ISSN 2616-7433 Vol. 4, Issue 3: 49-56, DOI: 10.25236/FSST.2022.040310

# Study on the Impact of Industrial Structure on Carbon Emissions in Sichuan Province -- Empirical Analysis Based on VAR Model

**Qianxin Ye**

*Chengdu University of Technology, Chengdu, Sichuan, China*
*2771394990@qq.com*

***Abstract:*** *This paper analyses the dynamic relationship between industrial structure and carbon emissions in Sichuan Province using VAR models, using data on industrial structure and 8 carbon emissions of major energy consumption in Sichuan Province from 2001-2018. The results of the study show that in the short term, the advanced industrial structure will suppress the growth of carbon emissions, and the change in industrial structure, i.e., the increase in the share of secondary industry, will lead to an increase in carbon emissions; in the long term, the optimization of industrial structure has a significant impact on carbon emissions and specifically shows a suppressive effect. Therefore, in the short term, upgrading the industrial structure will not immediately reduce carbon emissions, but in the long term, adjusting the industrial structure is an important measure to reduce carbon emissions. In order to develop a low-carbon economy and accelerate the construction of a "clean energy demonstration province", Sichuan Province needs to optimise and upgrade its industrial structure, and specific measures are suggested, including: strengthening the role of regional radiation and promoting the balanced development of industries between regions; making full use of the province's human resources, increasing investment in research and development, and creating an important industrial cluster in China; strengthening the cooperation between Chengdu and Chongqing to promote the transformation and upgrading of the industrial structure.*

***Keywords:*** *Sichuan Province; Carbon Emissions; Industrial Structure; VAR Model*

## 1. Introduction

In recent years, climate change has posed a huge challenge to the development of human society. Due to the increase in energy consumption caused by economic development and urbanisation, China's carbon emissions have continued to rise [1] rapidly in the past two decades. China is currently in a critical period of economic and ecological development and faces a serious challenge [2] in reconciling economic growth with the reduction of carbon emissions. Against this backdrop, China has clearly proposed that carbon dioxide emissions will peak 2030by the end of the year and that carbon neutrality will be achieved 2060by the end of the year. Sichuan Province continues to have a high-carbon energy consumption pattern throughout the year, and although it is an important high-quality clean energy base in China, there is still enormous pressure on economic and social development and the ecological environment due to unreasonable energy consumption. With the construction of the Chengdu-Chongqing twin-city economic circle rising as a national strategy, Sichuan Province will become one of the components forming an important growth pole for high-quality regional development, which also provides new impetus and goals for Sichuan Province to carry out industrial structure upgrading. Therefore, it is important to analyse the dynamic relationship and impact of industrial structure and its advancement with carbon emissions in Sichuan Province, to explore the potential of carbon emission reduction in Sichuan Province, and to propose pathways for upgrading the industrial structure in Sichuan Province, in order to build the Chengdu-Chongqing twin-city economic circle and to achieve China's dual carbon goals.

### *1.1. Review of the literature*

In general, the existing studies on carbon emission reduction factors at home and abroad have focused on industrial and energy structures, economic growth, technological progress, population size and other socio-economic factors [3-4], and many scholars have applied various methods to analyse [5-6] them qualitatively and quantitatively. Among them, industrial structure has been widely regarded as the main

ISSN 2616-7433 Vol. 4, Issue 3: 49-56, DOI: 10.25236/FSST.2022.040310

grip [7]and important influencing factor [8] for regional carbon emission reduction.

In the research on the relationship between industrial structure and carbon emissions, the academic community has mainly argued that industrial structure is one of the important factors influencing carbon emissions, and the analysis methods include log-average diagram (LMDI) decomposition [9], input-output method [10] and driver analysis [11] including regional heterogeneity [12]. Firstly, as most of the secondary industries are energy-intensive sectors, the dependence of economic development on energy and resource consumption will gradually decrease[13] in the process of optimising and upgrading the industrial structure to tertiary industries such as the service sector; at the same time, the upgrading of the industrial structure can also promote more efficient allocation and use of production factors, accelerating the transformation[14] of the economy and society into a green society.

