ISSN 2616-5902 Vol. 6, Issue 8: 149-156, DOI: 10.25236/AJBM.2024.060822

# Analytical Study on the Relationship between Carbon Emission and Industrial Structure in Jiangsu, Zhejiang and Shanghai Regions—Analysis Based on Data from 2000 to 2020

**Haidan Yan**

*School of Applied Physics, Tiangong University, Tianjin, 300380, China*

***Abstract:*** *The shift towards a more sustainable economic model, hastening the restructuring of industrial sectors, and fostering a robust low-carbon economy are crucial steps for China to concurrently advance economic prosperity and environmental preservation. Among the most economically vibrant, open, and innovation-driven regions in Eastern China, Jiangsu, Zhejiang, and Shanghai have significantly fueled China's economic expansion. This study examines the evolution of industrial structures and carbon emissions in these three regions from 2000 to 2020, constructs a mathematical model linking the two, and reveals a long-run equilibrium association between carbon emissions and industrial structure. It also identifies the secondary industry's growth as the primary driver of increased emissions. To mitigate this, Jiangsu, Zhejiang, and Shanghai are recommended to decrease the secondary industry's share while promoting the tertiary sector; adopt and harness low-carbon technologies to enhance equipment efficiency; and boost the substitution rate of novel energy sources, thereby diversifying from fossil fuel-dominated energy consumption patterns.*

***Keywords:*** *carbon emissions, industrial structure, Jiangsu, Zhejiang and Shanghai*

## 1. Introduction

Along with the rapid economic development, climate warming has become a global environmental problem today. The increase of greenhouse gases in the atmosphere, especially $CO_2$, is an important factor contributing to the global climate and environmental changes, and poses a serious threat to the survival of human beings and the sustainable development of society and economy[1]. Energy consumption is an important way to realize energy saving and emission reduction, which is deeply influenced by industrial structure, science and technology, and other factors, among which the most basic way is the adjustment of industrial structure. Research on the relationship between energy and carbon emissions and industrial structure has been the focus of academic attention, Miller and Blair used the input-output method to empirically analyze the energy consumption and pollutant emissions in the industrial production process, which provides a research basis for optimizing the industrial structure[2]. Chihiro Watanabe analyzed the significant impact of the adjustment of industrial structure on carbon emissions and energy consumption, and the results show that the degree of its impact is 20%[3].Craig M. Meisner's empirical study of the data of developing countries from 1987 to 1995 found that the development of primary industry reduces a certain amount of $CO_2$ emissions, while the increase in the proportion of secondary industry leads to an increase in $CO_2$ emissions . The increase of the proportion of secondary industry leads to the increase of $CO_2$ emission[4].

Since the reform and opening up, the rapid development of China's economy has consumed a large amount of fossil energy, such as coal, oil and natural gas, and in the process of rapid industrialization, China's $CO_2$ emissions will continue to increase rapidly[5] Controlling $CO_2$ emission is an important task to deal with the global warming problem, and it is of great significance to promote the sustainable development of society and economy, accelerate the transformation of economic development mode, and promote the new industrial revolution[6].

China's total $CO_2$ emissions have tripled in the past 20 years, mainly concentrated in North China and East China. As one of the regions in East China with the most active economic development, the highest degree of openness and the strongest innovation ability, Jiangsu, Zhejiang and Shanghai have made great contributions to China's economic growth, and the adjustment of their industrial structure and optimization of their carbon emissions play a pioneering role in China's emission reduction endeavors. There is a close connection between national economic growth and industrial structure, which affects the local GDP of Inner Mongolia and more profoundly affects the local ecological environment. The blind pursuit of economic growth, carbon emissions with the use of coal and other resources used in large quantities and increasing, so that the environment and the sustainable development of the economy is deeply affected.

This paper combines the actual situation of Jiangsu, Zhejiang and Shanghai, analyzes the relationship between carbon emissions and industrial structure in Jiangsu, Zhejiang and Shanghai, and puts forward the optimization countermeasures of industrial structure that are conducive to carbon emission reduction in Jiangsu, Zhejiang and Shanghai, which is especially necessary for energy conservation and emission reduction and the development of low-carbon economy in Jiangsu, Zhejiang and Shanghai[7].

