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# Research on the coupling and coordinated development of new quality productivity and carbon emission efficiency and influencing factors

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## Abstract

It is of great significance for China to study the internal relationship and coordination level between new productivity and carbon emission efficiency. Based on the panel data of 30 provinces and cities in China from 2014 to 2022, this paper measures the level of new productivity, carbon emission efficiency and their coupling coordination, and studies the main factors with the help of xgboost and shap model. The results show that the coupling coordination level of China is on the rise, and the coupling coordination level of the eastern region is much higher than that of the central and western regions; Per capita disposable GDP. The first three factors are promotion and the last two are inhibition. With the increase of disposable income, urban employment has changed from negative adjustment to positive adjustment, and the length of optical cable has a positive adjustment effect on GDP.

## CCS Concepts

• **Applied computing Law**; • **social and behavioral sciences Sociology**;

## Keywords

coupling coordination, new quality productivity, carbon emission efficiency, machine learning, SHAP

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## 1 Introduction

As one of the main gases generated by energy consumption, carbon dioxide is imbalanced in its concentration, which will cause glacier melting and global climate change. To date, my country's carbon dioxide emissions are as high as 12.6 billion tons, accounting for 34% of the world, ranking first in the world. February 27, 2025.[1] The National Energy Administration issued the "Guiding Opinions on Energy Work in 2025" pointing out that it is necessary to strengthen the coordinated promotion of energy security guarantees and green and low carbon transformation and promote the upgrading of the energy system toward high quality and high resilience through systematic reform and technological innovation.[2] To achieve my country's "dual carbon" goal, we need to get rid of the traditional economic growth model, lagging development path, and explore a sustainable development path that conforms to my country's new concept of economic growth.[3] Undoubtedly, the emergence of new quality productivity provides a new path and new angle for my country to improve carbon emission efficiency.

## 2 Research and design

### 2.1 Source of data

In view of the availability of data, this article uses 30 provinces and cities in my country (excluding Tibet, Hong Kong, Macao and Taiwan) as the original data for research from 2014 to 2023, mainly from the statistical yearbooks of various provinces, the websites of the National Bureau of Statistics, the "China Energy Statistical Yearbook" and the "China High-tech Industry Statistical Yearbook". In addition, the carbon dioxide data comes from the CEADs China Carbon Accounting Database, and the Digital HP Financial Index and Innovation Level Index are from the Digital Research Financial Center and the Enterprise Big Data Research Center of Peking University respectively. Some missing data are

**Table 1: New quality productivity index system**

| Target layer | First-level indicator | Second-level indicator | Measurement Method | Attribute | Weight | Variable Name |
|---|---|---|---|---|---|---|
| New Quality Productivity | Laborers | Cultural Quality | Average number of college students per 100,000 population | + | 0.0074 | $x_1$ |
| | | | Advanced Vocational Certificates | + | 0.0455 | $x_2$ |
| | | Development Support | Local fiscal education expenditure / General budget expenditure | + | 0.0628 | $x_3$ |
| | | | Disposable Income | + | 0.0581 | $x_4$ |
| | Labor Objects | Ecological Environment | Green coverage rate in built-up areas | + | 0.0267 | $x_5$ |
| | | | Sulfur dioxide emissions / GDP | - | 0.0078 | $x_6$ |
| | | | Industrial wastewater discharge / GDP | - | 0.0091 | $x_7$ |
| | | | Energy consumption / GDP | - | 0.0007 | $x_8$ |
| | | Technology Industry | Profit of high-tech industries / Number of high-tech enterprises | + | 0.0058 | $x_9$ |
| | | | Technology market turnover / GDP | + | 0.0285 | $x_{10}$ |
| | Means of Production | Infrastructure | Highway mileage | + | 0.0935 | $x_{11}$ |
| | | | Optical cable line length (km) | + | 0.0636 | $x_{12}$ |
| | | | Mobile phone penetration rate (units per 100 people) | + | 0.0086 | $x_{13}$ |
| | | Technological Innovation | Patents granted per capita | + | 0.2278 | $x_{14}$ |
| | | | R&D expenditure / GDP | + | 0.0916 | $x_{15}$ |
| | | | Total innovation level index | + | 0.0432 | $x_{16}$ |
| | | Digital Development | Internet broadband access ports per 10,000 people | + | 0.0602 | $x_{17}$ |
| | | | Total telecommunications business revenue (10,000 yuan) | + | 0.1546 | $x_{18}$ |
| | | | Digital Inclusive Finance Index | + | 0.0045 | $x_{19}$ |

