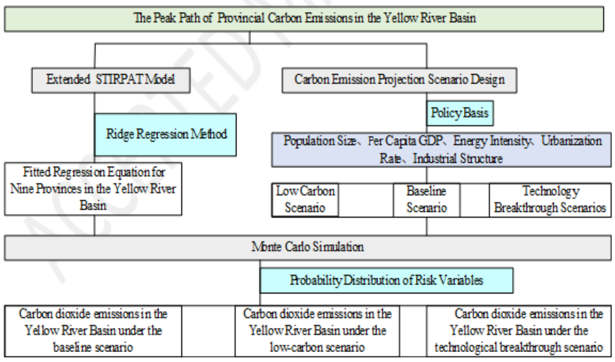
Global NEST Journal, Vol 25, No X, pp 56-69
Copyright© 2023 Global NEST
Printed in Greece. All rights reserved

# The peak path of provincial carbon emissions in the Yellow River Basin of China based on scenario analysis and Monte Carlo simulation method

**Wang C.[1,2], Gong W.[1,2*], Wang Y.[1], Fan Z.[3] and Li W.[1,2]**
[1]School of Economics, Qufu Normal University, Rizhao 276826, China
[2]School of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211006, China
[3]Taixi Branch, Taian City Commercial Bank, Taian 271021, China
Received: 07/12/2022, Accepted: 03/01/2023, Available online: 05/01/2023
*to whom all correspondence should be addressed: e-mail: gongweifeng0539@163.com
https://doi.org/10.30955/gnj.004619

## Graphical abstract




## Abstract

The Yellow River Basin is an important economic zone in China and an important base for energy, chemical, raw materials and basic industries. However, the sloppy development pattern of "high consumption and high pollution" in nine provinces along the Yellow River Basin has become an important obstacle to achieving the carbon peaking and carbon neutrality goals. Using the extended STIRPAT model and combining scenario analysis and Monte Carlo simulation to build a prediction model, the future trend of carbon emissions in the nine provinces of the Yellow River Basin was predicted and the optimal path to reach the peak of carbons in the Yellow River Basin was explored. The results show that the nine provincial areas in the Yellow River Basin will not be able to reach the carbon peaking before 2035 under the baseline scenario. By further comparing the carbon peaking conditions of provinces under the low-carbon scenario and the technology breakthrough scenario, it is found that the peaking time, carbon peak value and the number of provinces under the technology breakthrough scenario are significantly better than those under the low-carbon scenario. Under the technology breakthrough scenario, the energy efficiency of the nine provinces in the Yellow River Basin will be greatly improved, the innovation capacity will be significantly enhanced, and the synergistic emission reduction mechanism and related policies between provincial areas will be perfected. Technological breakthroughs will become an important engine for high-quality development in the Yellow River Basin.

**Keywords:** Yellow River Basin, carbon peaking, scenario analysis, Monte Carlo Simulation

## 1. Introduction

As the world's largest emitter of carbon dioxide, China has made great efforts to combat climate change. In his speech at the General debate of the 75th session of the UN General Assembly in September 2020, President Xi first proposed that China's carbon dioxide emissions "strive to reach the carbon peaking by 2030 and work towards carbon neutrality by 2060". The Yellow River Basin is an important economic zone in China and an important energy, chemical, raw material and basic industrial base, but the "high consumption and high pollution" pattern of rough development in the nine provinces along the Yellow River Basin has become an important obstacle to achieving the carbon peaking and carbon neutrality goals. Therefore, it is important to analyze the peak path of provincial carbon emissions to achieve ecological protection and high-quality development in the Yellow River Basin.

Kaya (1989) proposed the Kaya constant equation, which mainly decomposes and analyzes the influence of factors such as economic, demographic, and energy on carbon emissions. Ang (1997) proposed the Logarithmic Mean Divisia Index (LMDI) to improve the Kaya constant equation and make up for the shortcomings of the Kaya constant equation in the calculation. Fu (2021) decomposed the carbon emission drivers of China's manufacturing industry based on the LMDI method and found that economic development is the primary factor that makes carbon emissions increase. Yang (2020) combined the Kaya constant equation with the LMDI method and analyzed that carbon emissions and energy intensity in Inner Mongolia showed a significant negative effect. Chen and Zhou (2020) used LMDI method to analyze the drivers of carbon emissions in 29 provinces of China in terms of economic growth, structural transformation, and technological upgrading.