## 2. Emission and Industrial Structure in Jiangsu, Zhejiang and Shanghai Region

As a representative region of heavy industry development, Jiangsu, Zhejiang and Shanghai region has been at the forefront of carbon emission in the country while its economy is developing. In this paper, a large number of samples are selected in combination with the analysis needs. The sample period is from 2000 to 2020; industrial structure refers to the composition of each industry and the connection and proportion relationship between each industry. In this paper, the ratio of primary, secondary and tertiary industries to GDP reflects the industrial structure of Jiangsu, Zhejiang and Shanghai, and the data are obtained from China Statistical Yearbook and CEADs China Carbon Accounting Database.

This paper adopts the emission coefficient method to measure $CO_2$ emissions[8]. Because fossil energy consumption is the main source of $CO_2$ emissions, which is the key factor causing environmental changes and pollution, coal, oil and natural gas are mainly considered in this paper to measure carbon emissions. The formula for calculating $CO_2$ is as follows:

$$C = \sum_i C_i = \sum_i P_i \times R_i \tag{1}$$

Where $P_i$ is the consumption of the three types of energy, $R_i$ is the carbon emission factor of the three types of energy; i=1,2,3, are the three types of energy mentioned above, where P_i is the data from the China Energy Statistics Yearbook and CEADs China Carbon Accounting Database.

The data of $P_i$ are obtained from China Energy Statistics Yearbook and CEADs China Carbon Accounting Database, and the value of $R_i$ is based on the studies of many domestic and foreign literatures. Since the raw data of various energy consumption are all physical statistics with different units, it is not easy to compare them, therefore, in the calculation, we need to firstly convert the physical amount of various energy consumption into standard statistics according to a certain coefficient[9] and then multiply it by the respective carbon emission coefficients, so as to get the carbon emission of various energy consumption. The conversion coefficients of standard coal and carbon emission coefficients of various energy sources are shown in Tables.1 and 2, where the conversion units of coal, oil and natural gas in the conversion coefficients of standard coal are referenced to the China Statistical Yearbook of 2020, as shown in Table 1, Table 2 and Table 3.

*Table 1: Standard coal conversion factors for various energy sources*

| Type of energy (kg standard coal) | conversion factor |
|---|---|
| coals | 0.7143 |
| petrochemical | 1.4286 |
| petroleum | 1.33 |

*Table 2: Carbon emission factors for various energy sources*

| Type of energy (t charcoal/ton of standard coal) | Carbon emission factor |
|---|---|
| coals | 0.7476 |
| petrochemical | 1.5854 |
| petroleum | 0.4479 |

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*Table 3: Industrial structure and carbon emissions in Jiangsu, Zhejiang and Shanghai, 2000-2020*

