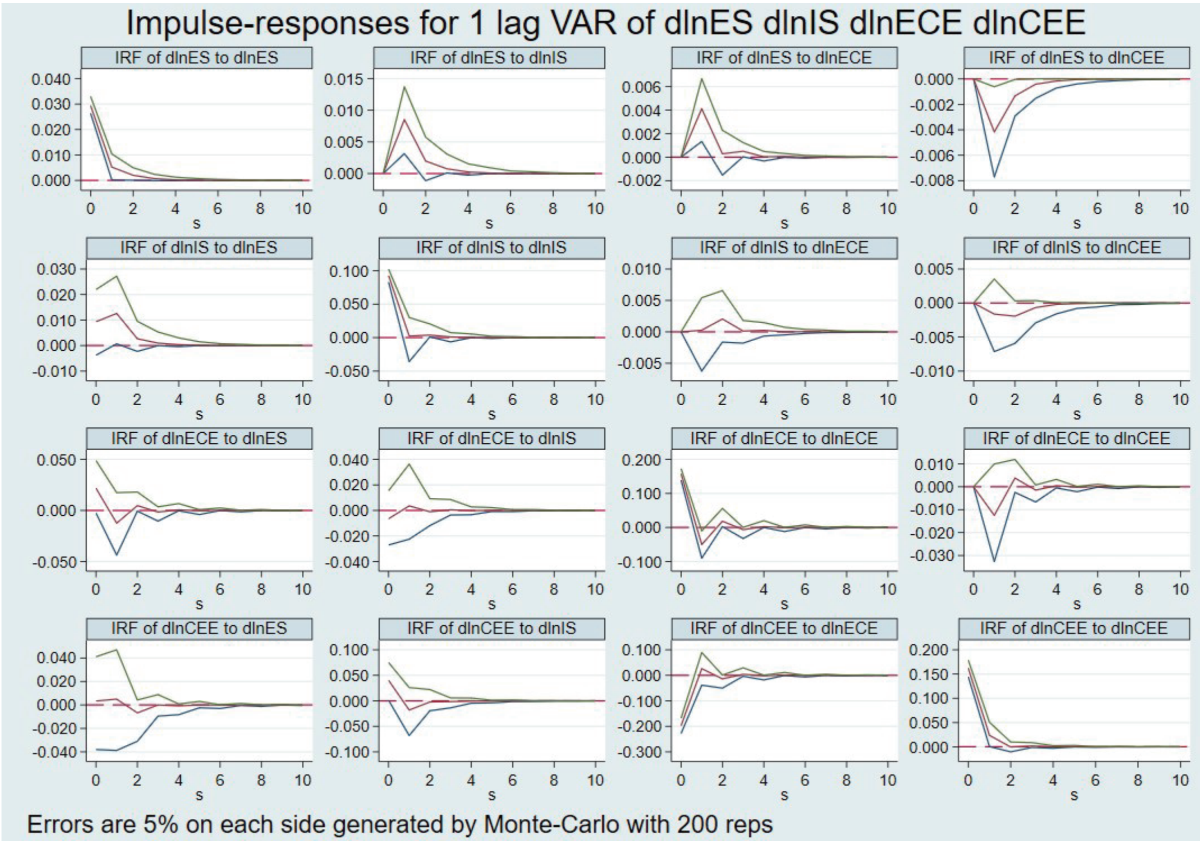

Fig. 4. Impulse response diagrams of the eastern region.