Econometric research methods on the drivers of carbon emissions are multilevel. Most of them focus on ''IPAT'' model (Cramer JC., 1997), STIRPAT model (York, 2003), Granger causality test and so on (Zeng, 2021). For the selection of influencing factors of carbon emissions, most of them focus on energy intensity, industrial structure, residents' income improvement (Hao, 2016), and the adjustment of economic openness to analyze the influencing factors of carbon emissions (Zhou Peng, 2020). Tang *et al*. (2021) used STIRPAT model to analyze the driving factors of carbon emissions in typical cities in China from the perspectives of per capita income, energy intensity and urban population. Yin *et al*. (2019) used SVAR model to find that EU carbon trading prices and AQI have a direct impact on China's carbon trading prices. Harin (2020) used the STIRPAT model to empirically evaluate the driving forces of CO2 emissions in ASEAN countries. Wang (2021) used a Random Forest (RF) machine learning algorithm to assess urban carbon emissions in 73 cities in three urban agglomerations in the Yangtze River Economic Belt, and found that factors such as population, industry, technological level, consumption, and opening up have different impacts on different cities. Based on the CGE model, Shi (2015) found that the carbon trading mechanism has a significant role in promoting the reduction of carbon intensity. The above researches often give people an illusion: the change of carbon emissions is only caused by the change of economic and social factors in the region, while Hu (2019) pointed out that trade activities make goods transfer from production place to final consumption place, which changes the spatial and temporal distribution characteristics of carbon emissions. Meanwhile, carbon dioxide itself has a certain diffusion effect, further indicating that the increase in carbon emissions in a certain area is caused by many reasons.

With the rapid development of economy, carbon emissions are also increasing rapidly at a certain speed. When carbon emissions increase to a certain extent, the trend of carbon emissions will change from rapid growth to gradual decline, and the inflection point of this change is the peak value of carbon emissions. There are many methods to predict the peak value of carbon emissions, which can be summarized into three categories: The first category is to judge whether there is a long-term relationship between carbon emissions and economic growth through the relationship between the two factors, and then calculate whether the EKC curve will have an inflection point, which is the turning point of carbon emissions change trend-carbon emissions peak (Lin, 2009). The second category is to construct a carbon emission model by analyzing the driving factors of carbon emissions. Combined with the scenario analysis method, the change trend of carbon emissions under multiple scenarios is simulated, and then the optimal path of carbon peak is selected. Wang (2018) used the LMDI decomposition analysis method to conclude that the level of economic development is the main factor affecting China's carbon emissions, and then used six scenarios to predict the future development trend of China's fossil fuels and carbon emissions. Wang (2021) used scenario analysis to predict the condition of reaching peak of each province in the Yellow River Basin from 2020 to 2050 under three scenarios. The third category is to construct a prediction model to directly analyze the future trend of carbon emissions, including gray forecasting, neural network model and other prediction models. Wang (2016) used grey correlation and grey prediction methods to analyze the influence of per capita GDP and energy structure on carbon peak condition in Jilin Province. Gong (2022) used the established carbon emission prediction model to analyze the drivers of the peaking and decoupling between CO2 emissions and economic growth around 2030 in China.

There are many methods to predict the peaking of carbon emissions. Different regions and different industries have different peak time of carbon emissions. Zhuang (2017) predicted the traffic carbon peak in Guangdong Province and found that there were some differences in the peaking time under different scenarios. Li (2019) predicted that Tianjin's carbon emissions could peak in 2025 under the scenario of medium growth and strong emission reduction by constructing six scenarios. Wang (2022) conducted a multi-scenario analysis of carbon emissions in the Pearl River Delta urban agglomeration and found that cities such as Shenzhen and Zhuhai all peak before 2020. Hu (2022) constructed an extended STIRPAT model and set four scenarios to find that the carbon emissions of transportation industry in Hubei Province will peak in 2030. Hu (2022) predicted the future trend of China's carbon emissions at a certain economic level based on the LSTM neural network model, and analyzed the possibility of China completing the carbon peaking by 2030.

The existing researches mainly focus on the whole nation or the provinces with more prominent economic development. Based on the high-quality development strategy of the Yellow River Basin, it is of great significance to explore the driving factors of carbon emissions in the provinces of the Yellow River Basin, and then predict the future trend of carbon emissions. In addition, there is a spatial spillover effect of carbon emissions and economic development among provinces. The coordinated emission reduction among provinces is particularly important. Therefore, this paper focuses on the provinces in the Yellow River Basin, and uses Monte Carlo simulation to make a dynamic and reasonable prediction of the peak time in the nine provinces of the Yellow River Basin. On this basis, the collaborative emission reduction mechanism among different provinces is explored, so as to make efforts for the coordinated development of the whole Yellow River Basin.