At the same time, the concept of industrial structure change is broader, and there are other evaluation perspectives and methods such as rationalisation, advanced and imbalance levels in addition to proportions. In early studies on the proportional relationship between the three major industries, Liu lancui (2007) [15], Yu Yihua et al. (2011) [16], Zhang zhixin (2011) [17]and Li Jian and Zhou Hui (2012) [18] have found that the scale ratio of the secondary industry shows a positive impact on carbon emissions and is the main factor influencing carbon emissions. Specifically, Li Jian and Zhou Hui (2012) conducted an in-depth study on the correlation between carbon emission intensity and the three major industries in China [18] using grey correlation analysis, and found that the secondary industry is the main factor influencing carbon emissions, and that the correlation between the secondary industry and carbon emission intensity is the largest in 16one of the regions in China.

Combined with the existing literature, scholars at home and abroad have researched the relationship between industrial structure and carbon emissions in various aspects, but the current research on carbon emissions is less specific to a particular province, especially in Sichuan Province, and mostly from a national or global perspective, and there are fewer studies that combine the advanced industrial structure and carbon emissions, while the research on industrial structure and its advanced impact on carbon emissions The results may vary depending on the regions chosen. Based on this, this paper examines the relationship between industrial structure and its advancedization and carbon emissions in Sichuan Province using VAR models based on industrial structure and energy consumption data from 2001-2018, with a view to providing references and suggestions for energy conservation and emission reduction, improving ecological and environmental quality, and helping to achieve the national double carbon goal in Sichuan Province.

## 2. Empirical Analysis

### *2.1. Indicators and methods*

#### *2.1.1. Construction of the econometric model*

Firstly, this paper studies the impact of industrial structure on carbon emissions in Sichuan Province. In order to better illustrate the specific impact and differences between the 20182-year001 industrial structure of Sichuan Province and its advancement on carbon emissions, a VAR model is established and an econometric empirical study is conducted using data on carbon emissions in Sichuan Province from 2001-2018.

(1) Introduction to vector autoregressive (VAR) models

The VAR model is an unstructured multi-equation model proposed by Christopher Sims in 1980 year. The basic form of the model is:

$$Y_t = \alpha + \sum\nolimits_{1}^{p} \beta_i Y_{t-i} + \varepsilon_i$$

Of these, the$E(\varepsilon_i) = 0, E(\varepsilon_i, Y_{t-i}) = 0, i = 1,2,\cdots,p$; $Y_{t-1}$ , is$(n \times 1)$ a linear stochastic process with homoskedasticity and smooth variance consisting of vectors, and$\beta_i$ is the$(n \times n)$ the coefficient matrix of$Y_{t-i}$ is the$Y_t$ the vector of$i$ lagged variables of order, and$\varepsilon_i$ is a random perturbation term that satisfies the classical assumption of zero mean, homoskedasticity and no autocorrelation.

The VAR model can study the dynamic development of the relationship between variables and solve the problems of estimation errors caused by the endogeneity of variables. The model analyzes the short-run and long-run dynamic relationship between two or more interrelated time series variables according to the relevant statistical properties of the variables, which goes beyond the basic economics research theoretical framework and also provides empirical support and validation basis for its development. Therefore, this paper chooses to use a VAR model to study the impact of industrial structure and its sophistication on carbon emissions in Sichuan Province.

#### *2.1.2. Data processing and description of indicators*

This paper studies the impact of industrial structure and its advancedization on carbon emissions in Sichuan Province from 2001 to 2018, with data from the China Energy Statistical Yearbook and the Sichuan Statistical Yearbook. For the selection of indicators in this paper, we choose carbon emissions (Y), industrial structure advanced ($X_1$), industrial structure ($X_2$). In terms of the selection of variables, considering the possible heteroskedasticity and multicollinearity of time series data, this paper takes a logarithmic treatment of the carbon emission data of Sichuan Province, which is denoted as $lnY$ The advanced industrial structure is denoted as $X_1$ The industrial structure is denoted as $X_2$ .

(1) Accounting for carbon emissions in Sichuan Province, the explanatory variable

There are currently no official statistics on carbon emissions in China, so this paper takes a reasonable measurement approach to carbon emissions calculation. Currently, the common measurement method is the product of activity level and emission factors. In this paper, we refer to the 2-year006 IPCC National Greenhouse Gas Guidelines and choose the IPCC default emission factors for carbon emission measurement (Table 1).

$$CB = \sum_{i=1}^{n}(E_i \times \delta_i), \text{ and}$$

Where: CB is carbon emissions.$E_i$ is the amount of$i$ consumption of the energy category.$\delta_i$ is the$i$ is the carbon emission factor of the energy category.