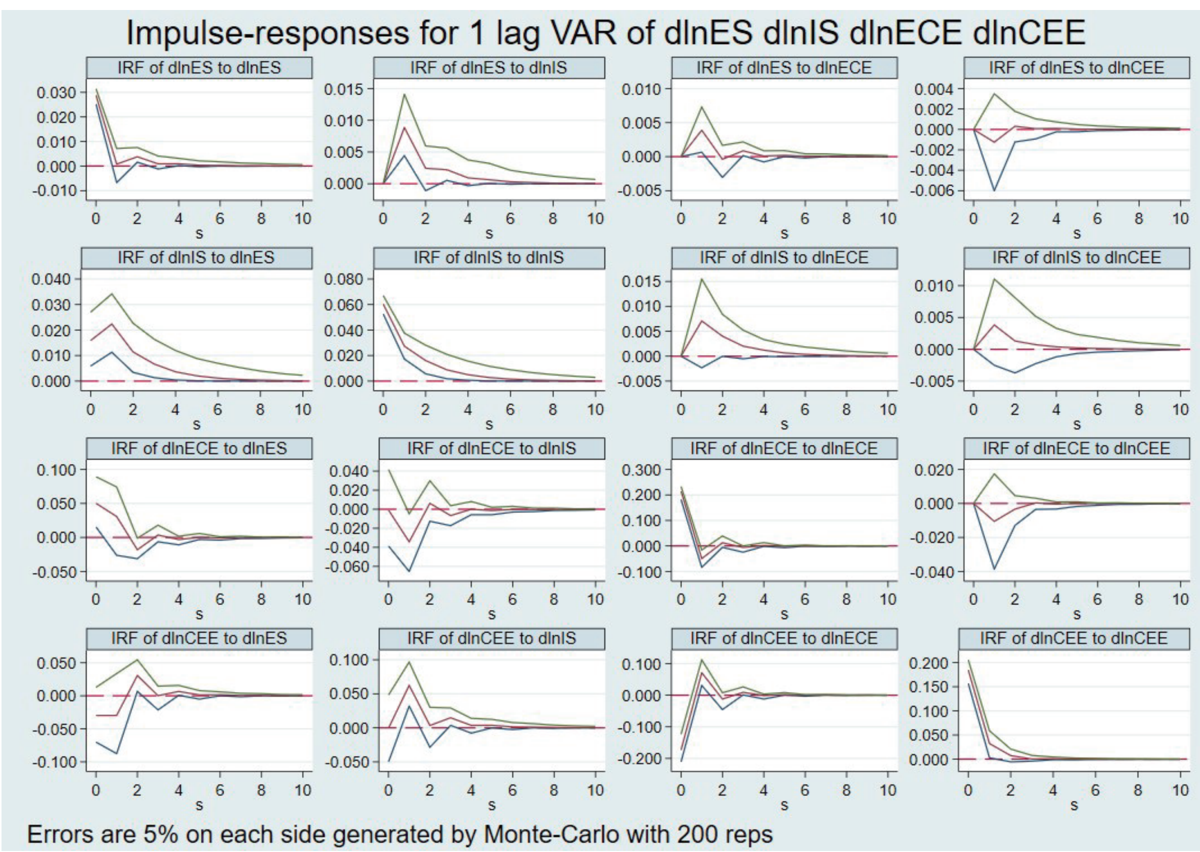

Fig. 5. Impulse response diagrams of the central region.

