

Research on Interrelationship between Economic Growth, CO₂ Emissions, and Industrial Structure Upgrading Based on PVAR Model by Big Data Computation

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Abstract: We proposed a panel vector autoregressive (PVAR) model by big data computation for the empirical analysis of data related to the Beijing-Tianjin-Hebei region from 2003-2019. The study result shows that economic growth, CO₂ emissions, and industrial structure upgrading in the Beijing-Tianjin-Hebei region interact with each other. Specifically, economic growth reduces CO₂ emissions, and in turn, CO₂ emissions contribute to a certain extent to economic growth. Economic growth facilitates the upgrading of the industrial structure, and the advanced industrial structure also promotes economic growth, but the rationalization of the industrial structure has a limiting effect on economic growth. CO₂ emissions impede industrial upgrading and contribute to the rationalization of industrial structures in the short term, and conversely, industrial upgrading reduces CO₂ emissions. The advanced and rationalized industrial structure reinforces each other in the short term. On this basis, we propose relevant recommendations.

Keywords: economic growth, carbon emissions, industrial structure, PVAR model

1. Introduction

Since the reform and opening up, China's economy has developed rapidly and the Beijing-Tianjin-Hebei region, the third largest economic circle in China and has also seen rapid economic development. However, there are problems such as high pollution and carbon emissions, which cause environmental pressure. CO₂ emission is one of the factors that hinder rapid and sustainable economic development. At the same time, the unreasonable industrial structure may also affect CO₂ emissions as well as economic growth. Promoting the collaborative development of Beijing-Tianjin-Hebei is conducive to resolving the contradiction of the unbalanced development of China's regional economy, environment, and resources. Therefore, we explore the relationship between economic growth, CO₂ emissions, and industrial structure upgrading through the analysis of relevant data from the Beijing-Tianjin-Hebei region.

Economic growth, CO₂ emissions and industrial structure upgrading have become popular topics of research among scholars. For the study of economic growth and CO₂ emissions, Zhao et al. pointed out that there is a long-term balance relationship between CO₂ emissions and economic growth, and that CO₂ emissions and economic growth are mutually responsible [1]. For the study of economic growth and industrial structure, Feng et al. analyzed the dynamic relationship between industrial structure change, green eco-efficiency, and regional economic growth using the panel vector autoregressive (PVAR) model, indicating that economic growth has a dragging effect on industrial structure change in the short term [2]. For the study of industrial structure optimization and CO₂ emissions, Wang et al. used a broad decomposition model of decoupling elasticity to analyze indicators of decoupling industrial growth and environmental pressures in the Beijing-Tianjin-Hebei area from 1996 to 2010 [3]. In general, academics have conducted relatively mature studies on the relationship between economic growth, CO₂ emissions, and industrial structure upgrading. However, there are still many issues that deserve further exploration. On the one hand, most of the existing literature has studied the two-two relationship between economic growth, carbon dioxide emissions, and industrial structure upgrading, and there is a lack of research results that integrate the three into the same framework to explore their interrelationship. On the other hand, most of the existing literature focuses on the study of the relationship between economic growth, CO₂ emissions, and industrial structure upgrading at the national, provincial, and city levels. There is not enough research on urban agglomerations. Therefore, we establish a PVAR model based on panel data

from Beijing, Tianjin, and Hebei from 2003 to 2019, on which the dynamic relationship between economic growth, CO₂ emissions, and industrial structure upgrading is studied.

2. Model Construction and Variable Selection

2.1. Model Construction

As the PVAR model allows for both individual and time differences in effects and reflects the dynamic effects of multiple variables [4]. Therefore, we chose to adopt the PVAR model to investigate the interrelationship between economic growth, CO₂ emissions, and industrial structure upgrading. The calculation equation is as follows.

$$y_{i,t} = \beta_i + \alpha_0 + \sum_{j=1}^k \alpha_j y_{i,t-j} + v_t + u_{i,t} \quad (1)$$

where i represents different regions, t represents different years, $y_{i,t}$ is a vector containing the endogenous variables, $y_{i,t-j}$ is the j th order lag term of the endogenous variables, α_0 is a vector of intercept terms, α_j is a parameter matrix, β_i is individual heterogeneity, v_t is a time point effect responding to a time trend, $u_{i,t}$ is a random disturbance term and follows a normal distribution.