*Table 1: Carbon emission factors for various types of energy*

| Fuels Type | Default carbon content/ (kgC/GJ) | Average low level heat generation/ (KJ/kg-$m^3$) | Carbon emission factor/ (kgC/kg-$m^3$) |
|---|---|---|---|
| Raw Coal | 25.8 | 20908 | 0.53943 |
| Coke | 29.2 | 28435 | 0.83030 |
| Crude Oil | 20.0 | 41816 | 0.83632 |
| Petrol | 18.9 | 43070 | 0.81402 |
| Paraffin | 19.6 | 43070 | 0.84417 |
| Diesel | 20.2 | 42652 | 0.86157 |
| Fuel oil | 21.2 | 41816 | 0.88232 |
| Natural gas | 15.3 | 38931 | 0.59564 |

(2) Explanatory variables

① Advanced industrial structure ($X_1$): The advanced industrial structure is a specific measure of the optimisation of industrial structure, also known as the advanced industrial level, and to a certain extent can measure the upgrading of industrial structure. In this paper, the proportion of tertiary and secondary industries in Sichuan Province is used to indicate the advanced industrial structure, and this proportion can better judge whether the industrial structure has truly achieved the advanced industrial structure.

② Industrial structure ($X_2$): Industrial structure refers to the share of each industry in all industries, and this paper uses the share of secondary industry output in each region's annual GDP to reflect the industrial structure.

### *2.2. Empirical Results and Analysis*

#### *2.2.1. Relevance analysis*

*Table 2: Data description and statistical description of the variables*

| Variable name | Variable name | Average value | Standard deviation | Mini-mum value | Maximum value |
|---|---|---|---|---|---|
| $lnY$ | Logarithm of carbon emissions | 8.87 | 0.32 | 8.11 | 9.21 |
| $X_1$ | Advanced industrial structure | 0.99 | 0.18 | 0.79 | 1.40 |
| $X_2$ | Industrial structure | 0.42 | 0.04 | 0.37 | 0.48 |

Based on the data of carbon emissions in Sichuan Province for 2-2001018 years, statistical descriptive and correlation analysis of the relevant variables was carried out using Eviews software. The mean value of carbon emission LNY is 8.87, the minimum value is8.11 and the maximum value is 9.21. The mean value of X1 is 0.99, the minimum value is 0.79 and the maximum value is 1.40. The analysis of this result shows that the change in industrial structure is more advanced. The mean value of X2 is 0.42, the minimum value is 0.37 and the maximum value is 0.48.

At the same time, by using the software to correlate the variables, the results are presented in the table3 below. From the correlation results it is possible to obtain the industry advanced ($X_1$) and the logarithm of carbon emissions ($lnY$) has a correlation coefficient of -0.31, which indicates that industrial upgrading and carbon emissions are mutually suppressive. The correlation between industrial structure ($X_2$) and the logarithm of carbon emissions ($lnY$) The correlation coefficient between industrial structure ($X_2$) and the logarithm of carbon emissions ($lnY$) is 0.75. This result indicates that the industrial structure, i.e. the share of secondary industries and carbon emissions are mutually reinforcing.

*Table 3: Correlation coefficients of variables*

| | LNY | X1 | X2 |
|---|---|---|---|
| LNY | 1.00 | -0.31 | 0.75 |
| X1 | -0.31 | 1.00 | -0.84 |
| X2 | 0.75 | -0.84 | 1.00 |

### *2.2.2. Stability check*

In order to avoid the pseudo-regression phenomenon of the series, the smoothness characteristics of all variables must be checked before building the model, this paper chooses the unit root test (ADF) to test the smoothness of the data series, the results obtained are shown in the table4, the results3 show that the results of the variables at the level of order show that all are not smooth, that is, it is confirmed that The results show that all the variables are non-stationary at level order, i.e. confirming the existence of unit roots for X1, X2 and $lnY$. Therefore, further differential first order processing was performed. The non-stationary variables were processed using the difference method and the differenced variables were expressed as first order lny, first order X1, first order X2. The ADF unit root test was continued and the results are shown in the table below. From the p-value data of the differenced data in the table below, we can see that they all reject the original hypothesis at the confidence level of 5%, i.e.3 the series are all first order single integer smooth series. At this point, the first-order difference series of each variable are all smooth series, so $lnY$, X1, X2 are all first-order single integer series.