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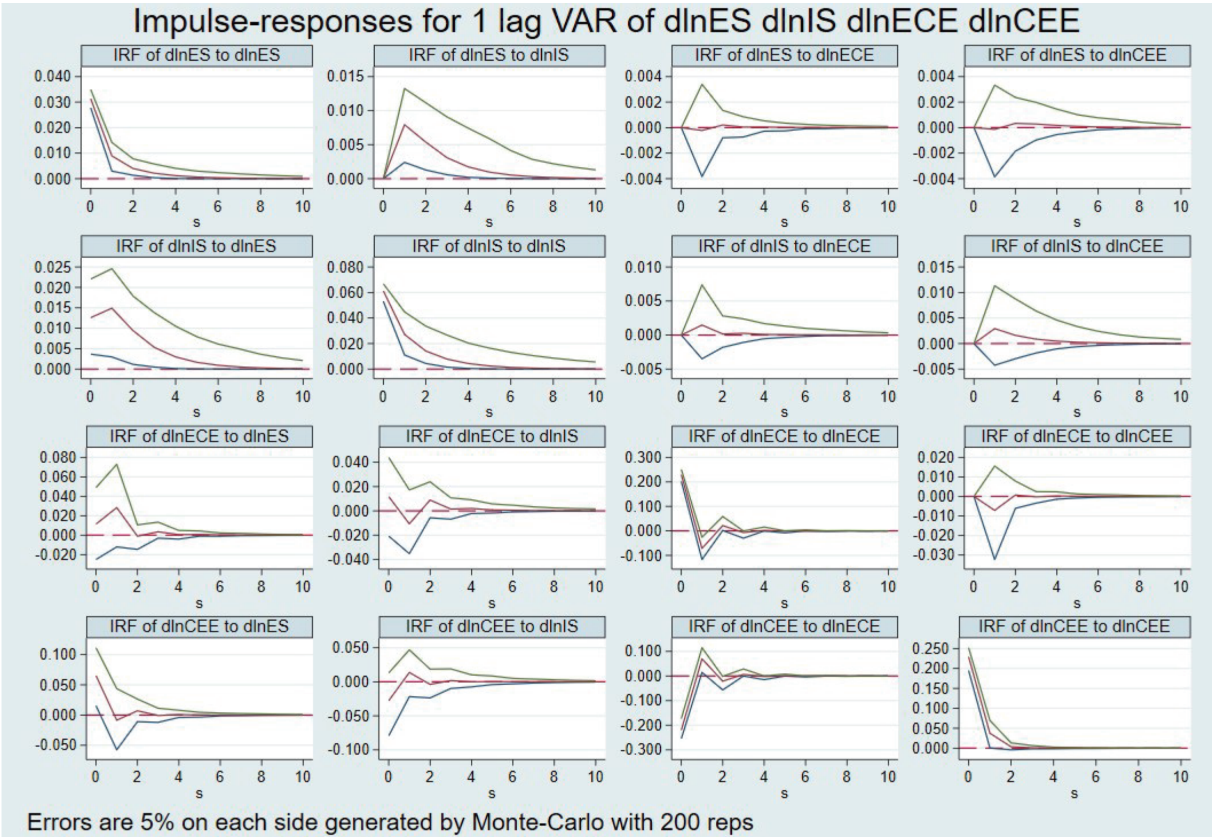

Fig. 6. Impulse response diagrams of the western region.

that these four variables have not formed a long-term dynamic coupling relationship in the regions and that the long-term coordination between variables needs to be strengthened.

4.6 Variance decomposition

The total variance of a variable can be divided into partial variances from different sources. Such variance decomposition can help us understand the contributions of other variables to the total variance of the explained variables. By decomposing the total variance into partial variances from different sources, we can quantitatively evaluate the relative importance of each factor. This helps us understand why the explained variables fluctuate, and that information helps managers adjust their policies accordingly. Table 6 shows the variance decomposition of the PVAR models in various regions, presenting the variance decomposition results of each variable in the 10th, 20th, and 30th periods.

Fig. 7 illustrates the variance decomposition results to more intuitively show the main sources of variance of each variable in various regions. The purple, pink, yellow, and green arrows in the figure correspond to the main sources of the total variances of ESO, ISU, ECE, and CEE, respectively.

Table 6 shows that the variance contribution rate of each impact variable to the response variable is basically stable after the 20th period. Fig. 7 shows that, except for the ECE in the central region, the ESO, ISU, ECE, and CEE of the whole country and other regions strongly coordinate with themselves, which shows that they have development inertia.

The variance decomposition of ESO shows that it is affected mainly by itself and by CEE in the whole country and the central and western regions. ESO in the eastern region is greatly influenced not only by itself and CEE but also by ECE. This result may be because the ECE of the eastern region is relatively high, so the promotion of ESO is obvious. ISU is influenced mainly by the optimization of the energy structure and itself in the whole country. From east to west, CEE has a greater impact on industrial structure upgrading. Except for the western region, industrial structure upgrading is affected mainly by itself and CEE. The reason may be that the development of the western region focuses on primary industries including agriculture and mining, meaning CEE has a great influence on industrial structure upgrading.