2.2. Variable Selection

2.2.1. Economic Growth

For economic growth (EG), since GDP is a key indicator of the level of economic development, and because an increase in total population also affects economic growth, GDP per capita was used in this study.

2.2.2. Carbon Dioxide Emissions

For CO₂ emissions, the consumption of fossil energy is the main cause of CO₂ emissions. Therefore, the CO₂ emissions of China can be indirectly calculated based on the consumption of fossil energy. Taking into account the usability of data and the accuracy of the calculation, we selected seven fossil energy sources such as paraffin, coke, gasoline, fuel oil, diesel, natural gas, and coal. According to the IPCC guidelines [5], combined with the number of fuels burned and the default emission factors, the calculation of calculating CO₂ emissions is as follows.

$$CO_2 = \sum_{i=1}^n E_i \times NCV_i \times CEF_i \times COF_i \times \left(\frac{44}{12}\right) \quad (2)$$

where CO_2 represents CO₂ emissions, i is the type of energy, E_i is the consumption of energy i , NCV_i is the mean low-level heat content of energy i , CEF_i is the carbon content per unit calorific value of energy i , COF_i is the CO₂ oxidation factor of energy i , and $(44/12)$ is the CO₂ gasification factor.

2.2.3. Upgrading of Industrial Structure

For the upgrading of the industrial structure, we measured it in terms of the advanced industrial structure and the rationalization of the industrial structure respectively [6].

Advanced industrial structure (AIS) refers to the process of gradual upgrading of industries from lower to higher levels. The secondary industry is mainly labor-intensive, while the third industry is mainly technology- and knowledge-intensive, so we used the proportion of the output of the third industry to the output of the second industry to measure the sophistication of the industrial structure.

Industrial structural rationalization (ISR) refers to the coordinated development of industries to enhance economic returns. Based on the accessibility of the data, the Thiel index was adopted in this paper to assess the rationalization of the industrial structure. The equation is as follows:

$$ISR = \sum_{i=1}^n \frac{Y_i}{Y} \ln\left(\frac{Y_i}{L_i} / \frac{Y}{L}\right) = \sum_{i=1}^n \frac{Y_i}{Y} \ln\left(\frac{Y_i}{Y} / \frac{L_i}{L}\right) \quad (3)$$

where ISR represents industrial structural rationalization, i is the type of industry, $\frac{Y_i}{Y}$ represents the ratio of the output of primary, secondary and third industries to the total output of the local area, and $\frac{L_i}{L}$ represents the share of employment in primary, secondary and tertiary industries in local employment. When the Thiel index becomes small, the level of industrial structure rationalization is increasing.

2.3. Data sources and Descriptive Statistical Analysis

We selected relevant data from 2003 to 2019, with energy consumption from “China Energy Statistics Yearbook”, average low-level heat generation for each type of energy taken from “General Rules for Calculating Comprehensive Energy Consumption”, the unit calorific value of carbon content, and oxidation factor of carbon from 2006 “IPCC Guidelines Catalogue for National Greenhouse Gas Inventories”, and industrial output, employment and GDP per capita from the statistical yearbooks of Beijing, Tianjin, and Hebei.

The results of the descriptive statistical analysis of the variables are illustrated in Table 1. There are significant differences between Beijing, Tianjin, and Hebei in terms of economic growth, CO₂ emissions, advanced industrial structure, and rationalization of industrial structure.

Table 1: Descriptive statistical analysis of the variables

Variable	AVG	SD	Min	Max
EG	5.91	3.70	0.94	16.18
CO2	335.72	331.10	82.99	933.28
AIS	1.96	1.43	0.753	5.23
ISR	7.04	5.69	1.49	21.85

3. Analysis of PVAR model

We adopted Stata 17 and EViews 12 for the processing and analysis of data. Using the above-mentioned models and selected variables, this paper measured the specific values of economic growth, CO₂ emissions, advanced industrial structure, and rationalizations for each province and city from 2003 to 2019, and then analyzed the dynamic relationship between economic growth, CO₂ emissions, advanced industrial structure, and rationalization of industrial structure.