**Table 2: Carbon emission efficiency index system**

| Indicator | Primary Indicator | Secondary Indicator | Variable Name |
|---|---|---|---|
| Input Indicators | Labor Input | Employed Personnel in Urban Units | $x_{20}$ |
| | Capital Input | Fixed Asset Investment | $x_{21}$ |
| | Energy Input | Energy Consumption | $x_{22}$ |
| Output Indicators | Desired Output | GDP | $x_{23}$ |
| | Undesired Output | Carbon Dioxide Emissions | $x_{24}$ |

filled with interpolation. Construction of the Indicator Evaluation System.

## 2.2 Construction of indicator evaluation system

*2.2.1 New quality productivity index system.* This article builds a new quality productivity index system from three aspects: workers, workers, and means of production.[4] The entropy weight method was modified using the AHP method, and the Topsis method was used to measure the new quality productivity level in each province from 2014 to 2022. The index system was shown in the table below.

*2.2.2 Carbon Emission Efficiency Indicator System.* In this study, labor, energy, and capital are selected as inputs, Gross Domestic Product (GDP) as the desirable output, and carbon dioxide emissions as the undesirable output. The results are presented in Table

## 2.3 Model Specification

*2.3.1 AHP-Entropy Weight-Topsis Method.* This paper solves the weight of the new quality productivity evaluation index from both quantitative and qualitative aspects and uses the meaning of the weights of the two as the index weights to measure the level of new quality productivity in each province and city through the Topsis method. Due to the differences in the dimensions of different indicators of new quality productivity.[5] this paper chooses to use the Max-Min normalization method to eliminate the impact of the dimensions between indicators. The calculation formula is:

*2.3.2 DEA-SBM Model.* Treating each province and municipality in China as a single Decision-Making Unit (DMU), let the $i$-th input variable of the $k$ th DMU be denoted as $x_{ik}$. We will construct an Undesirable Output Slack-Based Measure (SBM) model. The general form of the SBM model with undesirable outputs is as follows:

$$min\rho = min\rho = min\rho = min\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{s_1+s_2}\left(\sum_{i=1}^{s_1}\frac{s_i^g}{y_{ik}^g}+\sum_{i=1}^{s_2}\frac{s_i^b}{y_{ik}^b}\right)} \quad (1)$$

$$s.t.\begin{cases}\sum_{j=1}^{n}\Lambda_j x_{ij}+s_i^- = x_{ik}|||||i=1,2,\cdots,m\\ \sum_{j=1}^{n}\Lambda_j y_{uj}^g+s_u^g = y_{uk}^g|||||u=1,2,\cdots,s_1\\ \sum_{j=1}^{n}\Lambda_j y_{vj}^b+s_v^b = y_{vk}^b|||||v=1,2,\cdots,s_2\end{cases} \quad (2)$$

Here, $s^-$,$s^g$,$\mathbf{s}^b$ represents the slack variable, $y^g{}_{ik}$,$y^b{}_{ik}$ respectively denote the $i$-th desired output and undesired output of the $k$-th DMU,$A$ represents non-negative multipliers, and $\rho$ is the efficiency value of the currently evaluated DMU.

