

Industrial Transformation's Impact on Carbon Emission Models' Secondary Industry Default Assumptions: A Zhejiang Case via STRIPAT

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Abstract. Against the backdrop of the "carbon peak" and "carbon neutrality" goals, as well as the imperative for industrial structure transformation and upgrading, understanding how industrial structural changes impact carbon emissions—and assessing the practical applicability of relevant analytical models—has taken on crucial real - world significance. Against this context, this paper selects Zhejiang Province, a region with notable trends in industrial transformation and upgrading in China, as the subject of study. Using the STRIPAT model, the relationship between industrial structure changes and carbon emissions in Zhejiang Province is examined, and the validity of assumptions taken for granted in previous research is tested against real-world developments. The model results show that the traditional approach of using secondary industry output as a proxy for industrial structure is valid in the current economic context. However, empirical evidence shows that the tertiary industry's influence on carbon emissions is becoming more prominent as it expands and outputs. Future research should account for both output volume and the proportional share of the tertiary industry to better understand the relationship between industrial structure and environmental impact. The paper concludes with policy recommendations for sustainable development strategies and environmentally responsible economic growth.

Keywords: Zhejiang Province, carbon emissions, industrial structure, STRIPAT method

1. Introduction

The increasing carbon emissions have significantly impacted global climate change, leading to a global consensus on controlling emissions and mitigating climate change. To alleviate pressure, countries like China have made voluntary commitments to achieve carbon peak by 2030 and carbon neutrality by 2060. However, China's industrial system remains unbalanced, with industrial sophistication outpacing rationalization, resulting in lower modernization in agriculture and slower growth in agricultural production labor productivity. Research from Renmin University of China suggests that China needs to transition from high-speed development to high-quality development and upgrade its industrial structure [1]. Meanwhile, the globalized economy is still experiencing a reversal, and the external challenges posed by the US and Western countries' attempts to decouple

and disrupt China's connections with other nations are becoming increasingly severe. All of this is pressure on China's industrial structure to transform and upgrade [2].

This paper employs the STRIPAT-LMDI method and relies on official data such as "Zhejiang Statistical Yearbook" and "China Statistical Yearbook" to discuss the relationship between the rationality of the hypotheses in the research on industrial transformation and carbon emissions in Zhejiang Province. In recent years, with the support of the "eight-eight" strategies, Zhejiang Province, as an important component of the Yangtze River Delta region, which is the most economically powerful area in China [3], not only formulate an action plan related to carbon peak and carbon neutrality innovation and technology firstly [4] but also is a pioneer in the upgrading of its industrial structure. If Zhejiang Province can achieve the challenges of carbon peak by 2030 and carbon neutrality by 2060 while upgrading its industrial structure, this success will have a huge demonstration effect. It would not only offer valuable lessons from its successful practices but also provide significant reference for the development trajectories of other Chinese provinces and cities.

2. Literature review

At present, various aspects of research on carbon emissions and related factors in Zhejiang Province have been conducted by the academic community, and considerable achievements have been made. Zhejiang A&F University, in collaboration with the Zhejiang Provincial Institute of Rural Revitalization, has conducted in-depth investigations into the spatio-temporal patterns and influencing factors of carbon emissions at the county level in Zhejiang [5]. Meanwhile, regarding carbon emissions in various industries and fields in Zhejiang Province, certain achievements have already been made in the research [6]. Several studies, such as "Spatio-temporal Evolution Law and Driving Factors of Carbon Emissions in Zhejiang's Planting Industry" and "Carbon Emission and Scenario Prediction of Zhejiang's Water System Based on the Whole Life Cycle of Water Resources," have been successfully published [7]. However, a considerable portion of the research focuses on a specific industry or a specific field, a comprehensive perspective on overall changes. Research on global carbon emissions has limitations and differing opinions on industries' impact. Secondary industry's proportion is believed to have the most significant impact [8]. Nevertheless, other scholars have challenged this view, arguing that the proportion of the tertiary industry has the greatest influence on carbon emissions in Zhejiang. Therefore, in this paper, the extended STRIPAT model will be employed to separately analyze the carbon emissions and their influencing factors in Zhejiang Province, aiming to conduct a comprehensive analysis of the carbon emissions and their contributing factors of the three industries in Zhejiang Province.