According to the variance decomposition results of ECE, ECE in the eastern region is less affected by ISU, indicating that the inertia of economic growth in the eastern region is strong. At this stage, the adjustment of the industrial structure has not been fully transformed into a direct driving force for the improvement of ECE, and there is a certain blockage in the transmission mechanism between the two. Except for the central region, ECE in other regions has a significant effect on their own future development, suggesting that the economic development at the eastern, western, and national levels has strong path dependence characteristics. This phenomenon reflects the persistence of the inherent patterns formed in the development process of the economic system.

The variance decomposition of CEE reveals that in the national and western regions, CEE is influenced mainly by itself and ECE, implying that the mode of economic growth significantly shapes carbon emission efficiency. In the process of economic development, the western region has not

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Table 6. Variance decomposition results.

Region	Response variable	Impact variable				
		Forecast period	dlnESO	dlnISU	dlnECE	dlnCEE
National	dlnESO	10	0.9552678	0.0038464	0.0008469	0.0400389
	dlnESO	20	0.9284574	0.0037474	0.0016204	0.0661748
	dlnESO	30	0.9162509	0.0037024	0.0019752	0.0780715
	dlnISU	10	0.0961591	0.4699374	0.0095310	0.4243725
	dlnISU	20	0.0830253	0.3740849	0.0132223	0.5296674
	dlnISU	30	0.0785027	0.3410101	0.0145015	0.5659857
	dlnECE	10	0.1141067	0.0163877	0.2737032	0.5958025
	dlnECE	20	0.0865059	0.0109851	0.1903582	0.7121508
	dlnECE	30	0.0789097	0.0095176	0.1677115	0.7438611
	dlnCEE	10	0.0510413	0.0054033	0.1049977	0.8385578
	dlnCEE	20	0.0443346	0.0036329	0.0774056	0.8746270
	dlnCEE	30	0.0425303	0.0031687	0.0701682	0.8841329
Eastern	dlnESO	10	0.7137617	0.0112303	0.1225445	0.1524634
	dlnESO	20	0.7041205	0.0114516	0.1244110	0.1600169
	dlnESO	30	0.7035975	0.0115133	0.1244638	0.1604254
	dlnISU	10	0.1220190	0.7833131	0.0217876	0.0728803
	dlnISU	20	0.1262819	0.7734448	0.0228291	0.0774442
	dlnISU	30	0.1265562	0.7729465	0.0229444	0.0775529
	dlnECE	10	0 .4652240	0.0123918	0.2394931	0.2828911
	dlnECE	20	0.4648406	0 .0131088	0.2320262	0.2900244
	dlnECE	30	0.4650114	0.0131405	0.2319534	0.2898946
	dlnCEE	10	0.4075371	0.0126603	0 .2358088	0.3439938
	dlnCEE	20	0.4094047	0.0134590	0.2293094	0.3478270
	dlnCEE	30	0.4097336	0.0134822	0.2292227	0.3475616
Central	dlnESO	10	0.9027377	0.0451639	0.0185569	0.0335415
	dlnESO	20	0.5910214	0.1262639	0.0218166	0.2608981
	dlnESO	30	0.3824043	0.1794091	0.0237791	0.4144075
	dlnISU	10	0.2910618	0.2774606	0.0184827	0.4129949
	dlnISU	20	0.3400877	0.1976267	0.0235450	0.4387406
	dlnISU	30	0.3452004	0.1896144	0.0240657	0.4411196
	dlnECE	10	0.3724336	0.2427570	0.0915610	0.2932485
	dlnECE	20	0.3491377	0.1947925	0.0316460	0.4244238
	dlnECE	30	0.3460993	0.1893422	0.0248732	0.4396853
	dlnCEE	10	0.3465487	0.2100810	0.0413106	0.4020598
	dlnCEE	20	0.3459137	0.1907081	0.0257057	0.4376725
	dlnCEE	30	0.3457759	0.1889307	0.0242775	0.4410159
Western	dlnESO	10	0.8808621	0.0208664	0.0025674	0.0957040
	dlnESO	20	0.8608544	0.0206134	0.0030973	0.1154350
	dlnESO	30	0.8576110	0.0205724	0.0031832	0.1186335
	dlnISU	10	0.0752155	0.4462011	0.0072840	0.4712995
	dlnISU	20	0.0716434	0.4066507	0.0088860	0.5128199
	dlnISU	30	0.0711100	0.4007452	0.0091252	0.5190195
	dlnECE	10	0.2547024	0.0150001	0.6620641	0.0682333
	dlnECE	20	0.2496405	0.0148886	0.6473309	0.0881399
	dlnECE	30	0.2488196	0.0148705	0.6449411	0.0913688
	dlnCEE	10	0.1028662	0.0101627	0.1517977	0.7351733
	dlnCEE	20	0.0940833	0.0101649	0.1351778	0.7605740
	dlnCEE	30	0.0928384	0.0101652	0.1328219	0.7641746