| year | Share of primary industry(%) | Share of secondary industry(%) | Share of tertiary sector(%) | carbon footprint($t\times10^4$) |
|---|---|---|---|---|
| 2000 | 2.467600442 | 90.41948166 | 7.112917898 | 425.5068889 |
| 2001 | 2.722173393 | 89.15623684 | 8.121589766 | 433.5225971 |
| 2002 | 2.533943409 | 89.08536581 | 8.380690783 | 480.3749895 |
| 2003 | 2.207150179 | 88.83068551 | 8.962164313 | 543.6406409 |
| 2004 | 1.814438323 | 89.04197371 | 9.143587963 | 653.2534097 |
| 2005 | 1.599262202 | 89.85765531 | 8.543082489 | 779.4737488 |
| 2006 | 1.471695406 | 89.87037375 | 8.657930843 | 863.2437247 |
| 2007 | 1.396200318 | 89.5690337 | 9.034765977 | 930.7501971 |
| 2008 | 1.315328286 | 89.36818239 | 9.316489322 | 963.9792969 |
| 2009 | 1.439323961 | 88.37634188 | 10.18433416 | 912.0517386 |
| 2010 | 1.300299881 | 89.50313474 | 9.196565376 | 1094.124169 |
| 2011 | 1.412349022 | 88.98394806 | 9.603702916 | 1085.189844 |
| 2012 | 1.407643145 | 89.27601297 | 9.316343888 | 1174.69974 |
| 2013 | 1.195981322 | 89.66089336 | 9.143125315 | 1236.527538 |
| 2014 | 1.242016253 | 89.1398167 | 9.618167047 | 1218.720226 |
| 2015 | 1.306793444 | 88.74485174 | 9.948354817 | 1229.740087 |
| 2016 | 1.285059218 | 88.40595031 | 10.30899047 | 1245.531312 |
| 2017 | 1.273622565 | 88.11766243 | 10.608715 | 1271.247051 |
| 2018 | 1.251786849 | 88.26308887 | 10.48512428 | 1280.819923 |
| 2019 | 1.167966869 | 88.41437495 | 10.41765818 | 1312.6411 |
| 2020 | 1.170460915 | 88.65557735 | 10.17396173 | 1276.85855 |

The trends of industrial structure and carbon emissions in Jiangsu, Zhejiang and Shanghai from 2000 to 2020 are shown in Figures 1, 2 and 3.From Figure 1, it can be seen that the carbon emissions in Jiangsu, Zhejiang and Shanghai have been continuously increasing. The aggregate energy-related carbon emissions in the Jiangsu, Zhejiang, and Shanghai region exhibit an ascending trend, albeit at a decreasing pace. The growth rate of carbon emissions in 2001-2005 is obvious, which is the fastest growth rate in the last 23 years; during 2006-2010, the growth rate of carbon emissions is still obvious, but the speed decreases compared with the previous period; and after 2010, the total carbon emissions in Jiangsu, Zhejiang and Shanghai region show a fluctuating upward trend. In the 13th Five-Year Plan period from 2016 to 2020, the goal of "overall improvement of ecological and environmental quality" has been proposed for the first time, and green development will be carried out in all fields and aspects of economic and social development in the 13th Five-Year Plan. "The philosophy of sustainable development infiltrates every sector and facet of socioeconomic growth, with the green ideology shaping the predominant narrative for regional progress. Notably, the aggregate carbon emissions in Jiangsu, Zhejiang, and Shanghai display a stabilizing pattern.