*2.3.3 Coupling Coordination Model.* The coupling coordination model can be used to evaluate the interaction and coordination between two or more systems.[6] In this paper, new quality productivity and carbon emission efficiency levels are treated as subsystems, and the coupling coordination level between them is measured using the coupling coordination model. The formula for this is as follows:

$$C = \frac{2\sqrt{U_1 \times U_2}}{U_1 + U_2} \quad (3)$$

$$T = \alpha_1 U_1 + \alpha_2 U_2,\ \alpha_1 + \alpha_2 = 1 \quad (4)$$

$$D = \sqrt{C \times T} \quad (5)$$

Here, $U_1$,$U_2$ represent the levels of new quality productivity and carbon emission efficiency, respectively.$C$ is the coupling degree. $T$ is the coordination effect index. $D$ is the coupling coordination degree. $\alpha_1$,$\alpha_2$ are undetermined coefficients. Given that new quality productivity and carbon emission efficiency are equally important, both are set to 0.5.

*2.3.4 XGBoost Model and SHAP Values.* The XGBoost model, which is derived from decision tree models, is a machine learning algorithm. Its training objective function is formulated as follows:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_t^{(t)}\right) + \Omega\left(f_t\right) \quad (6)$$

Where $\sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)})$ is the loss function, $y_i$ is the true value of the coupling coordination level for the $i$-th predicted sample, $\hat{y}_i^{(t)}$ is the predicted value, and $\Omega(f_t)$ is the regularization term.

SHAP values, proposed based on game theory, fairly distribute cooperative gains by considering the contributions made by each agent. In 2010, Erik Rumbelj and Igor Kononenko first applied this method in machine learning, marking the beginning of using SHAP values to explain machine learning models. The expression is given as:

$$shap = \sum_{S\cup A\ x_i \notin S} \frac{|S|!\,(N-|S|-1)!}{N!}\left(val\left(S_a \cup \{x_i\}\right) - val\left(s_a\right)\right) \quad (7)$$

Where *shap* is the SHAP value for the $j$-th feature of the $i$-th sample, $N$ represents the set of all features, and $S$ represents the set without the $j$-th feature. In this paper, SHAP values are applied to the XGBoost model to identify the influencing factors of coupling coordination levels.

# 3 Coupling and coordination measurement results and analysis of new quality productivity and carbon emission efficiency

Using Python to solve the coupling coordination measurement results between China's new quality productivity and carbon emission efficiency, the results are shown in the table below.

From the above table, we can see that the coupling and coordination level between new quality productivity and carbon emission efficiency in my country has shown an upward trend, from the initial stage of stalemate imbalance to the coordination stage, indicating that the development of new quality productivity has brought positive impacts on the improvement of carbon emission efficiency, and at the same time, the improvement of carbon emission efficiency provides a sustainable development environment for the development of new quality productivity.[7] However, there are certain differences in the coordination levels between different regions. The eastern region has rich geographical resources and talent reserves, and its coordination level is far better than that in the central and western regions. From the urban perspective, there are also big differences within the region. For example, the coordination level of Liaoning, Shanxi, Jilin and other regions is far lower than the regional average. It is necessary to increase policy support and talent training for the region to help steadily improve the coordination level.

# 4 Analysis of factors influencing the coupling coordination of new quality productivity and carbon emission efficiency

## 4.1 Feature Selection and Prediction

According to relevant literature research, this paper takes variables of the new mass productivity and carbon emission efficiency index system as the characteristics of the model.[8] In addition, the high correlation between variables can cause serious multicollinearity problems, resulting in a significant discount on the solvability and prediction effect of the model. Therefore, it is necessary to filter the features of the model before XGBoost training.

Lasso regression is a common method used to reduce dimensionality of features. By introducing regular terms into the loss function, it can reduce the multicollinearity of the model and improve the model prediction and generalization ability. Based on this, this paper uses Lasso regression to filter the features and selects variables with regression coefficients not 0 as model features.