*Table 4: Results of unit root tests for variables*

| | adf t-Statistic | Prob.* | Stability |
|---|---|---|---|
| lny | -2.55372 | 0.1224 | non-stationary |
| First order lny | 0.0445 | 0.0008 | Stable |
| x1 | -2.45491 | 0.1438 | non-stationary |
| First order x 1 | -3.82617 | 0.0138 | Stable |
| x2 | -0.3686 | 0.5355 | non-stationary |
| First order x2 | -3.94723 | 0.0391 | Stable |

### *2.2.3. Cointegration test*

Testing for cointegration is the second step in constructing a regression model. A regression model can only be applied when there is a cointegrating relationship between the variables, which means that there is a long-term stable equilibrium relationship between those variables being tested. The Johansen cointegration test is used here to verify the existence of cointegration between DLNY, DX1 and DX2 after processing. Before conducting the cointegration test, the optimal lag order of the model is determined. It is generally accepted that the smaller values of FPE, AIC and SC for multiple regression models of different orders are reasonable regression models. From the table below, it can be seen that at the 5% test level, there is a long-term stable cointegration relationship between DLNY, DX1 and DX2, which means that there is a stable equilibrium relationship between the variables DLNY, DX1 and DX2, and therefore their dynamic relationship can be analysed using the VAR model.

*Table 5: Johansen co-integration test results*

| Original assumptions | Eigenvalue | Trace statistics | 5 % significance level | Maximum feature statistics | 5 % significance level |
|---|---|---|---|---|---|
| No co-integration | 0.803040 | 31.43669 | 29.79707 | 33.93627 | 21.13162 |
| R=1 | 0.375183 | 7.065353 | 15.49471 | 8.782059 | 14.26460 |
| R=2 | 0.000727 | 0.010911 | 3.841466 | 1.227432 | 3.841465 |

ISSN 2616-7433 Vol. 4, Issue 3: 49-56, DOI: 10.25236/FSST.2022.040310

***2.2.4. Empirical results of the VAR model***

(1) Unit circle test

The results of the information criterion showed that two lags were selected as the VAR model condition. To further verify the robustness of the vector autoregressive model, a unit circle test was made to test the stability of the model and the model was found to be stable with all roots of the equation having their inverse within the unit circle. The results of the stability test for this model are shown in the figure.1

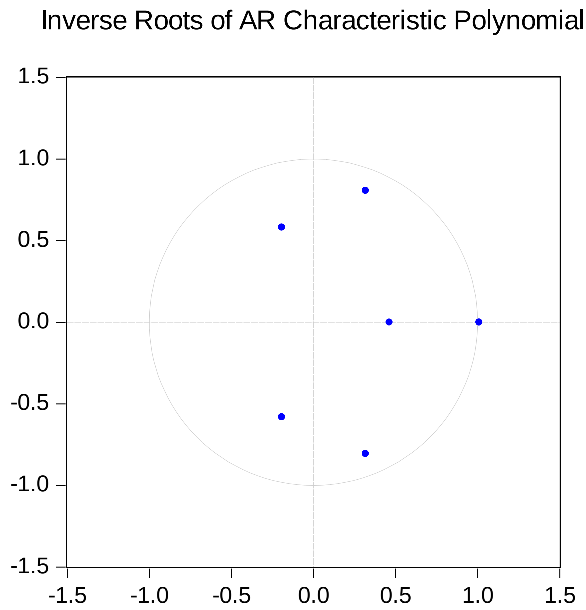


*Figure 1: Unit circle test*

(2) Vector autoregressive model analysis

In order to demonstrate in detail the effect of industrial structure and its advanced on the variables related to carbon emissions, this paper designs a VAR regression model with carbon emission indicators as the explanatory variables and industrial structure as the explanatory variable. The model is designed to demonstrate the effect of industrial structure on carbon emissions and other related variables. The regression results of the VAR model are shown in the table below, and the results of the model regressions used are as follows. The VAR model is an analysis of the regression results demonstrating the specific impact of industrial structure on carbon emissions.