3. Research methods

3.1. Model construction

3.1.1. The STRIPAT model

The STRIPAT model is an improved version based on the IPAT model. The IPAT model is often used to study the relationship between environmental impacts(I) and population(P), affluence(A), and science and technology(T) [9],

$$I = P \times A \times T \quad (1)$$

However, although this model is simple, it also has limitations such as being unable to handle nonlinear assumptions and model simplification. To better conduct analysis and capture the high-order relationships among variables, York et al. optimized the IPAT model and proposed the STRIPAT model [10].

$$I = aP^bA^cT^de \quad (2)$$

By incorporating the correction coefficient a and the error term e , while retaining the mathematical structure of the IPAT model, the model is more flexible and probabilistic. Because now it allows empirical testing of relationships and accounts for randomness in the real world. So it is widely adopted to mitigate environmental factors.

3.1.2. LMDI method

The Logarithmic Mean Divisia Index (LMDI) method, [11] which introduced the logarithmic average weight, was initially constructed through in-depth research and repeated experiments. The method's performance was significantly improved through in-depth analysis, continuous testing, and adjustments. The LMDI method offers several advantages, including a decomposition characteristic period without residuals, which accurately decomposes the total effect into sub-effects of each influencing factor, avoiding errors caused by residuals. It also has an additive property, allowing each component effect to be restored to the total effect in the form of addition, facilitating the analysis and understanding of complex systems. Additionally, the method maintains stable and consistent analytical performance under different combinations of factors, ensuring its effectiveness in various fields.

3.1.3. Ridge regression

The ridge regression method was proposed by Arthur E. Hoerl and Robert W. Kennard in 1970 [12]. As an improvement over the ordinary least squares method, ridge regression adds an L2 regularization term to the regression, that is, the sum of the squares of the regression coefficients to constrain the magnitudes of the regression coefficients. By further constraining the regression coefficients, ridge regression effectively addresses potential multi-col-linearity issues, thereby enhancing the model's stability and regulating its complexity. In this paper, the variables I have chosen have already been proven to have a correlation, so ridge regression method was adopted to reduce errors.

3.1.4. The interrelationship among various methods

The three methods employed in this paper collectively form a whole, namely the STRIPAT-LMDI method. The STRIPAT method is used to depict the relationships among variables, while the LMDI method is employed to handle data. By applying logarithmic transformations, the STRIPAT-LMDI method eliminates the differences caused by factors such as units and orders of magnitude, and transforms the difficult-to-handle multiplicative form into a linear form that has been theoretically mature for a long time. Ridge regression is used for the specific calculation of the regression equation, in order to minimize the impact of multi-col-linearity.

3.2. Variable description

3.2.1. Dependent and independent variables

The main research object of this paper is carbon emissions. To eliminate the influence of the total GDP, this paper measures the total carbon emissions per unit of GDP (in billion tons) in Zhejiang Province. As for independent variables, this paper use explanatory variable represents industrial structure, which is the proportion of the three industries in GDP. Many research studies, assume that the secondary industry is the principal contributor to carbon emissions, and use the proportion of secondary - industry output value to total output value as a proxy for industrial structure [13]. However, China is now in a critical period of industrial transformation and upgrading. The proportion of the three industries is gradually changing, and at the same time, there will be spontaneous transformation and upgrading within the industries. The tertiary industry will contribute more to economic growth and attract more job seekers. In this context, continuing to assume that the secondary industry is the main source of carbon emissions is likely to lag behind the actual situation. Therefore, simulations are actually conducted for all three industries.