**Table 3: Coupling coordination level measurement results**

| Area | Province | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern | Beijing | 0.705 | 0.739 | 0.754 | 0.786 | 0.810 | 0.854 | 0.899 | 0.962 | 0.974 | 0.994 | 0.848 |
| | Jiangsu | 0.639 | 0.669 | 0.708 | 0.738 | 0.768 | 0.817 | 0.866 | 0.927 | 0.946 | 0.976 | 0.805 |
| | Shanghai | 0.718 | 0.734 | 0.765 | 0.799 | 0.729 | 0.740 | 0.802 | 0.862 | 0.887 | 0.945 | 0.798 |
| | Guangdong | 0.659 | 0.667 | 0.706 | 0.725 | 0.721 | 0.813 | 0.841 | 0.871 | 0.896 | 0.924 | 0.782 |
| | Zhejiang | 0.640 | 0.674 | 0.690 | 0.722 | 0.731 | 0.795 | 0.822 | 0.862 | 0.880 | 0.892 | 0.771 |
| | Fujian | 0.599 | 0.582 | 0.609 | 0.637 | 0.694 | 0.772 | 0.821 | 0.875 | 0.902 | 0.924 | 0.741 |
| | Shandong | 0.564 | 0.581 | 0.608 | 0.624 | 0.652 | 0.655 | 0.678 | 0.723 | 0.755 | 0.767 | 0.661 |
| | Tianjin | 0.544 | 0.548 | 0.542 | 0.581 | 0.647 | 0.654 | 0.694 | 0.753 | 0.757 | 0.765 | 0.648 |
| | Hebei | 0.448 | 0.470 | 0.500 | 0.561 | 0.630 | 0.658 | 0.679 | 0.717 | 0.740 | 0.756 | 0.616 |
| | Hainan | 0.426 | 0.453 | 0.647 | 0.733 | 0.463 | 0.574 | 0.591 | 0.637 | 0.664 | 0.705 | 0.589 |
| | Liaoning | 0.331 | 0.395 | 0.479 | 0.532 | 0.509 | 0.536 | 0.565 | 0.601 | 0.615 | 0.629 | 0.519 |
| | Mean | 0.570 | 0.592 | 0.637 | 0.676 | 0.669 | 0.715 | 0.751 | 0.799 | 0.820 | 0.843 | 0.707 |
| Central | Hunan | 0.522 | 0.549 | 0.583 | 0.614 | 0.668 | 0.672 | 0.710 | 0.764 | 0.800 | 0.848 | 0.673 |
| | Jiangxi | 0.588 | 0.509 | 0.533 | 0.579 | 0.666 | 0.653 | 0.684 | 0.735 | 0.754 | 0.777 | 0.648 |
| | Hubei | 0.487 | 0.511 | 0.551 | 0.587 | 0.640 | 0.647 | 0.672 | 0.728 | 0.756 | 0.784 | 0.636 |
| | Anhui | 0.475 | 0.510 | 0.545 | 0.572 | 0.603 | 0.632 | 0.665 | 0.708 | 0.728 | 0.747 | 0.619 |
| | Henan | 0.484 | 0.486 | 0.507 | 0.535 | 0.613 | 0.627 | 0.646 | 0.673 | 0.682 | 0.710 | 0.596 |
| | Heilongjiang | 0.406 | 0.409 | 0.405 | 0.430 | 0.505 | 0.565 | 0.591 | 0.608 | 0.637 | 0.646 | 0.520 |
| | Jilin | 0.300 | 0.342 | 0.338 | 0.366 | 0.455 | 0.428 | 0.465 | 0.495 | 0.502 | 0.525 | 0.422 |
| | Shanxi | 0.231 | 0.151 | 0.235 | 0.371 | 0.411 | 0.426 | 0.447 | 0.535 | 0.568 | 0.570 | 0.395 |
| | Mean | 0.436 | 0.433 | 0.462 | 0.507 | 0.570 | 0.581 | 0.610 | 0.656 | 0.678 | 0.701 | 0.564 |
| Western | Chongqing | 0.486 | 0.514 | 0.549 | 0.591 | 0.615 | 0.665 | 0.727 | 0.777 | 0.807 | 0.855 | 0.659 |
| | Yunnan | 0.473 | 0.498 | 0.510 | 0.536 | 0.612 | 0.690 | 0.717 | 0.757 | 0.787 | 0.821 | 0.640 |
| | Sichuan | 0.469 | 0.499 | 0.546 | 0.599 | 0.634 | 0.670 | 0.679 | 0.712 | 0.736 | 0.759 | 0.630 |
| | Shaanxi | 0.475 | 0.457 | 0.484 | 0.495 | 0.596 | 0.638 | 0.653 | 0.716 | 0.732 | 0.750 | 0.599 |
| | Guangxi | 0.485 | 0.450 | 0.531 | 0.542 | 0.525 | 0.550 | 0.570 | 0.628 | 0.655 | 0.670 | 0.561 |
| | Qinghai | 0.342 | 0.373 | 0.406 | 0.437 | 0.586 | 0.604 | 0.620 | 0.653 | 0.679 | 0.698 | 0.540 |
| | Xinjiang | 0.429 | 0.377 | 0.399 | 0.419 | 0.574 | 0.574 | 0.587 | 0.630 | 0.648 | 0.666 | 0.530 |
| | Ningxia | 0.162 | 0.262 | 0.327 | 0.396 | 0.438 | 0.728 | 0.659 | 0.736 | 0.797 | 0.796 | 0.530 |
| | Guizhou | 0.402 | 0.449 | 0.461 | 0.486 | 0.552 | 0.538 | 0.564 | 0.592 | 0.603 | 0.624 | 0.527 |
| | Inner Mongolia | 0.291 | 0.371 | 0.401 | 0.441 | 0.518 | 0.533 | 0.549 | 0.649 | 0.686 | 0.756 | 0.520 |
| | Gansu | 0.355 | 0.354 | 0.370 | 0.490 | 0.515 | 0.550 | 0.559 | 0.600 | 0.623 | 0.651 | 0.507 |
| | Mean | 0.397 | 0.419 | 0.453 | 0.494 | 0.561 | 0.613 | 0.626 | 0.677 | 0.705 | 0.731 | 0.568 |
| Mean | China | 0.471 | 0.486 | 0.523 | 0.564 | 0.603 | 0.642 | 0.667 | 0.716 | 0.740 | 0.764 | 0.618 |