From the results of the vector autoregression in the table below, the coefficient on lagged one-period DLNY is0.441, which means that lagged one-period DLNY is contributing to the variable DLNY. In other words, for every one unit change in lagged one-period DLNY, the current period DLNY changes0.441 by one unit. The coefficient of lagged second period DLNY is -0.387, which means that lagged second period DLNY has a depressing effect on the variable DLNY. In other words, for every unit change in DLNY in the second period, the current period DLNY changes by 0.387one unit in the opposite direction. The coefficient of the lagged one-period DX1 is0.657, i.e. it means that the lagged one-period DX1 is contributing to the variable DLNY. In other words, for every one unit change in lagged DX1, the current period DLNY changes0.657 by one unit. The coefficient on lag 2 DX1 is -2.557, which means that lag 2 DX1 has a depressing effect on the variable DLNY. In other words, for every one unit change in lagged DX1, the current period DLNY changes by 2.557one unit in the opposite direction. The coefficient 2of the lagged one-period DX is5.147, i.e. it means that the lagged one-period DX1 is contributing to the variable DLNY. In other words, for every one unit change in lagged DX2, the current period DLNY changes5.147 by one unit. The coefficient 2of lagged second-period DX is -8.858, which means that lagged second-period DX2 has a depressing effect on the variable DLNY. In other words, 2for every one unit change in lagged DX, DLNY changes by 8.858one unit in the current period. Therefore, it can be concluded from the analysis that the advanced industrial structure and the optimisation and upgrading of the industrial structure in Sichuan Province have an impact on carbon emissions, which may show a facilitating effect in the short term, but a specific inhibiting effect in the long term.

ISSN 2616-7433 Vol. 4, Issue 3: 49-56, DOI: 10.25236/FSST.2022.040310

*Table 6: Vector autoregression results*

| | DLNY |
|---|---|
| DLNY(-1) | 0.441329 |
| | (0.17394) |
| | [ 2.53719] |
| DLNY(-2) | -0.387738 |
| | (0.19479) |
| | [-1.99049] |
| DX1(-1) | 0.657091 |
| | (0.98633) |
| | [ 0.66620] |
| DX1(-2) | -2.557831 |
| | (0.94936) |
| | [-2.69426] |
| DX2(-1) | 5.147367 |
| | (3.21830) |
| | [ 1.59941] |
| DX2(-2) | -8.858793 |
| | (3.34917) |
| | [-2.64507] |
| C | 0.050044 |
| | (0.02595) |
| | [ 1.92876] |

Note: Standard error in (), t-statistic in [].

### *2.2.5. Granger's causality test*

The Granger causality test is an effective way to determine whether there is a causal relationship between the variables, so further Granger causality tests need to be carried out on DLNY, DX1 and DX2. The results of the Granger causality test for DLNY, DX1 and DX2 are shown in the table below.

*Table 7: Granger causality test*

| Original assumptions | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DX1 does not Granger Cause DLNY | 15 | 5.57182 | 0.0237 |
| DLNY does not Granger Cause DX1 | | 2.14927 | 0.1673 |
| DX2 does not Granger Cause DLNY | 15 | 4.96495 | 0.0318 |
| DLNY does not Granger Cause DX2 | | 2.04727 | 0.1798 |

From the results of the Granger causality test for DX1 in the table we get Prob=0.0237, which indicates that at the confidence5 % level the original hypothesis DX1 variable is not variable DLNY Granger causality is rejected, this result indicates that DX1 is Granger causality affecting the change in DLNY. Similarly it can be shown that by rejecting the original hypothesis that the DX2 variable is not variable DLNY Granger causality at the % confidence5 level, DX2 is Granger causality affecting DLNY changes. However, conversely, DLNY is not Granger causality affecting the changes in DX1 and DX2. This shows that the optimisation of industrial structure in Sichuan Province affects the carbon emissions in Sichuan Province.

## 3. Conclusions and Recommendations

This paper constructs a VAR model between industrial structure and its advanced and carbon emissions in Sichuan Province from 2001 to 2018, and analyses the dynamic relationship between them in conjunction with Granger causality tests to draw the following conclusions.