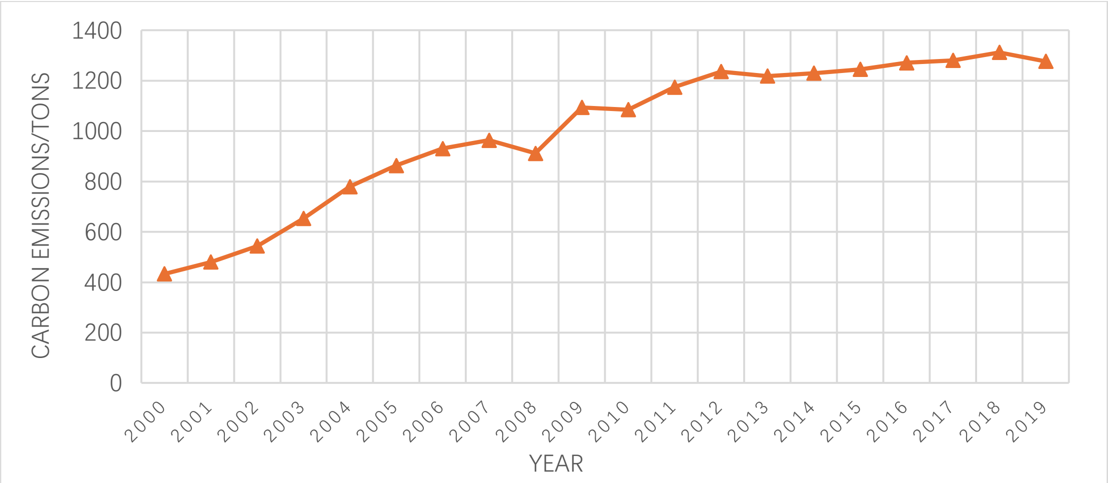


*Figure 1: Carbon Emissions in Jiangsu, Zhejiang and Shanghai, 2000-2020*

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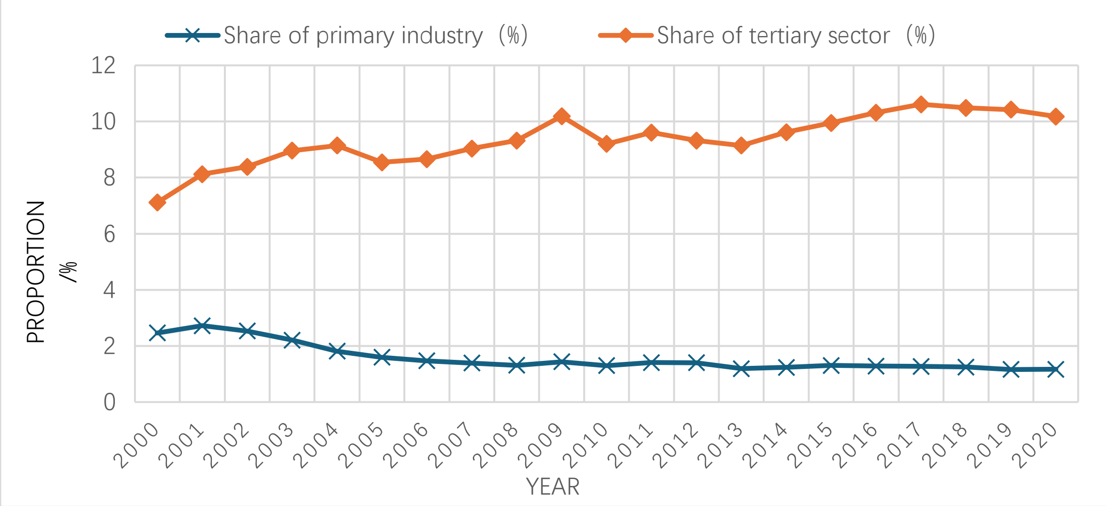


*Figure 2: Carbon Emission Trends of Primary and Tertiary Industries in Jiangsu, Zhejiang and Shanghai, 2000-2020*

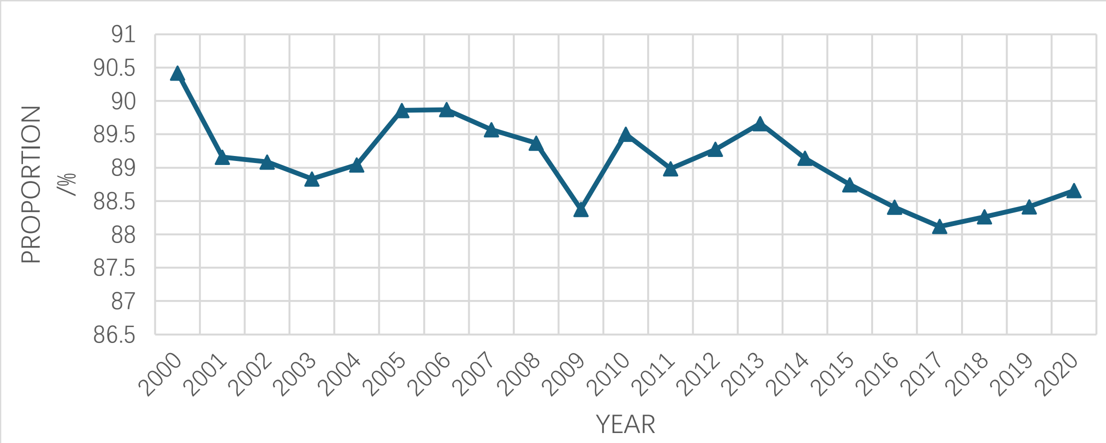


*Figure 3: Trend of carbon emissions from secondary industry in Jiangsu, Zhejiang and Shanghai, 2000-2020*

## 3. Research Modeling and Methodology

### *3.1 Unit root test*

In order to solve the fallacious regression, a smooth time series is generally used to establish a regression equation, or a non-smooth time series is converted into a smooth time series and then regressed on it. In order to prevent the phenomenon of pseudo-regression, it is first necessary to test the smoothness of the time series of the variables.