## 2. Description of data sources

### *2.1. Description of variables and data sources*

In this paper, panel data of nine provinces in the Yellow River Basin from 2000 to 2020 are selected as the research sample, and carbon emissions are estimated by the emission factor method. The economic and social data involved in the paper are obtained from *the China Regional Economic Statistical Yearbook*, *the China Energy Statistical Yearbook* and *the Statistical Yearbook* of each province and region in the past years, and the latitude and longitude information of different regions are collected through Baidu Maps.

Explained variables. In this paper, the more common IPCC emission factor method is used to measure carbon emissions in nine provincial areas along the Yellow River Basin, among which, eight types of energy consumption, such as raw carbon, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas, are mainly collected and accounted for. The calculation formula is:

$$I=\sum_{i=1}^{n}\sum_{j=1}^{m}(E_{ij}\times NCV_i\times CC_i\times O_i)\times\frac{44}{12} \tag{1}$$

Among them, $I$ represents carbon emissions, $i$ represents the $i$-th energy source, $j$ represents the $j$-th province, and $E_{ij}$ represents the consumption of the $i$-th energy in the $j$-th province. $NCV_i$ represents the average low-level heat content of the $i$-th energy sources,$CC_i$ represents the average carbon content per unit calorific value of the $i$-th energy sources, $O_i$ represents the carbon oxidation rate of the i-th energy sources, and 44/12 is the ratio of the molecular weight of carbon dioxide to the molecular weight of carbon.

**Table 1**. Meaning of the variables and description of the units

| Targets | Symbolic | Connotation | Unit |
|---|---|---|---|
| Carbon emissions | *I* | Energy carbon emissions | million tons |
| Population size | *P* | Total resident population | Ten thousand people |
| per capita GDP | *pGDP* | GDP/total population | Yuan/person |
| energy intensity | *T* | Total energy consumption/GDP | million tons of standard coal per million yuan |
| urbanization rate | *U* | Urban population/resident population | % |
| industrial structure | *IS* | Value added of the secondary sector/GDP | % |

Due to the differences in the current socio-economic situation in terms of population size, resource factor endowment and economic development level, there have also obvious regional heterogeneity in carbon emissions in the nine provinces along the Yellow River Basin, and the trends of carbon emissions in the nine provinces from 2000 to 2020 are analyzed.

As can be seen from Figure 1, carbon emissions of the nine provinces in the Yellow River Basin showed an obvious upward trend in general, and the growth rate is accelerating year by year. Shandong Province had the highest carbon emissions. The growth rate of carbon emissions in Shandong was much faster than other provinces. In addition, Shanxi, Inner Mongolia and Henan provinces had a high level of carbon emissions and also show an overall increasing trend in spite of a slight fluctuation. Shaanxi and Sichuan provinces had comparable emission levels from 2000 to 2009, carbon emissions of Shaanxi exceeded Sichuan from 2009 to 2020. Ningxia, Gansu and Qinghai provinces had lower levels of carbon emissions, and Qinghai province has the lowest total emissions and a more moderate growth trend.

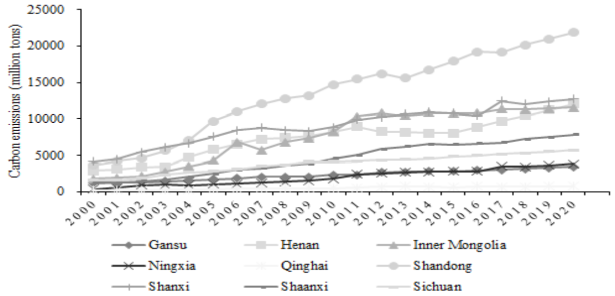



**Figure 1**. The trends of carbon emissions in nine provinces along the Yellow River Basin from 2000 to 2020 years

Explanatory variables. this paper uses per capita GDP (*pGDP)* to characterize the economic development level and incorporates the quadratic term of per capita GDP into the model to analyze the embodiment of environmental Kuznets curve theory in the sample period. Industrial structure (*IS) is* measured by the share of the secondary sector in total output, as the secondary sector is more dependent on fossil energy and generates more carbon emissions compared to the primary and tertiary sectors. The level of technology (*T*) is characterized by energy intensity, i.e., energy consumption per unit of GDP. The larger the population size (*P)* is, the greater the demand for energy and thus the greater the pollutants produced and the greater the pressure on the environment. The urbanization rate (*U*) is expressed as the share of urban population in the total population. To eliminate the effect of heteroskedasticity, the variables are all analyzed by taking logarithms. The meanings of the above variables and unit descriptions are given in Table 1.