3.1. Unit Root Test

Before carrying out the empirical evidence of the PVAR model, to avoid the phenomenon of pseudo-regression, the data need to be tested for smoothness. The Fisher-ADF method was applied to conduct the test. Table 2 shows the results of the unit root test. The data of three variables, namely economic growth, CO₂ emissions, and advanced industrial structure, are not smooth, and only industrial structure rationalization has a data smoothness. Thus, so we cannot directly use the variables to construct the model. Instead, these four variables are all first-order single integers, so a PVAR model can be developed for analysis by introducing the differential variables *dEG*, *dCO2*, *dAIS*, and *dISR*.

Table 2: Panel unit root test (ADF) results

Variable name	P value	Test results	Variable name	P value	Test results
EG	1.0000	unstable	<i>dEG</i>	0.0386	stable
CO2	0.8661	unstable	<i>dCO2</i>	0.0031	stable
AIS	1.0000	unstable	<i>dAIS</i>	0.0425	stable
ISR	0.0009	stable	<i>dISR</i>	0.0185	stable

3.2. Co-integration Test

Through the unit root test, we found that several variables were unstable. Therefore, we conducted a panel cointegration analysis to examine whether there is a long-run equilibrium relationship between the variables [7]. We employed the Kao test to conduct the cointegration test using EViews software and obtained a p-value of 0.0005. All variables passed the cointegration test, indicating that there is a stable equilibrium relationship between these variables over time.

3.3. Model Lag Selection

To build a PVAR model, a suitable lag order needs to be determined. The optimal lag order of the model is identified by the AIC, BIC, and HQIC criteria and is generally chosen based on the principle of the minimum value of each criterion. As shown in Table 3, the optimal lag order for the three criteria is order 1, so the PVAR(1) model is established.

Table 3: Lag order test result

Lag	AIC	BIC	HQIC
1	10.7014*	11.8599*	11.126*
2	11.0914	12.9682	11.7648
3	44.9372	47.5764	45.8583
4	50.5592	54.0057	51.7189
5	32.8223	37.1194	34.197

Note: * denotes the optimal lag order chosen for this criterion.

3.4. Robustness tests

A PVAR model with *dEG*, *dCO2*, *dAIS*, and *dISR* was developed for empirical analysis based on the examination of panel data of each factor. To ensure the validity of the subsequent impulse responses and variance decomposition, the model needs to be tested for robustness, i.e., whether the mode of the dynamic matrix eigenvalues is less than 1. Figure 1 shows that the four estimation points of the PVAR model in this paper are all within the unit circle, indicating that the PVAR model constructed in this paper is robust.

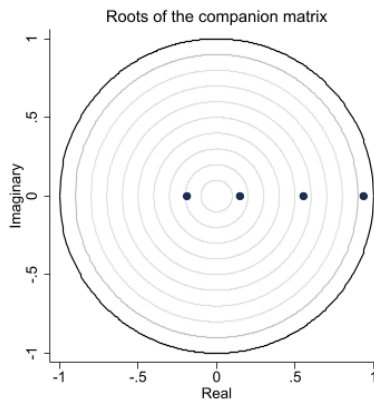


Figure 1: Test of the robustness of the PVAR model.

3.5. Impulse Response Analysis

Impulse response analysis of the PVAR model was performed to obtain the dynamic relationship between two factors while controlling for other factors [8]. The impulse response diagram between economic growth, CO2 emissions, advanced industrial structure, and industrial structural rationalization is shown in Fig. 2, where the horizontal axis indicates the number of lags and the dash represents the impulse response value of the response variable after a shock given a standard deviation of a particular shock variable.

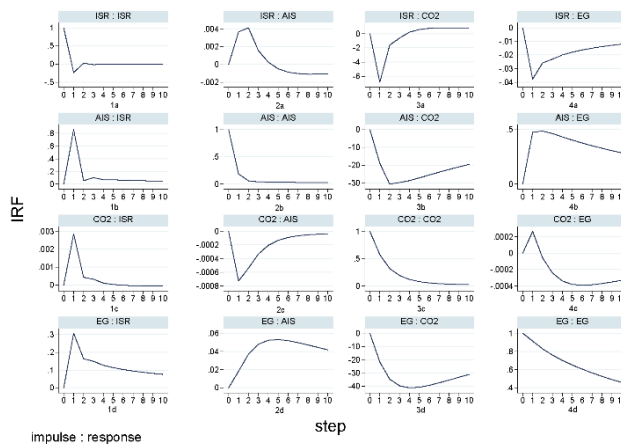


Figure 2: Impulse response chart.