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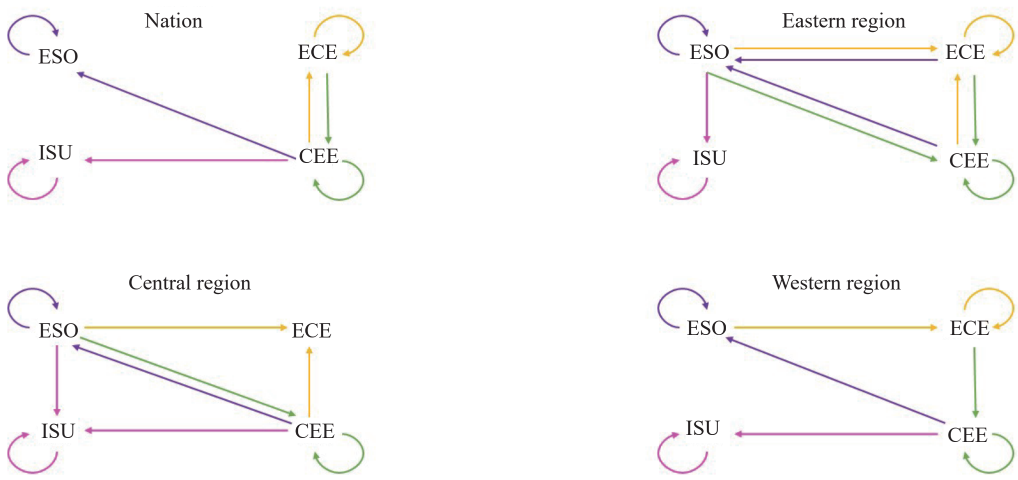

Fig. 7. Graphical representation of the results of variance decomposition.

fully broken away from the constraints of the traditional extensive growth model, where improvements in ECE are often accompanied by increased energy consumption, making it difficult to rapidly improve CEE through industrial or energy structure adjustments. In the central region, CEE is influenced primarily by itself and ESO, indicating a relatively close linkage between ESO and CEE improvement. In the eastern region, only ISU has a small effect on CEE, suggesting that although the eastern region has achieved progress in production technology and factor allocation optimization during industrial structure optimization, it has not effectively translated the achievements of industrial upgrading into comprehensive improvements in CEE. This may be due to issues such as energy utilization efficiency lagging behind industrial development speed and insufficient innovation in environmental governance technologies. It is urgent to strengthen the research and application of green and low-carbon technologies simultaneously during the process of industrial upgrading to build a new model of coordinated progress between industrial upgrading and low-carbon development.

4.7 Granger test

The Granger test is often used to evaluate whether there is a causal relationship between two time series variables. It can reveal whether a time series variable can provide prediction information about another time series variable. By examining the causality between variables, we can determine which variables should be included in the model to better explain and predict the data. Table 7 and Fig. 8 summarize the Granger causality test findings, with each arrow in the figure representing a significant Granger causality between paired variables.