(1) There is a long-term stable equilibrium relationship between the industrial structure and its advancement and carbon emissions in Sichuan Province. Even though there may be fluctuations between the industrial structure and carbon emissions in the short term, there is an equilibrium relationship between them in the long term.

(2) There is a strong correlation between the industrial structure of Sichuan Province and its upgrading and carbon emissions. In the short term, the increase in carbon emissions will be suppressed by the upgrading of the industrial structure, but the increase in the share of the secondary industry will lead to

ISSN 2616-7433 Vol. 4, Issue 3: 49-56, DOI: 10.25236/FSST.2022.040310

an increase in carbon emissions; in the long term, the optimisation of the industrial structure will have a significant impact on carbon emissions, specifically in the form of a suppression effect. This suggests that the optimisation and upgrading of the industrial structure of Sichuan Province has an important role to play in controlling and reducing carbon emissions.

(3) There is a one-way dynamic relationship between industrial structure and carbon emissions. In the short term, upgrading the industrial structure does not immediately reduce carbon emissions, while in the long term, restructuring and upgrading the industrial structure is an important measure to reduce carbon emissions. However, the results of this paper show that there is no significant influence of carbon emissions on the optimisation and upgrading of industrial structure in Sichuan Province in the short and long term.

According to the above conclusions, industrial structure is an important factor affecting carbon emissions; in the context of the structural transformation of the national economy and the construction of the Chengdu-Chongqing twin-city economic circle, the following measures can be taken when Sichuan Province carries out the adjustment and transformation of its industrial structure.

(1) Strengthen the role of regional radiation and promote the balanced development of inter-regional industries. Firstly, as the construction of the Chengdu-Chongqing twin-city economic circle is one of the major national strategies, Sichuan Province, especially Chengdu City, should actively integrate into the Chengdu-Chongqing twin-city economic circle and strengthen the efforts of the core city in radiating the development role of the surrounding cities. Secondly, focus on the construction work in the neighbouring areas such as Deyang, Meishan and Ziyang. Make use of the region's own industrial advantages, deeply explore the development potential of local advantageous characteristic industries, differentiate development between regions while strengthening industrial synergy cooperation between regions, guide enterprises to reasonably allocate resources in the region, while the government should increase policy support to create a new engine for regional economic growth. Chengdu and Chongqing should strengthen exchanges and cooperation, form heterogeneous industrial chains and complementary industrial cooperation relationships, build advantageous characteristic industrial parks together, and use this development opportunity to promote the transformation and upgrading of industrial structures.

(2) Make full use of Sichuan's talent resources and increase innovation and research and development. Sichuan is a large education province with many universities and rich resources of high-end talents. Therefore, Sichuan Province should increase innovation, strengthen the combination of schools and enterprises, look for new dynamic energy and new opportunities for economic development, seize the opportunity of the integration of information technology and manufacturing technology, vigorously develop the smart manufacturing industry, and devote to the development of an important smart manufacturing industry cluster in China. The secondary industry in Sichuan Province is relatively deficient in terms of scientific and technological innovation output and financial investment. As a large economic province in the southwest, the key to the industrial transformation and development of Sichuan Province is to increase the investment in scientific and technological research and development, bring into play the spatial agglomeration effect of high-tech industries, and form a regional industrial ecosystem for green development.

(3) Optimise energy structure and improve energy efficiency. Most cities in Sichuan province have high carbon emission secondary industries as their pillar industries, relying on traditional high energy consumption energy, but Sichuan province has the advantage of high quality clean energy, so in the future, the proportion of clean energy and renewable energy use should be increased, the energy utilisation rate of high energy consumption enterprises should be improved, and traditional manufacturing industries should be guided to optimise and expand into new service industries, so as to effectively control the generation and growth of carbon emissions at the source.