3.2.2. Other control variables

The paper also uses three auxiliary variables: urbanization level, economic development level, and economic growth rate. The urbanization level is measured by the urban population size, the economic development level is represented by per capita GDP, and the economic growth rate is operationalized using the GDP index.

3.3. Data source

A large amount of collated data comes from major domestic forums and data think tanks such as CSDN and Oweidata. Some disputed data are verified based on official statistical yearbooks, and older data are downloaded from the Statistical Yearbook download website. The main sources of the data are the China Statistical Yearbook, the Zhejiang Statistical Yearbook and the China Energy Statistical Yearbook. The data I collected is from 1970 to 2021. However, years have passed, there are many missing values in the data I collected. In order to ensure the completeness and validity of the data, I excluded all the rows contain missing value. So I only used data from 1997 to 2021.

4. Data analysis

4.1. Multi-Col-linearity analysis

This paper checked the multi-col-linearity situation by VIF and the results shows that there is a more obvious multi-col-linearity in the set of indicators elected. In order to overcome the interference caused by this phenomenon, ridge regression method is selected in this paper, and the error is reduced by regularization coefficients.

Table 1. Styles available in the word template

	Cities Population	Primary industry Proportion of industries	Secondary industry Proportion of industries	Tertiary industry Proportion of industries	Per capital GDP	GDP index
Cities Population	15.7071	80.3938	31.3092	101.3023	89.2374	5.1923

4.2. Analysis of correlation

coefficients, which are statistical measures of the strength and direction of the linear relationship between two variables. In this paper, we use MATLAB to calculate the correlation coefficient to confirm that there is a linear correlation between variables. The results show that there is a strong linear correlation between the variables, as shown in Figure 1. :

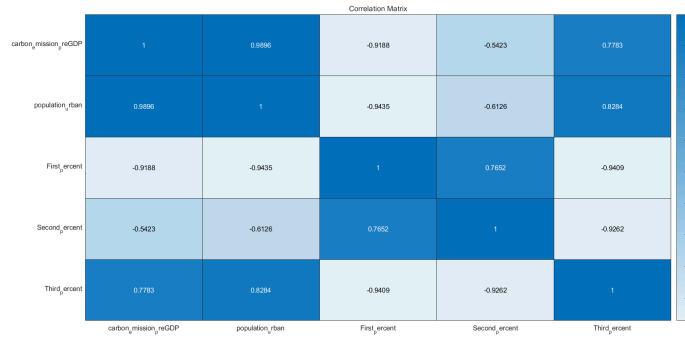


Figure 1. MATLAB correlation coefficient heatmap

4.3. Ridge regression analysis

Ridge regression is an improvement on least squares regression, exchanging a decrease in the accuracy of unbiased coefficients for a more realistic regression equation to better handle data with pathological conditions such as multi-col-linearity. The key to improving the accuracy of ridge regression lies in finding the appropriate regression coefficients. Therefore, OLS is used for regression analysis first to obtain the appropriate ridge regression coefficient k [14]. The regression equation is as follows:

$$\ln CO2_i = \beta_1 \ln stru + \beta_2 \ln pu + \beta_3 \ln ec + \beta_4 \ln eci + \beta_5 \quad (3)$$

CO2 represents total carbon emissions, stru represents industrial structure, pu represents urban population, ec represents economic level, and eci represents economic growth rate. The correlation coefficients and statistical parameters were obtained by OLS. The subscript 1, 2 and 3 mean conducting separate analyses towards the first industry, the second industry and the third industry:

$$\ln CO2_1 = -98.73 + 8.8952 \ln pu + 2.4893 \ln stru_{first} + 0.81936 \ln ec + 8.0257 \ln eci \quad (4)$$

square: 0.982, f-statistic (constant model): 258, p-value = 2.91e-16

square: 0.988, F-statistic (constant model): 403, p-value = 4.43e-18

$$\ln CO_{2_2} = -50.187 + 7.4151 \ln pu + 10.052 \ln stru_{second} + 1.1723 \ln ec - 8.0624 \ln eci$$