As far as the whole country is concerned, ESO is a one-way Granger cause of ECE, ECE is a one-way Granger cause of CEE, and there is a two-way Granger causal relationship between the ESO and the ISU. In the eastern region, ISU and CEE are both one-way Granger paths for ESO. In the central region, both ESO and ISU are one-way Granger causes of ECE, and a two-way Granger causal relationship exists between ESO and ISU. ESO, ECE, and ISU are all one-way Granger causes of CEE. In the western region, ISU is a one-way Granger cause of ESO, and ECE is a one-way Granger cause of CEE.

Table 7. Granger test results.

Region	Effects	Causes			
		h_dlnESO	h_dlnISU	h_dlnECE	h_dlnCEE
National	h_dlnESO	\	Yes***	No	No
	h_dlnISU	Yes***	\	No	No
	h_dlnECE	Yes*	No	\	No
	h_dlnCEE	No	No	Yes***	\
Eastern	h_dlnESO	\	Yes**	No	Yes*
	h_dlnISU	No	\	No	No
	h_dlnECE	No	No	\	No
	h_dlnCEE	No	No	No	\
Central	h_dlnESO	\	Yes***	No	No
	h_dlnISU	Yes***	\	No	No
	h_dlnECE	Yes*	Yes*	\	No
	h_dlnCEE	Yes*	Yes***	Yes***	\
Western	h_dlnESO	\	Yes**	No	No
	h_dlnISU	No	\	No	No
	h_dlnECE	No	No	\	No
	h_dlnCEE	No	No	Yes***	\

"Yes" means there is causality, and "no" means the opposite. *, **, and *** denote significance at the confidence levels of 10%, 5%, and 1%, respectively. "\" indicates that a Granger test is not conducted on itself.

A comparison of Fig. 8 and Fig. 2 reveals that, except for the influence of each variable on itself, the other influence relationships are the same. This confirms the accuracy of the GMM estimation results.

5 Conclusions

On the basis of provincial panel data of China from 2010 to 2023, this paper constructs PVAR models and empirically

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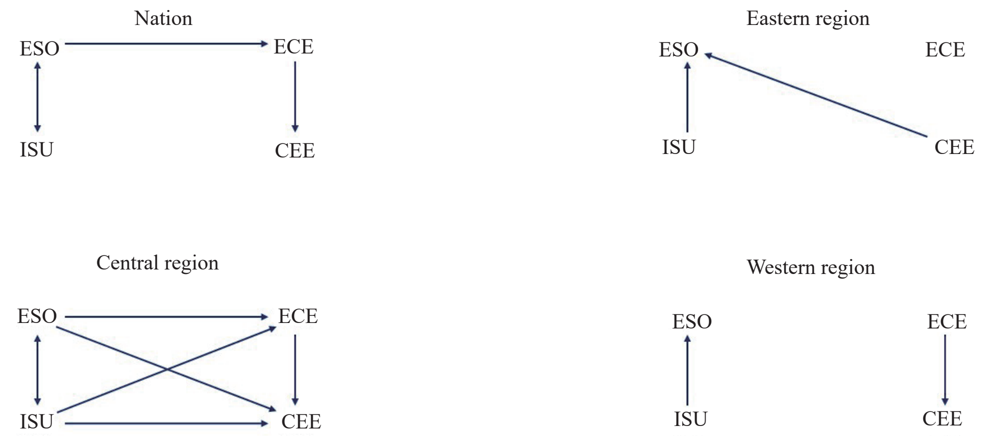

Fig. 8. Graphical representation of the Granger test results.