As shown in Figs. (1a), (2b), (3c), and (4d), the rationalization of industrial structure, advanced industrial structure, CO₂ emissions, and economic growth all show significant positive effects in the face of shocks of one standard deviation of their own. However, this positive effect diminishes in the long term. This indicates that the variables themselves have relative economic inertia.

In Fig. 2 (2a), it is clear that faced with shocks from industrial structure rationalization, there is a positive impact on the advanced industrial structure in the first four periods. Subsequently, there is a weak negative effect. This suggests that industrial structure rationalization will promote advanced industrial structure. However, it limits the growth of advanced industrial structures in the long run. Figure 2 (3a) shows that there is a strong negative impact of industrial structural rationalization on CO₂ emissions, which suggests that it can regulate industries to achieve the effect of reducing CO₂ emissions. Figure 2 (4a) shows that the negative effect of industrial structural rationalization on economic growth is greatest in the 1st period and decreases thereafter, suggesting that it can have a dampening effect on economic growth.

Figure 2 (1b) shows that advanced industrial structure has a positive impact on the rationalization of the industrial structure, with the greatest contribution in the 1st period, and then a decreasing contribution. This indicates that it is conducive to the rationalization of the industrial structure. Figure 2 (3b) indicates that the negative effect of advanced industrial structure on the growth of CO₂ is still significant until the 10th period, indicating that it can effectively reduce CO₂ emissions. In Fig. 2 (4b), there is a positive impact of advanced industrial structure on economic growth, which weakens in the later stages. This suggests that advanced industrial structure will always contribute to economic growth, but a different extent in different periods.

Figure 2 (1c) presents that when faced with the impact of CO₂, the industrial structural rationalization increases to a certain extent and then gradually decreases to no effect, which indicates that CO₂ emissions do not have a significant impact on the rationalized industrial structure for a long time. Figure 2 (2c) indicates that the response value of the advanced industrial structure is always negative, indicating that CO₂ emissions are a barrier to advanced industrial structure. Figure 2 (4c) shows that the economic growth response reaches a maximum in the 1st period, decreases to zero in the 2nd period, and then remains significantly negative, indicating that CO₂ emissions contribute to economic growth in the short run. However, it hinders economic growth in the long term.

The reaction of industrial structural rationalization to economic growth is positive and increases before it decreases (Fig. 2 (1d)). This suggests that economic growth contributes to a certain extent to the growth of industrial structural rationalization. Figure 2 (2d) shows that the response of advanced industrial structures also increases and then decreases. Figure 2 (3d) indicates that there is a large negative effect of economic growth on CO₂ emissions, which suggests that economic growth contributes to a reduction in CO₂ emissions.

3.6. Variance decomposition

The variance decomposition method enables the analysis of the strength of the contribution of each variable to the shocks in the change process. Table 4 shows the degree of contribution of economic growth, CO₂ emissions, advanced industrial structure, and industrial structural rationalization to the impact of CO₂ emissions in the first 10 periods.

Table 4: Variance decomposition results from CO₂ emissions.

Forecast horizon	Impulse variable			
	EG	CO ₂	AIS	ISR
1	0.0001104	0.9998896	0	0
2	0.0321361	0.9294773	0.003715	0.0346717
3	0.0868791	0.8710771	0.0103387	0.0317051
4	0.1473336	0.8085886	0.0152503	0.0288275
5	0.2028502	0.7516592	0.0189852	0.0265055
6	0.2499221	0.7034793	0.0217687	0.0248299
7	0.2885388	0.6639523	0.0238808	0.0236282
8	0.3198967	0.6318469	0.0255134	0.022743
9	0.3453673	0.6057625	0.0267994	0.0220709
10	0.366157	0.5844674	0.0278294	0.0215461

Table 4 reveals that CO₂ emissions are influenced by two main sources firstly from CO₂ emissions

and secondly from economic growth. The impact of CO₂ emissions is 99.99% in the 1st period and then decreases to 58.45% in the 10th period. The impact of economic growth is weak in the 1st period. However, it gradually increases from the 2nd period until it reaches 36.63% in the 10th period. The influence of advanced industrial structure and industrial rationalization on CO₂ emissions is relatively weak compared to the other two factors at 2.78 and 2.15% by the 10th period.