R-square: 0.988, F-statistic (constant model): 403, p-value = 4.43e-18

$$\ln CO_{2_3} = -26.611 + 7.4398 \ln pu - 10.703 \ln stru_{third} + 2.4018 \ln ec + 1.0429 \ln eci \quad (5)$$

R-square: 0.988, F-statistic (constant model): 398, p-value = 4.99e-18

According to the OLS regression equation and the relevant statistical coefficients, select

$$k = \frac{\sum_{i=1}^n e_i^2}{\sum_{i=1}^n \beta_i^2} \quad (6)$$

as an estimate of k, that is, the sum of the squares of the residuals divided by the sum of the squares of the coefficients. Based on the obtained k, ridge regression was performed on the primary, secondary, and tertiary industries respectively, resulting in the fitting ridge regression equation as:

$$\ln CO_{2_1} = -86.7174 + 8.4311 \ln pu + 1.3845 \ln stru_{first} + 0.5299 \ln ec + 7.3036 \ln eci \quad (7)$$

$$\ln CO_{2_2} = -51.2879 + 7.3452 \ln pu + 10.1308 \ln stru_{second} + 1.2323 \ln ec - 7.9128 \ln eci \quad (8)$$

$$\ln CO_{2_3} = -27.3383 + 7.4322 \ln pu - 10.5332 \ln stru_{third} + 2.3750 \ln ec + 1.1347 \ln eci \quad (9)$$

5. Result analysis

Based on the coefficients obtained from ridge regression, we can obtain the regression equation of the corresponding STRIPAT model:

$$CO_{2_1} = \exp(-86.7174 + 8.4311 \ln pu + 1.3845 \ln stru_{first} + 0.5299 \ln ec + 7.3036 \ln eci) \quad (10)$$

$$CO_{2_2} = \exp(-51.2879 + 7.3452 \ln pu + 10.1308 \ln stru_{second} + 1.2323 \ln ec - 7.9128 \ln eci) \quad (11)$$

$$CO_{2_3} = \exp(-27.3383 + 7.4322 \ln pu - 10.5332 \ln stru_{third} + 2.3750 \ln ec + 1.1347 \ln eci) \quad (12)$$

The subscripts 1, 2 and 3 represent the first industry, the second industry, and the third industry respectively.

By comparing the correlation coefficients in the equation, it can be pointed out that under the condition that other factors remain unchanged, the three industries have different impacts on carbon emissions as the process of industrial upgrading progresses.

5.1. Primary industry (agriculture)

In the process of industrial structure adjustment, capital and labor are transferred from the primary industry to the secondary industry and then to the tertiary industry. Correspondingly, the industry with the largest share of GDP in terms of output value also undergoes a similar shift, moving from the primary industry to the secondary industry and then to the tertiary industry. The data I collected showed that in 1977, the output value of the secondary industry in Zhejiang Province accounted for

41 percent, while the output value of agriculture was less than 40 percent. The province had already completed the upgrading of its industrial structure from agriculture to industry. Since then, the share of agricultural output in GDP has continued to decline steadily, from 39 percent in 1977 to 3 percent. Correspondingly, agricultural carbon emissions have become a negligible factor in the province's total carbon emissions, as evidenced by the coefficient of agriculture in the regression equation being nearly zero.

5.2. Secondary industry (industry and construction)

Many papers default to the proportion of output value from the secondary industry as a measure of industrial structure when calculating carbon emissions, and the equations obtained in this paper partially support this default: The equation obtained through ridge regression shows that the proportion of the secondary industry has a large positive coefficient, whose value is 10.1308. This suggests that, in general, using the proportion of secondary - industry output as an indicator of industrial structure is a reasonable assumption for researching carbon emissions. However, when it comes to the transformation and upgrading of the industrial structure, the rationality of this assumption is questionable.