In addition, a cross-validation set of 50% off time series is constructed. Through the grid search method, the minimum cross-validation set RMSE of the 50% time series is aimed at, and the learning rate of XGBoost is 0.2, the maximum depth is 6, and the number of iterations is 200. In addition, the data training set and the remaining data from 2014 to 2021 are trained for training, which shows that the fitting effect is very excellent.

## 4.2 Analysis of Influencing Factors

This paper chooses to use global SHAP values to analyze the influencing factors of the coupling coordination level of new quality productivity and carbon emission efficiency. From the average absolute value of SHAP, we can see that disposable income, GDP, optical cable line length, carbon dioxide emissions, and urban employment are important features that affect my country's new quality productivity and carbon emission efficiency coupling and coordination level, while the average number of students in school and advanced professional skills certificates have relatively low impact.

Per capita disposable income has a positive impact on the level of coupling coordination. Since the new era, the main social contradiction in our country has changed from the contradiction between material culture and backward social production to the contradiction between the growing need for a better life and the unbalanced and inadequate. When the income reaches a certain level, residents' requirements for the ecological environment will increase, and the government will strengthen investment and management of the ecological environment. In addition, the increase in income has increased people's demand for low-carbon products, prompting enterprises to increase investment in green technology research and development, and promoting the transformation of traditional industries to higher-end and green.