4. Conclusions and Recommendations

4.1. Conclusions

The PVAR model between economic growth, CO₂ emissions, and the upgrading of industrial structure in the Beijing-Tianjin-Hebei region were constructed in this study. Furthermore, we analyzed the dynamic relationship between them by using impulse response function and variance decomposition. Finally, we reached the following conclusions.

In the short term, economic growth greatly reduces CO₂ emissions, and CO₂ emissions, to a certain extent, contribute to economic growth. However, in the long term, economic growth always has a hindering effect on CO₂ emissions, and CO₂ emissions also hinder economic development. At the same time, there is a stronger effect of economic growth on CO₂ emissions.

Economic growth and advanced industrial structure reinforce each other. Among the factors driving the growth of the advanced industrial structure, economic growth dominates. Economic growth is conducive to the rationalization of industrial structure. However, there is a limiting influence of the rationalization of industrial structure on economic growth.

CO₂ emissions hinder advanced industrial structures in the same way that the advanced industrial structure reduces CO₂ emissions. CO₂ emissions benefit the rationalization of the industrial structure in the short term. However, there is a limiting influence in the long term. In addition, the rationalization of the industrial structure reduces CO₂ emissions in the short run. However, in the long run, this effect will disappear.

The advanced industrial structure and the rationalization of the industrial structure can be mutually conducive in the short term. However, the influence of the advanced industrial structure on the rationalization of industrial structure disappears in the long run. More importantly, the rationalization of industrial structure may hinder the development of the advanced industrial structure.

4.2. Recommendations

The empirical results showed that economic growth, CO₂ emissions, advanced industrial structure, and rationalization of industrial structure influence each other. The following recommendations are proposed in light of the above findings.

Energy efficiency and emission reduction policies can contribute to the economic growth of the Beijing-Tianjin-Hebei region from an economic growth aspect. Therefore, the policy of energy saving and emission reduction needs to be promoted to reduce CO₂ emissions. In terms of CO₂ emissions, advanced industrial structure and rationalization of the industrial structure reduces CO₂ emissions. Optimizing the industrial structure and changing the reliance on the secondary industry can reduce CO₂ emissions, too. Therefore, we must vigorously develop environment-friendly and green-driven low-carbon industries. As far as the upgrading of the industrial structure is concerned, efforts need to be made to promote economic growth to make it possible to improve the advanced industrial structure. When carrying out the rationalization of the industrial structure, factors of economic growth at the time need to be taken into account. At the same time, it is important to take care of the appropriate rationalization of the industrial structure to avoid hindering the advanced industrial structure from proceeding.

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References

- [1] Zhao A. W., and Li D. Co-integration and causal relationship between carbon emissions and economic growth in China [J]. *Resources and Environment in the Yangtze Basin*, 2011,20(11): 1297-1303. (In Chinese)
- [2] Feng X.M., and Zhang R.M. Industrial structure transformation, green eco-efficiency and regional economic growth [J]. *Statistics & Decision*, 2021,37(21): 104-109. (In Chinese)
- [3] Wang Z. H., and Yang L. Delinking indicators on regional industry development and carbon emissions: Beijing–Tianjin–Hebei economic band case [J]. *Ecological Indicators*,2015,48: 41-48.
- [4] Wang J., Rickman D., and Yu Y. H. Dynamics between global value chain participation, CO2 emissions, and economic growth: Evidence from a panel vector autoregression model [J]. *Energy Economics*, 2022, 109(105965):1-20.
- [5] Zhou D., and Wang X.Q. Research on coupling degree and coupling path between China's carbon emission efficiency and industrial structure upgrade [J]. *Journal of Natural Resources*, 2019, 34(11):2305-2316. (In Chinese)
- [6] Feng X. M., Yin Q., and Zhang Y. F. Research on Coupling Relationship between Sci-tech Finance and Industrial Structure Upgrading in China[J]. *Science and Technology Management Research*, 2022, 1(1):79-85. (In Chinese)
- [7] Onofrei M., Vatamanu A. F., and Cigu E. The Relationship between Economic Growth and CO2 Emissions in EU Countries: A Cointegration Analysis [J]. *Frontiers in Environmental Science*, 2022, 10(934885): 1-11.
- [8] Cheng T. J., and Da Y. J. Income Balance, Carbon Emissions and Economic Growth [J]. *Soft Science*, 2022, 36(3): 68-74. (In Chinese)