The primary application of the unit root test lies in ascertaining the stability of a time series. When the mean or covariance function of a sequence varies across time, it signifies that the series is characterized by non-stationarity.If the time series becomes smooth after first-order differencing, it is called a first-order single-integrated series, denoted as I(1); if it is smooth after n times of differencing, it is called an n-order single-integrated series, denoted as I(n). In this paper, we utilize SPSSAU software to conduct unit root test on time series. The original hypotheses of the test are: $H_0$:$r = 0$; $H_1$: $r < 0$. If the ADF value is greater than the critical value of the unit root test, the series contains unit root, and vice versa, the series does not contain unit root.

### *3.2 Gray correlation analysis*

In gray correlation analysis, the size of the degree of correlation between the factors is judged by the ordering of the size of the gray correlation value. Gray correlation analysis has fewer requirements for

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samples and data than other measurement models. The development trend of carbon emissions is affected by the energy structure, industrial structure, technology level, human factors, etc., and the information is usually incomplete, which is an uncertain gray quantity. Moreover, the carbon emissions in Jiangsu, Zhejiang and Shanghai are not precise, they are roughly estimated by correlation data, and do not meet the requirements of other econometric models. We do not pay attention to the value of the correlation, but only pay more attention to the ranking of carbon emissions and the comprehensive correlation between the three industries, and explore how to improve the industrial structure of Jiangsu, Zhejiang and Shanghai to reduce carbon emissions in the future based on the ranking. Therefore, this paper adopts gray correlation analysis method to illustrate the relationship between the two.

### *3.3 Pearson correlation analysis*

The Pearson correlation coefficient is derived by normalizing the covariance with the standard deviations of both variables. Although covariance provides insight into the connection between two random variables (positive covariance implies a positive link, while negative covariance suggests a negative one), its absolute magnitude doesn't effectively quantify their degree of correlation. To improve this measurement, the Pearson correlation coefficient comes into play, which is computed as the covariance divided by the standard deviations. It's evident that this coefficient ranges from -1 to 1. As the linear relationship between variables strengthens, the coefficient approaches either 1 or -1. A value of 1 or -1 indicates strong positive or negative correlation, respectively. When one variable rises with the other, they are positively correlated, with a coefficient above 0. Conversely, if one increases as the other decreases, it signifies a negative correlation with a coefficient below 0. A coefficient of 0 signals the absence of linear correlation between the variables.

## 4. Empirical Analysis

### *4.1 Data processing*

To explore the interplay between carbon emissions and industrial composition, the chosen variables in this study encompass: carbon emission intensity ($CE$) as the dependent variable, the proportion of primary industry ($P_1$), the proportion of secondary industry ($P_2$), the proportion of tertiary industry ($P_3$) as the independent variable. Where carbon intensity is the $CO_2$ emissions per unit of gross domestic product (GDP). If the CO2 emissions per unit of GDP decrease while the economy grows, the region realizes a low-carbon development mode. Before the empirical analysis, in order to avoid the drastic fluctuation of variable data and eliminate the heteroskedasticity of the data series respectively, the logarithm of each variable is expressed by $\ln(CE)$,$\ln(P_1)$,$\ln(P_2)$,$\ln(P_3)$, respectively, see Table 4.