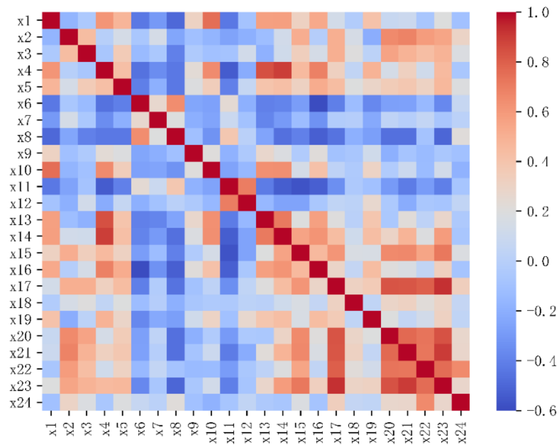


**Figure 1: Thermogram of correlation coefficient between features**

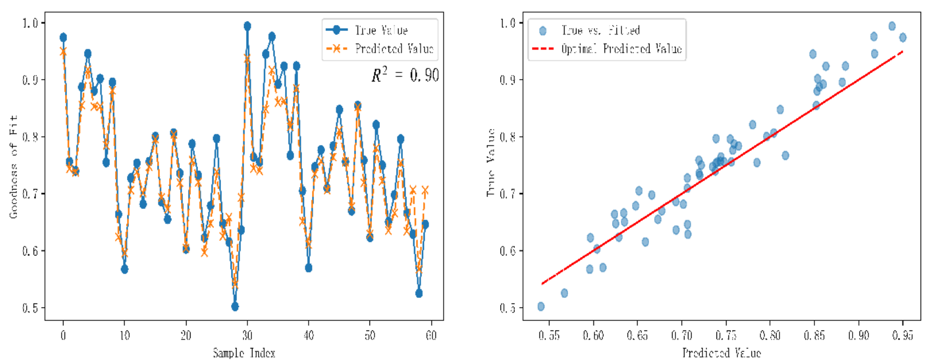


**Figure 2: Test set prediction results**

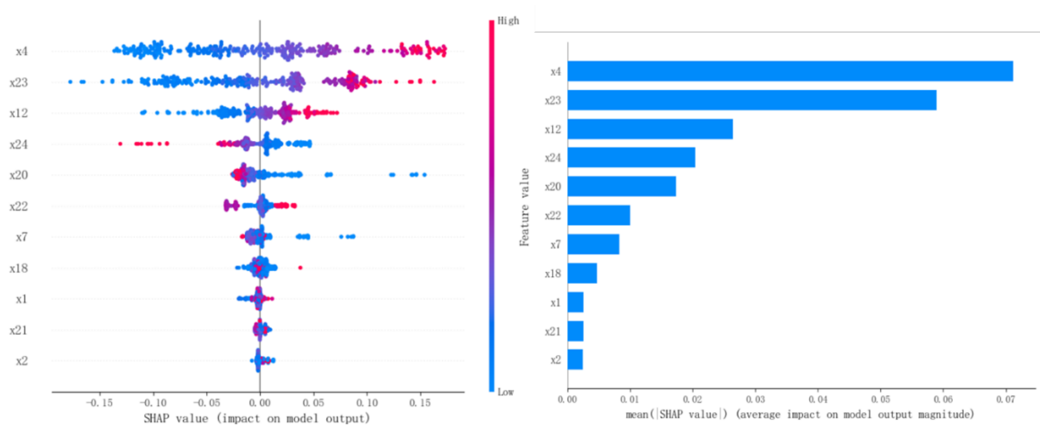


**Figure 3: Importance of coupling and coordination characteristics of new quality productivity and carbon emission efficiency**

GDP can have a positive impact on new quality productivity and carbon emission efficiency through industrial upgrading, technological innovation, energy structure optimization, etc. GDP growth provides a material basis for the improvement of my country's low-carbon technology and digital technology. By optimizing resource allocation and industrial structure, we will steadily improve my country's new quality productivity and carbon emission efficiency. However, achieving this goal requires in-depth integration of GDP growth with low-carbon paths, and taking new quality productivity as the core driving force, in order to achieve high-quality economic growth and the win-win goal of "dual carbon" goals.