5.3. Tertiary industry (service industry)

At present, Zhejiang Province has entered a critical period of industrial structure transformation and upgrading. The proportion of the tertiary industry surpassed that of the secondary industry in 2016 and reached 50%. For this reason, it is equally important to examine the activities of the tertiary industry and its carbon emissions, as is also shown in the regression equation follow Table 2, the Ridge Regression Coefficient.

Table 2. The ridge regression coefficient

Industry type	Error term	Urban population	Industrial structure	Economic level	Speed of development
First	-86.7174	8.4311	1.3845	0.5299	7.3036
Second	-51.2879	7.3452	10.1308	1.2323	-7.9128
Third	-27.3383	7.4322	-10.5332	2.3750	1.1347

The coefficient of the tertiary industry is -10.5332 while that of the secondary industry is 10.1308. The two coefficients show how the change of each unit of potions will influence the final carbon emission. So we can figure out that the influence of tertiary industry is greater than the secondary industry. As the industrial structure transformation deepens today, the impact of the tertiary industry on carbon emissions in Zhejiang Province has surpassed that of the secondary industry, becoming a key factor in determining carbon emissions.

The following are the graphs of the relevant prediction results.(Figure 2, Figure 3, Figure 4)

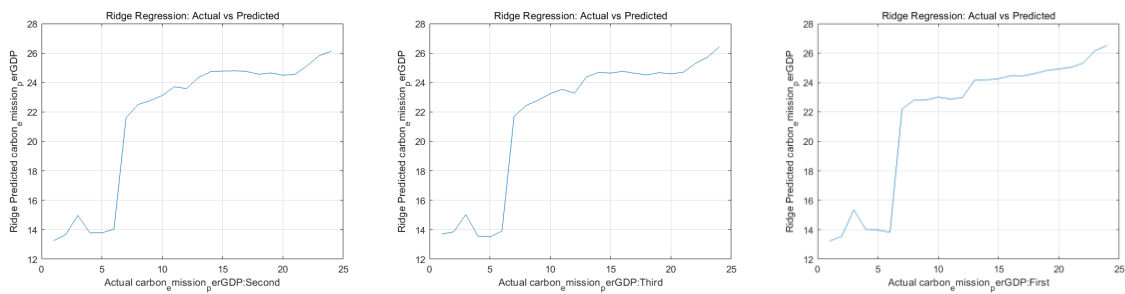


Figure 2. Prediction of first industry Figure 3. Prediction of second industry Figure 4. Prediction of third industry*

6. The impact of artificial intelligence

The impact of tertiary sector of the economy on carbon emissions exceeds that of secondary sector of the economy, and there are complex reasons behind it. Among them, the development of artificial intelligence has a huge impact and has been recognized as one of the main reasons for this change. The next part of this article will analyze the emerging technology of artificial intelligence, as well as the changes it brings and the reasons for them.

6.1. AI affects secondary sector of the economy

As for the impact of artificial intelligence in the process of secondary sector of the economy transformation and upgrading, most scholars believe that with the development of science and technology, artificial intelligence has increasingly become an important driving force for the transformation and green development of traditional industries, and can effectively reduce carbon emissions. Related research points out that by combining deep learning technology with production process, it can automatically analyze images and related data on the production line and identify product defects, and through timely feedback to adjust the production process, reduce scrap rate, to ensure stable production. At the same time, deep learning can optimize the production process and promote the efficient and energy-saving development of the industrial system. At present, the more widely used deep learning techniques in the industry are CNN (Convolutional neural network) and RNN (recurrent neural network). CNN is composed of convolution layer, pooling layer and kernel connection layer. The convolution kernel is used to extract features and abstract features, which is mainly used in computer vision and spatial data analysis RNN computes and extracts features by loop connection, and then processes natural language by using hidden states. It is mainly used for time series analysis. Both of them have been widely used in industry and good results have been obtained.