*Table 4: Logarithmic series for each variable*

| | $\ln(P_1)$ | $\ln(P_2)$ | $\ln(P_3)$ | $\ln(CE)$ |
|---|---|---|---|---|
| 2000 | -1.60773 | -0.04374 | -1.14795 | 3.34326 |
| 2001 | -1.56508 | -0.04985 | -1.09036 | 3.305453 |
| 2002 | -1.5962 | -0.05019 | -1.07672 | 3.291516 |
| 2003 | -1.65617 | -0.05144 | -1.04759 | 3.270549 |
| 2004 | -1.74126 | -0.05041 | -1.03888 | 3.269141 |
| 2005 | -1.79608 | -0.04644 | -1.06839 | 3.272982 |
| 2006 | -1.83218 | -0.04638 | -1.06259 | 3.248686 |
| 2007 | -1.85505 | -0.04784 | -1.04408 | 3.203708 |
| 2008 | -1.88097 | -0.04882 | -1.03075 | 3.153817 |
| 2009 | -1.84184 | -0.05366 | -0.99207 | 3.090621 |
| 2010 | -1.88596 | -0.04816 | -1.03637 | 3.098301 |
| 2011 | -1.85006 | -0.05069 | -1.01756 | 3.027598 |
| 2012 | -1.85151 | -0.04927 | -1.03075 | 3.01913 |
| 2013 | -1.92228 | -0.0474 | -1.03891 | 3.000254 |
| 2014 | -1.90587 | -0.04993 | -1.01691 | 2.96134 |
| 2015 | -1.88379 | -0.05186 | -1.00225 | 2.933937 |
| 2016 | -1.89108 | -0.05352 | -0.98678 | 2.900806 |
| 2017 | -1.89496 | -0.05494 | -0.97434 | 2.866717 |
| 2018 | -1.90247 | -0.05422 | -0.97943 | 2.833939 |
| 2019 | -1.93257 | -0.05348 | -0.98223 | 2.816993 |
| 2020 | -1.93164 | -0.05229 | -0.99251 | 2.787923 |

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### *4.2 ADF unit root test*

Not any cointegration relationship exists between any research variables, and the cointegration test is only meaningful if the time-series variables are all non-stationary and single-integrated of the same order. Therefore, the series of ln($CE$),ln($P_1$),ln($P_2$),ln($P_3$) are tested for smoothness respectively, with the H0 assumption: ln($CE$),ln($P_1$),ln($P_2$),ln($P_3$) all have a unit root. If the series is not smooth, generally the first difference and then do the ADF test to continue to determine its smoothness, if more than one variable with the same order of single integrality, it has the prerequisites of cointegration analysis.

As depicted in Figure 1, the model incorporating an intercept but devoid of a time trend is opted for. The optimal lag duration is determined by the SIC criterion, and the ensuing analysis is summarized in Table 5. With a significance level set at 5%, the first-order differences of the variables successfully undergo the stationarity test.

*Table 5: ln($CE$),ln($P_1$),ln($P_2$),ln($P_3$) unit root test results*

| sequences | ADF test value | 1% significant level | 5% significant level | 10% significant level | Judgement conclusions |
|---|---|---|---|---|---|
| ln($CE$) | -2.77 | -4.138 | -3.155 | -2.714 | uneven |
| ln($P_1$) | -1.689 | -3.809 | -3.022 | -2.651 | uneven |
| ln($P_2$) | -3.049 | -3.809 | -3.022 | -2.651 | smoothly |
| ln($P_3$) | -3.233 | -3.809 | -3.022 | -2.651 | smoothly |
| ln( $CE$ ) first-order difference | 1.049 | -4.223 | -3.189 | -2.73 | uneven |
| ln($P_1$) first-order difference | -2.536 | -3.859 | -3.042 | -2.661 | uneven |
| ln($P_2$) first-order difference | -5.696 | -3.833 | -3.031 | -2.656 | smoothly |
| ln($P_3$) first-order difference | -5.083 | -4.223 | -3.189 | -2.73 | smoothly |
| ln( $CE$ ) second-order difference | -5.716 | -4.223 | -3.189 | -2.73 | smoothly |
| ln( $P_1$ ) second-order difference | -4.942 | -3.889 | -3.054 | -2.667 | smoothly |
| ln( $P_2$ ) second-order difference | -3.091 | -4.138 | -3.155 | -2.714 | smoothly |
| ln( $P_3$ ) second-order difference | -4.515 | -3.889 | -3.054 | -2.667 | smoothly |

ln($CE$),ln($P_1$),ln($P_2$),ln($P_3$) all show significance at the level when the difference is of the 2nd order, and the series are all smooth time series, implying that there is a cointegration relationship between the variables, which can be directly regressed.