Optical cable lines are the cornerstone of emerging high-tech industries such as 5G and cloud computing, and provide core impetus for my country's intelligent and digital transformation. Through the improvement of optical cable line technology, breakthroughs in disciplines such as semiconductors and materials will be driven, while improving production efficiency, and providing technical support for the improvement of new quality productivity. The transmission method of optical cable transmission instead of traditional copper cables reduces the energy consumption lost in power transmission and improves the utilization rate of energy.

The increase in carbon dioxide has led to a sharp increase in my country's environmental protection costs, which is difficult to improve in the short term. At the same time, it will increase the operating costs of enterprises and inhibit the intensity of their investment in innovation. At present, my country's urban employment population is still concentrated in traditional high-energy-consuming industries such as manufacturing and construction. During the industrial transformation period, these labor forces will face the pressure of changing careers. At the same time, the shortage of talents in digitalization and green fields required by new quality productivity has led to insufficient supply of innovative talents and restricted the speed of industrial structure transformation.

Additionally, to mitigate model and data selection biases, this paper calculates the average SHAP values for each feature under the Gradient Boosting model, random forest, and test set respectively. The results show that while the SHAP values of individual features vary when switching models and datasets, the importance rankings of most features remain consistent with those from XGBoost, demonstrating the robustness of the conclusions.

## 4.3 Interaction Analysis

*4.3.1 Interaction between Per Capita Disposable Income and Urban Employed Population.* The increase in per capita disposable income can drive regional consumption upgrades and demand to increase, thereby expanding the production scale of enterprises and providing more jobs for urban employed people. Therefore, the impact of per capita disposable income and urban employment interaction on SHAP values was explored, and the results were shown in the figure below.

From the figure above, we can see that when per capita disposable income is at a low level, per capita disposable income contributes less to the coupling coordination level of new quality productivity and carbon emission efficiency. As the income increases, the contribution to coupling coordination continues to increase, and it tends to be flattened when it increases to 0.6. When the per capita

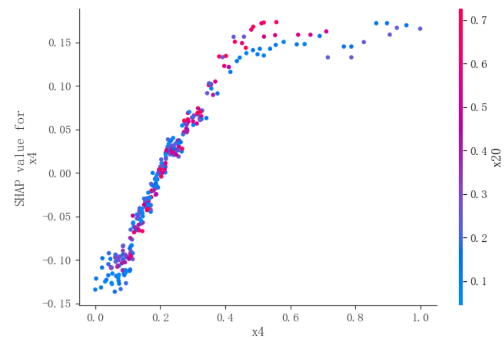


**Figure 4: Interaction chart of per capita disposable income and urban employment population**

disposable income of urban employed people is low, they have a slight negative regulation effect on the coupling coordination level, while when the per capita disposable income is high, they have a positive regulation effect. This is because urban employment in the low-income stage is concentrated in labor-intensive manufacturing and traditional services, and is characterized by high energy consumption. Although the increase in employment can help economic growth during this period, traditional production paths will also significantly increase the emission of polluted gases such as carbon dioxide. When entering the high-income stage, the knowledge-intensive service industry will gradually replace traditional high-energy-consuming industries and realize the transformation of traditional industries to high-tech industries. The proportion of green technology and high-quality talents in the labor market will gradually increase, that is, the increase in the number of employed people will give birth to scientific and technological innovation and improve the green and low-carbon system, thereby improving the productivity of new quality and carbon emission efficiency.

*4.3.2 Interaction between GDP and optical cable line length.* As the basic structure of communication facilities, optical cable length promotes the coupling and coordination level of GDP, new quality productivity and carbon emission efficiency. Therefore, the interaction terms of optical cable length and GDP were selected for research, and the results are shown in the figure below.