The company uses neural network technology to achieve automatic control by introducing convolutional neural network CNN to analyze spatial data and recurrent neural network RNN to analyze temporal data. This result not only reduces energy consumption by more than 10% and shortens response time by 50%, but also almost completely eliminates unplanned downtime caused by traditional PID control techniques [13]. Jiangsu University of Science and technology combines BP neural network with shipbuilding industry, studies the method of cost estimation and pollution control by using neural network, and accurately estimates the cost of building ships by neural network.

Moreover, by introducing artificial intelligence technology of natural language processing, intelligent customer service and virtual assistant systems are also widely used in business promotion

in all walks of life. AI can not only understand and respond to overcome language requirements, improve customer service efficiency and user experience, but also analyze historical data and optimize production plans to enable enterprises to be more flexible to respond to market changes, promoting the green and innovative development of enterprises. There are also successful industrial examples of this type of application. By combining the LSTM algorithm, the MEDIAPIPE image-processing model, and the operator's human Beijing Institute of Technology, the researchers have been able to optimize the human-machine relationship and improve production safety [15].

6.2. AI affects tertiary sector of the economy

The impact of AI on tertiary sector of the economy is far more complex than the impact of AI on secondary sector of the economy. Specifically, the author believes that, on the one hand, the large-scale and wide application of artificial intelligence in the service industry has promoted the development of tertiary sector of the economy informatization and intelligence, making it more efficient and less costly; however, the combination of widespread tertiary sector of the economy demand for artificial intelligence and the ongoing adjustment of the energy mix will result in tertiary sector of the economy energy consumption continuing to rise slowly until peak carbon is reached by 2030. After that, with the progress of Science and Technology and the adjustment of energy structure, carbon emissions will gradually decline, until 2060 to achieve the goal of carbon neutrality.

The view that the development of digital economy will still promote the slow rise of energy consumption at present has been supported by most scholars, and the author holds the same view, in "The William Stanley Jevons paradox in the Digital Economy: the AI race and the dual-carbon goal," researchers argue that as the digital economy continues to grow, so will the need for digital infrastructure, china's data centres are expected to 202420% annual growth in power consumption between now and 2030, with total consumption expected to reach 525.76 billion kwh by 2030, 4.8% of total electricity consumption [16] . Moreover, China's energy structure will also affect carbon emissions. Research shows that 117,181 gigawatts of China's total electricity consumption in 2018 came from coal-fired power plants, total emissions were 98.55 million tons of carbon dioxide, 23.4 million tons of sulfur dioxide, 22.3 million tons of carbon dioxide and 4.9 million tons of soot. But until China's energy mix shifts to cleaner sources of energy, the slow rise in carbon emissions associated with economic growth is inevitable [17] .

However, how AI development will affect the total and tertiary sector of the economy of carbon emissions in the long run has become a major factor in carbon emissions. The author believes that with the industrial transformation and upgrading, tertiary sector of the economy will gradually become the leading industry in our country, with its proportion of output value rising, the scale of the industry is expanding, the shift away from secondary sector of the economy as the dominant factor in carbon emissions is inevitable.

6.3. Research on the application of artificial intelligence to carbon emissions

The continuous development of artificial intelligence technology and the emergence of more sophisticated and more explanatory large-scale models have promoted the wide application of artificial intelligence in all walks of life, including the prediction and estimation of carbon emissions. Scholars have combined a variety of artificial intelligence tools with carbon emissions research, significantly improving the accuracy and interpretability of carbon emissions predictions. Among them, the main application methods include PSO-BP neural network, GRNN neural network

and so on. Among them, PSO-BP neural network is the optimization of back propagation neural network, BP neural network includes three layers, input layer, hidden layer and output layer, and PSO is the Particle swarm optimization, by iterating the relevant parameters repeatedly, the BP neural network has three layers, the input layer, the hidden layer and the output layer, the velocity and position of the particles in the model are updated. After the calculation error reaches the minimum, the global optimal particle position is output, and its related parameters are used to initialize the weights and thresholds of the BP neural network. The BP neural network is optimized to reduce the possibility of falling into local optimum rather than global optimum. GRNN (generalized regression neural network) consists of four layers: input layer, pattern layer, summation layer and output layer. Gauss function is used as the radial basis function, it is widely used in function series approximation and time series analysis. It has the advantages of fast training speed, high robustness of Shandong and simple parameter setting. It is also often used in carbon emission research.