### *4.3 Gray correlation analysis*

Employ the distinctive sequence indicators: percentage of primary industry, percentage of secondary industry, and percentage of tertiary industry; the base sequence variable being the carbon emission intensity (CE), with a discriminant coefficient ρ set to 0.5.Firstly, we perform the dimensionless processing (homogenization) for the data. After that, the gray correlation coefficient between the parent series (comparison series) and the characteristic series is solved, and the gray correlation value is solved. Finally, the gray correlation values are ranked and conclusions are drawn.

The results of the analysis are shown in Table 6.

*Table 6: Correlation results*

| evaluation unit | relatedness | rankings |
|---|---|---|
| Share of primary industry(%) | 0.74 | 1 |
| Share of secondary industry(%) | 0.606 | 2 |
| Share of tertiary sector(%) | 0.566 | 3 |

As can be seen from the above table: For this 3 evaluation items, the proportion of primary industry (%) has the highest correlation, followed by the proportion of secondary industry (%).

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### *4.4 Pearson correlation analysis*

To correlate ln($CE$),ln($P_1$),ln($P_2$),ln($P_3$) with X and Y, firstly, whether there is a statistically significant relationship between X and Y (P<0.05) is examined, and after that, we analyze the correlation coefficient for the degree of correlation and the degree of correlation, and then summarize the results of the analysis, which are shown in Figure 4.

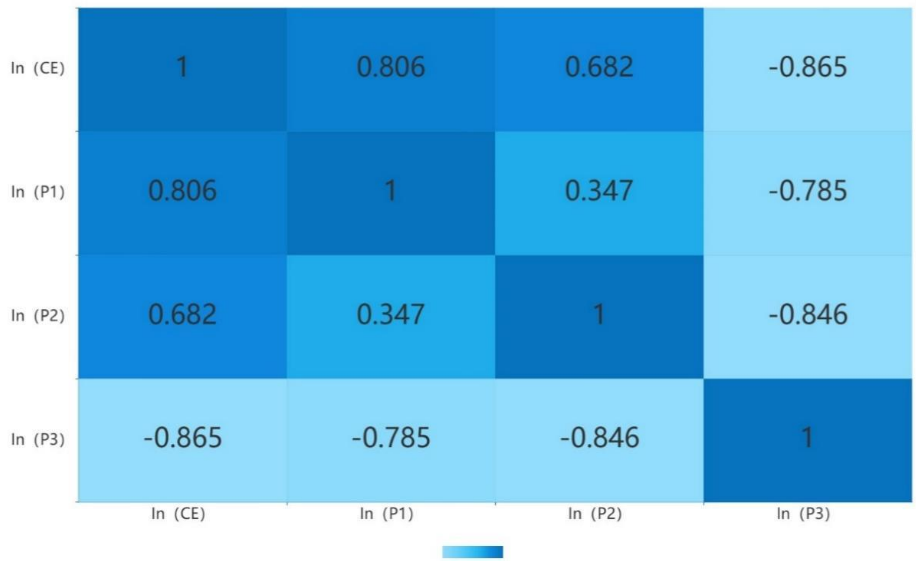


*Figure 4: Heat map of correlation coefficients*

As depicted in the diagram, there exists a positive association between the share of primary and secondary industries and carbon emission intensity, whereas a negative correlation is evident with the proportion of the service sector. It shows that there is a long-term stable equilibrium relationship between the dependent variables and the explanatory variables in the sample interval, i.e., industrial structure adjustment affects the change of carbon emissions.