**References**

*[1] Gao Jixi, Hou Peng, Zhai Jun, Chen Yan, Gao Haifeng, Jin Dodu, Yang Min. Taking the opportunity of achieving the "double carbon target" and enhancing the double cycle to vigorously promote the high-quality development of China's economy [J]. China Development, 2021, 21(S1): 47-52. DOI:10.15885/j.cnki.cn11-4683/z.2021.s1.006.*

*[2] Wu Yiqing, Yao Lianqian. Evaluation of China's provincial economic growth mode based on carbon productivity [J]. Journal of Hebei University of Economics and Business, 2021, 42(04): 67-73. DOI: 10.14178/j.cnki.issn1007-2101.20210701.005.*

ISSN 2616-7433 Vol. 4, Issue 3: 49-56, DOI: 10.25236/FSST.2022.040310

*[3] Hara Lulu, Xi Qiangmin, Sun Tieshan, Li Guoping. The impact of industrial structure on regional carbon emissions--an empirical analysis based on multi-country data [J]. Geography Research, 2016, 35(01): 82-94.*

*[4] Wang Zhao, Wang Lianghu. Research on the relationship between R&D input, industrial structure upgrading and carbon emission [J]. Industrial Technology Economics, 2019, 38(05): 62-70.*

*[5] Shaojian Wang, Guangdong Li, Chuanglin Fang. urbanization, economic growth, energy consumption, and* $CO^2$ *emissions: Empirical evidence from countries with different income levels [J]. Renewable and Sustainable Energy Reviews. 2018*

*[6] Ma Huiqiang, Liu Jiale, Gong Zhigang. Measurement of carbon emissions from tourism traffic and its evolution mechanism in Shanxi Province [J]. Economic Geography, 2019, 39(04): 223-231. DOI: 10.15957/j.cnki.jjdl.2019.04.027.*

*[7] Xu Chenglong, Ren Jianlan, Gong Canjuan. Impact of industrial restructuring on carbon emissions in Shandong Province [J]. Journal of Natural Resources, 2014, 29(02): 201-210.*

*[8] Zhao Yuhuan, Li Hao, Liu Ya, Cao Ye, Zhang Zhonghua, Wang Song. Beijing-Tianjin-Hebei* $CO^2$ *Study on the spatial and temporal differences of emissions and influencing factors [J]. Resource Science, 2018, 40(01): 207-215.*

*[9] Gu A-Lun, He Chong-Kai, Lu C-Q. Analysis of the impact of industrial structure changes on carbon emissions in China based on LMDI method [J]. Resource Science, 2016, 38(10): 1861-1870.*

*[10] Gao Jing, Liu Guoguang. Measurement, decomposition and allocation of power and responsibility of implied carbon emissions in global trade-a comparison based on single-region and multi-region input-output methods [J]. Shanghai Economic Research, 2016(01): 34-43+70. doi: 10.19626/j.cnki.cn31-1163/f.2016.01.004.*

*[11] Wang Shaojian, Huang Yongyuan. Spatial spillover effects and driving factors of carbon emission intensity in Chinese cities [J]. Journal of Geography, 2019, 74(06): 1131-1148.*

*[12] Hara Lulu, Xi Qiangmin, Sun Tieshan, Li Guoping. The impact of industrial structure on regional carbon emissions--an empirical analysis based on multi-country data [J]. Geography Research, 2016, 35(01): 82-94.*

*[13] Gu A-Lun, He Chong-Kai, Lu C-Q. Analysis of the impact of industrial structure changes on carbon emissions in China based on LMDI method [J]. Resource Science, 2016, 38(10): 1861-1870.*

*[14] Zhang Lei, Huang Yuanxi, Li Yanmei, Cheng Xiaoling. Analysis of regional patterns of carbon emissions in China and ways to reduce them [J]. Resource Science, 2010, 32(02): 211-217.*

*[15] Lan-Cui Liu, Ying Fan, Gang Wu, Yi-Ming Wei. Using LMDI method to analyze the change of China's industrial* $CO^2$ *emissions from final fuel use: An empirical analysis [J]. Energy Policy. 2007 (11)*

*[16] Yu Yihua, Zheng Xinye, Zhang Li. Economic development level, industrial structure and carbon emission intensity: An analysis of provincial panel data in China [J]. Economic theory and economic management, 2011(03): 72-81.*

*[17] Zhang Zhixin, Xue Qiao. Low-carbon economy, industrial structure and changes in China's development mode based on the data of 1996- 2009 in empirical analysis [J]. Energy Procedia. 2011*

*[18] Li Jian, Zhou Hui. Correlation analysis of carbon emission intensity and industrial structure in China [J]. China Population, Resources and Environment, 2012, 22(01): 7-14.*