In the current research results of carbon emissions, the method based on neural network has been widely used, and scholars have achieved good results. In studying the total amount of carbon dioxide emitted during the construction of expressways in Hebei province, the researchers used a PSO-BP neural network, optimized by a particle swarm algorithm, to predict the amount of carbon dioxide emitted [18]; in the literature on carbon emissions in the beijing-tianjin-hebei Express logistics industry, the authors select key variables to input into the GRNN by Lasso regression method, the results show that lasso-GRNN is better than pca-GRNN and pls-GRNN, and the prediction results are closer to reality [19].

7. Conclusion and prospect

By analyzing the data of Zhejiang Province from 1997 to 2022, this paper points out that with the gradual deepening of the transformation of industrial structure in Zhejiang province, the proportion of output value of the three industries in Zhejiang province is also gradually changing, the highest proportion shifted from primary sector of the economy to secondary sector of the economy and then to tertiary sector of the economy. Accordingly, the key factor in determining carbon emissions in the industrial structure is gradually shifting from the proportion of secondary sector of the economy to the proportion of tertiary sector of the economy. The reasons for this shift are complex, and the development and application of artificial intelligence is a major factor. Of course, this paper uses the STRIPAT method for coefficient decomposition and ridge regression method for regression, but there are still the following shortcomings: (1) there is a relatively obvious correlation between the indicators collected, there is even a clear linear and collinear relationship, resulting in a small number of indicators that can ultimately be used and there is a correlation (3) the STRIPAT method assumes that each factor is independent of each other. However, in reality, there are various links between various factors, such as economic development, the rise in per capita GDP is accompanied by the increase in urbanization rate, the interaction of secondary sector of the economy, tertiary sector of the economy development and urbanization makes the reality far more complex than the idealized, mutually exclusive models suggest. At the same time, this paper only discusses the relevant changes from the macro perspective of output value, the transformation and upgrading of the industry and the change of the proportion of each part and its impact, although the development of artificial intelligence has been discussed in this paper, there are still many other related factors and their interactions to be explored by researchers.

As for the impact of AI in this transition, the author argues that AI acts on both secondary sector of the economy and tertiary sector of the economy, however, AI does not play exactly the same role

in both. In secondary sector of the economy, the main role of artificial intelligence is to optimize production and energy saving and emission reduction, through artificial intelligence technology to optimize the production process, reduce inventory backlog, reduce cost input, stable production process; In tertiary sector of the economy, AI has transformed it far more deeply and broadly than secondary sector of the economy. On the whole, advances in AI and digital technology can improve the efficiency of industrial operations, carry out intelligent planning to save energy. However, the huge market for artificial intelligence has a huge demand for information technology-related infrastructure, and the construction of artificial intelligence infrastructure, the operation of a large number of electronic facilities, the training of large models and the storage of data, they all consume a lot of electricity. In our current energy structure, coal still accounts for more than half of the energy consumption. Therefore, before the transformation of our energy structure is basically completed and peak carbon is basically achieved, the tertiary sector of the economy under the influence of artificial intelligence will continue to exist as a leading industry of carbon emissions, with the continuous improvement of efficiency by artificial intelligence and the continuous optimization of social energy structure, tertiary sector of the economy will still exist as a leading industry of carbon emissions because of its high output value and large employment, but, carbon emissions would fall.

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