From the figure above, we can see that when GDP is around 0.2, it contributes the lowest rate to the coupling coordination level of new quality productivity and carbon emission efficiency. As GDP increases, it shows an upward, gentle and upward trend to the coupling coordination level. In addition, most of the red dots are above the blue dots, indicating that the length of the optical cable can positively adjust the role of GDP in promoting coupling coordination level. This is because a perfect optical cable network can improve the level of digitalization, accelerate information flow between regions, enterprises and industries, promote technological innovation and optimize resource allocation, improve regional economic efficiency and green performance, and positively regulate

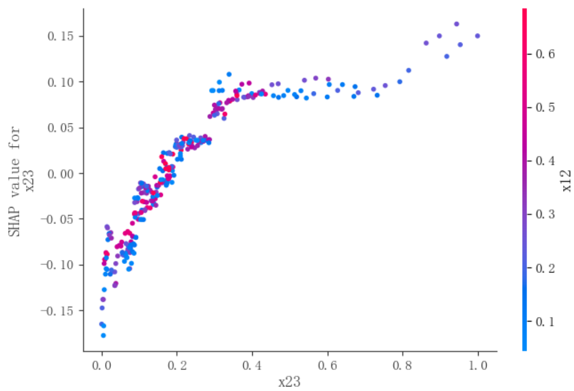


**Figure 5: GDP and optical cable line length interaction diagram**

the role of GDP in promoting the coupling and coordination level of new quality productivity and carbon emission efficiency.

## 5 Conclusions

This paper uses the AHP-entropy weight-Topsis method and SBM-DEA model to measure the new quality productivity level and carbon emission efficiency in 30 provinces from 2014 to 2022, respectively, uses the coupling coordination model to measure the coupling coordination level of the two, draws the nuclear density curve to study the spatiotemporal evolution trend of the coupling coordination level, and uses the XGBoost and SHAP models to analyze the main factors affecting the coupling coordination level, and further studies the interaction between the factors. The main conclusions are as follows:

1. my country's coupling coordination level of new quality productivity and carbon emission efficiency is showing an upward trend. The coupling coordination level of the eastern region is far better than that of the central and western regions, and there are certain differences in the coupling coordination level within various regions.

2. Per capita disposable income, GDP and optical cable length have a positive feedback mechanism for coupling coordination level, while carbon dioxide emissions and urban employment will inhibit the development of coupling coordination level. This is still true after replacing machine learning models and data sets for robustness testing.

3. There is an interaction between per capita disposable income and urban employed people, GDP and optical cable line length. The length of optical cable line can positively regulate the promotion of GDP on the level of coupling coordination. With the increase of disposable income, the urban employment population has changed from negative to positive.

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## References

[1] Acemoglu D, Aghion P, Bursztyn L, *et al.* The Environment and Directed Technical Change[J]. American Economic Review, 2012(1).
[2] Baltagi B H, Deng Y. EC3SLS Estimator for a Simultaneous System of Spatial Autoregressive Equations with Random Effects[J].Econometric Reviews,2015,34(6-10).
[3] Oh D. A GlobalMalmquist-Luenberger Productivity Index[J].Journal of Productivity Analysis, 2010,34(3).
[4] Tone K. A Slacks-based Measure of Efficiency in Data Envelopment Analysis[J].European Journal of Operational Research,2001,130(3).
[5] Shao S, Zhang Y, Tian Z, *et al.* The Regional Dutch Disease Effect within China: A spatial econometric investigation[J]. Energy Economics, 2020(88).
[6] Elhorst J P. Matlab Software for Spatial Panels[J].International Regional Science Review,2014,37(3).
[7] Qin Q, Li X, Li L, Zhen W, Wei Y M. Air Emissions Perspective on Energy Efficiency: An Empirical Analysis of China's Coastal Areas[J].Applied Energy,2017,185(1).
[8] Walte R I, Ugelow J L. Environmental Policies in Developing Countries[J].Ambio,1979,80:102-109.