Among the many methods used to study the factors influencing carbon emissions, the STIRPAT model constructed by Dietz and Rosa is more widely used (York, 2003). The general form of the STIRPAT model is as follows:

$$I=aP^bA^cT^d\mu \tag{2}$$

Where $I$ represents environmental pressure (Human impact); $P$ represents population size (Population); $A$ represents economic level (Affluence), which is represented by per capita GDP, and $T$ represents technology level (Technology), which is represented by energy intensity; *a, b, c, and d* are parameters to be estimated, and $\mu$is random error.

We use the expandable characteristics of the model to add the quadratic term of per capita GDP, industrial structure, urbanization level, energy intensity and other factors for more comprehensively analyzing the factors influencing carbon emissions. The model is expanded in logarithmic form as:

$$\ln I = \ln\alpha + \beta_1 \ln pGDP_{it} + \beta_2 (\ln pGDP_{it})^2 + \beta_3 \ln IS_{it} + \beta_4 \ln P_{it} + \beta_5 \ln T_{it} + \beta_6 \ln U_{it} + \varepsilon \quad (3)$$

Where *I* represents carbon emissions, *pGDP* denotes gross regional product per capita. *IS* represents the share of gross secondary sector product in total GDP (industrial structure), *P represents* population size, *T* represents energy intensity, and *U* represents the level of urbanization (urban). *Ɛ* is the stochastic perturbation term.

*2.2. Fitting Coefficient Measurements for the Yellow River Basin Provinces*

We select each economic and social factor and carbon emissions of nine provinces in the Yellow River Basin from 2000 to 2020, and apply equation (3) to obtain the fitted equation for carbon emissions in each province. The historical data of each province in the Yellow River Basin are time series data, and in the process of calculating the fitted model for each, it is necessary to test the multicollinearity of each explanatory variable. By calculating the variance inflation factor for the test, it was found that the variance inflation factor of each variable in several provinces appeared to be much greater than 10, which also verified again the existence of multicollinearity among the variables. Therefore, we used the ridge regression method to fit carbon emissions of each province in the Yellow River Basin with each economic and social factor. The ridge trace plots of nine provinces were analyzed, and the K values when the ridge regression coefficients tend to be stable were selected, so that the corresponding fitting equations were obtained as shown in Table 2.

**Table 2**. Regression coefficients for nine provinces in the Yellow River Basin

| variable | Shandong | Henan | Shaanxi | Shanxi | Sichuan | Inner Mongolia | Gansu | Qinghai | Ningxia |
|---|---|---|---|---|---|---|---|---|---|
| lna | 0.763* | -9.675* | 1.685** | 1.697** | -3.424* | 0.412* | 0.266** | -1.350* | -1.689** |
| lnP | 0.326** | 0.286* | 0.337* | 0.260** | 0.368* | -0.028** | -0.041* | 0.188*** | 0.341*** |
| lnpGDP | 0.229* | 0.147** | 0.274* | 0.280* | 0.290* | 0.312** | 0.219** | 0.266*** | 0.315* |
| (lnpGDP)$^2$ | 0.215** | 0.181** | -0.015* | 0.137* | -0.143** | 0.282*** | 0.106* | 0.194** | 0.139* |
| lnT | -0.245* | -0.244** | -0.220** | -0.125* | -0.314* | -0.300* | -0.220** | 0.023*** | -0.204*** |
| lnU | 0.047* | 0.162* | -0.200** | 0.266* | 0.208** | -0.020** | 0.220*** | 0.209*** | -0.187* |
| lnIS | 0.067** | 0.100* | -0.023* | 0.038* | 0.341** | -0.214* | -0.161* | 0.182* | 0.484** |
| $R^2$ | 0.991 | 0.970 | 0.982 | 0.993 | 0.986 | 0.980 | 0.990 | 0.972 | 0.991 |
| K-value | 0.2 | 0.2 | 0.06 | 0.1 | 0.09 | 0.05 | 0.2 | 0.2 | 0.2 |

*Note: Numbers in parentheses in the table represent t-test values and *, **, *** represent significant at the 10%, 5%, and 1% levels, respectively.*

The impact of each driver on carbon emissions varies widely among different provinces in the Yellow River Basin, and there are also large differences in the impact of different drivers on carbon emissions in the same province. The adjusted $R^2$ of each province is close to 1, so the above fitting results are reasonable. The impact of different drivers on carbon emissions varies widely across provinces.