studies the dynamic relationships among ESO, ISU, ECE, and CEE at the national, eastern, central, and western levels. Its practical application value spans multiple dimensions including policy-making, planning, collaboration, and corporate decision-making. In terms of policy formulation, it can provide differentiated guidance for the eastern, central, and western regions; in the context of industrial and energy planning, it can guide localities to achieve collaborative development by integrating their own resources and development stages; in regional collaboration, it helps break down regional barriers and enhance the overall development efficiency among regions; and at the corporate decision-making level, it enables enterprises to flexibly adjust their industrial layouts and production methods, optimize energy utilization, strengthen regional cooperation, and thereby enhance their market competitiveness on the basis of regional development trends. The conclusions are as follows:

(Ⅰ) From a national perspective, ESO, ISU, ECE, and CEE have positive or negative effects on each other. However, in the long run, the influence between variables gradually weakens with time until it is reduced to zero, indicating that they have not formed a long-term dynamic coupling relationship.

(Ⅱ) In the eastern region, the development of ESO, ISU, ECE, and CEE has a certain economic inertia in the short term. A benign interaction between ECE and ISU has not yet been formed, and the interaction between other variables gradually weakens in the short term.

(Ⅲ) For the central region, a significant mutual influence relationship is formed among the following four aspects: ESO, ISU, ECE, and CEE. However, there is still room for improvement in the terms of influence intensity and stability among variables. In the future, it is necessary to further strengthen policy guidance and deepen the coordination mechanism.

(Ⅳ) In the western region, each variable has short-term coordination with itself, and an interactive relationship between ISU and ECE has not yet been formed. This finding indicates that the development of the western region relies on the inertia of inherent models in the short term, and an endogenous dynamic mechanism for efficient coordination between industries and the economy has not been established.

On the basis of the above conclusions, the following policy suggestions are proposed:

(Ⅰ) Eastern China should give full play to its leading economic advantage, increase investment in industrial structure upgrading, and strengthen the link between economic efficiency and industrial structure upgrading. It should also adhere to the direction of marketization, industrialization, and socialization; improve policies and measures to support the service industry; and advance its sound and rapid development.

(Ⅱ) The central region is an important grain production base, energy and raw material base, modern equipment manufacturing and high-tech industrial base, and comprehensive transportation hub in China. With that foundation, traditional industries such as modern machinery manufacturing and textile manufacturing should be developed and strengthened, the upgrading of resource-oriented industrial structure should be promoted, the green transformation and development of industrie should be promoted, and industrial intelligence should be increased, thus supporting the rise of the central region.

(Ⅲ) The western region should deepen scientific and technological innovation, encourage enterprises to increase investment in technological research and development, promote the transformation of scientific and technological achievements, and enhance the innovative driving force for economic development. Moreover, it is also essential to improve infrastructure, reduce corporate operating costs, actively undertake industrial transfer from the eastern and central regions, attract the aggregation of high-quality resources, and gradually build a virtuous interactive relationship between industrial upgrading and economic efficiency improvement.

This study is subject to several limitations. First, based on the panel data of 30 provincial-level administrative regions in China, the research only classifies the samples into the eastern, central, and western regions. It does not further downscale the research scope to prefecture-level cities and counties, and thus fails to reveal the heterogeneous interactions among variables at smaller spatial scales. Second, this paper primarily employs the PVAR model to examine dynamic relationships, which focuses on linear correlations between variables. The potential nonlinear threshold effects and spatial spillover effects among various factors are not thoroughly explored. In view of the above limitations, future

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research can be carried out in two aspects. Firstly, the spatial scale can be refined by using panel data of prefecture-level cities combined with spatial econometric models to analyze the spatial correlation characteristics of factor linkages. Secondly, interaction effect models can be introduced to further explore the nonlinear interaction rules among relevant factors. This will provide more refined theoretical support and practical references for high-quality economic development in China.

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Conflict of interest

The authors declare that they have no conflict of interest.

Biography

Linlin Zhao is an Associate Professor at Nanjing Audit University. She received her Ph.D. degree in Management Science and Engineering from the University of Science and Technology of China in 2016. Her research mainly focuses on decision optimization, energy and environmental efficiency assessment, and low-carbon economic statistics.

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