### *4.5 Regression analysis*

The outcome of the ADF unit root test indicates the existence of a persistent cointegration link between the dependent variable and the explanatory factors. so that

$$\ln(CE) = \beta_1 In(P_1) + \beta_2 In(P_2) + \beta_3 In(P_3) + 32.355 \quad (2)$$

where $\beta_1, \beta_2, \beta_3$ are the coefficients of ln($P_1$),ln($P_2$),ln($P_3$), respectively, and c is a constant term. Least squares regression analysis is performed on the four columns of data of ln($CE$),ln($P_1$),ln($P_2$),ln($P_3$) to establish the regression equation, and the following regression equation is obtained.

$$\ln(CE)= 3.858 In(P_1) + 159.713 In(P_2) + 13.799 In(P_3) + 32.355 \quad (3)$$

Evaluation of the F-test outcomes reveals a substantial P-value, indicating significance at the stipulated level. This leads to the rejection of the null hypothesis asserting that the regression coefficients equal zero, thereby suggesting that the model fundamentally satisfies the necessary conditions. Regarding the covariance behavior of variable ln($P_1$),ln($P_2$),ln($P_3$) VIF value is greater than 10, there is a covariance relationship, easy to remove the covariance of the independent variable or to carry out the ridge regression or stepwise regression, where $R^2$=0.931.

### *4.6 Analysis of the relationship between carbon emissions and industrial structure*

From the ADF unit root test, it can be seen that there is a cointegration relationship between the proportion of the primary industry ($P_1$), the proportion of the secondary industry ($P_2$)), the proportion of the tertiary industry ($P_3$) and the carbon intensity ($CE$), and the regression equations can be set up by using a smooth time series; from the grey correlation analysis, the comprehensive correlation between carbon emissions and the three industries is ranked, and the future of the Jiangzhe, Zhejiang, and Shanghai regions is explored based on the ranking situation. The gray correlation analysis ranked the comprehensive correlation between carbon emissions and the three industries, and explored how to improve the industrial structure to reduce carbon emissions in the future in Jiangsu, Zhejiang and Shanghai; and the Pearson correlation analysis better measured the correlation degree between random variables, which showed the positive and negative correlation relationship between carbon emissions and the three industries.

Ultimately, the formulated regression equations illustrate that within a long-term equilibrium, a 1% rise in the primary sector corresponds to a 3.858% escalation in carbon emissions per GDP unit. Conversely, a parallel hike of 1% in the tertiary sector triggers a 13.799% surge in these emissions. The elasticity of contribution for the secondary sector's proportion to carbon emission intensity stands at 159.713, denoting that a 1% increase in the secondary sector's share leads to a 159.713% boost in emission intensity. This indicates that the nature of industrial composition significantly influences $CO_2$ emission intensity. The expansion of the secondary sector acts as the primary driver behind the rise in carbon emissions in Jiangsu, Zhejiang, and Shanghai, displaying a positive correlation with $CO_2$ emission intensity. Conversely, although the primary and tertiary industries also contribute to carbon emissions, their impact on emission increases is notably less substantial compared to the secondary sector.

## 5. Conclusion and Suggestion

In-depth scrutiny reveals that the secondary sector exerts the most substantial influence on carbon emissions among the three industries. This dominance of the secondary sector, primarily composed of heavy industries, serves as the primary catalyst for the escalation of carbon emissions in the Jiangsu, Zhejiang, and Shanghai region from 2000 to 2020. Conversely, the proportion of the environmentally friendly and low-carbon tertiary sector lags behind, demonstrating slower growth. The progression of the regional economic structure optimization is closely tied to the advancement of the tertiary industry. The intense burden on resources and the environment caused by the expansion of resource-intensive heavy industries can be mitigated by the tertiary sector, which, overall, consumes fewer resources and generates less pollution. Hence, restructuring the industrial composition and fostering industrial decarbonization will undeniably constitute the pivotal endeavor for fostering a low-carbon economy in this region.

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