Firstly, in terms of population size, except for Inner Mongolia and Gansu, all the other seven provincial areas have a positive impact on carbon emissions. And the extent of population size on carbon emissions is larger among the five influencing factors, which further verifies the theoretical hypothesis that as population size increases, the pressure on the environment also increases, which in turn leads to an increase in carbon emissions.

Secondly, per capita GDP is also one of the main factors affecting carbon emissions of the nine provinces in the Yellow River Basin, which has a greater impact on carbon emissions. The primary coefficients of per capita GDP in the nine provinces are positive, while the secondary coefficients of per capita GDP in Shaanxi and Sichuan are negative, which also indicates that the relationship between per capita GDP and carbon emissions in Shaanxi and Sichuan has an inverted "U" shape EKC curve. At the beginning of economic development, carbon emissions gradually increase as the level of economic development increases, and after reaching a certain level, carbon emissions increase. After reaching a certain level, carbon emissions will decrease with the growth of economic development.

Thirdly, the energy intensity of the nine provinces in the Yellow River Basin has a significant negative impact on carbon emissions, which further verifies the theoretical hypothesis that carbon emissions will decrease as the level of technology continues to increase.

Fourthly, the impact of urbanization on carbon emissions has been controversial as different scholars have different analytical results. On the one hand, with the accelerated urbanization, population explosion and transportation development, there will be certain pressure on the environment, thus making carbon emissions increase. For example, the urbanization rate coefficients of six provinces, namely Shandong, Henan, Shanxi, Sichuan, Gansu and Qinghai, are all positive, i.e. the urbanization rate has a positive contribution to carbon emissions. On the other hand, there are also views that accelerated urbanization shortens transportation distances and promotes the development of technology level, thus curbing the growth of carbon emissions. For example, carbon emissions in Shaanxi, Inner Mongolia and Ningxia provinces decrease with the increase of urbanization rate. Finally, the elasticity coefficient of industrial structure also has positive and negative effects, i.e., different drivers exhibit different effects in different provinces. Therefore, we should formulate local energy-saving and emission reduction policies according to the local characteristics of each province.

## 3. Scenario design for carbon emission prediction

### *3.1. Scenario design*

Through the construction of the prediction model, it is concluded that different influencing factors have different effects on carbon emissions in different provincial areas, and the magnitude of the effect of different influencing factors on carbon emissions in the same province and region also varies. However, in general, per capita GDP, population size, energy intensity, urbanization rate and industrial structure all have significant effects on carbon emissions. Therefore, this paper sets three scenarios based on the historical data of the above variables, existing policies and future emission reduction targets, and other relevant economic and social factors: the baseline scenario, the low-carbon scenario, and the technology breakthrough scenario. The trends of each variable under the three scenarios are set separately. The data are substituted into the prediction model of each province to analyze the trends of carbon emissions in the Yellow River Basin from 2021 to 2035.

**Table 3**. Relevant policy rationale for nine provinces in the Yellow River Basin

| provinces | Policy basis |
|---|---|
| **Shanxi** | In 2035, the per capita gross regional product to reach 20,000 U.S. dollars, GDP growth rate of 3.6 percent in 2020, in 2025, the urbanization rate reached 68 percent, and the rate of reduction of energy consumption per unit of gross regional product in 2020 to complete the national indicators issued in the same period. |
| **Inner Mongolia** | GDP growth of 0.2% in 2020, an average annual growth rate of 5% between 2020 and 2025, an urbanization rate of about 69% in 2025 and 72% in 2035, and a reduction rate of CO2 emissions per unit of GDP in 2025 to meet national requirements. |
| **Shandong** | The average annual growth rate of gross regional product in 2020-2025 will be 5.5 per cent, and the urbanization rate will reach 68 per cent in 2025 and 75 per cent in 2035. The State's target of reducing energy consumption per unit of GDP was achieved. |
| **Henan** | The average annual growth rate of gross regional product in 2020 will be 6.4 per cent, maintaining a medium-to-high growth rate, the urbanization rate will be 55.43 per cent in 2020, the urbanization rate will exceed 60 per cent in 2025, and the rate of reduction of energy consumption per unit of gross regional product in 2020 will complete the targets set by the State in the same period. |
| **Sichuan** | GDP growth of 2.8 per cent in 2020, with an average annual growth rate of 6 per cent in 2020-2025, and an urbanization rate of 55 per cent in 2020 and 60 per cent in 2025. The target of reducing energy consumption per unit of gross regional product set by the State is completed. |
| **Shaanxi** | The regional GDP will reach 3.6 trillion yuan in 2025, the per capita GDP will reach about 90,000 yuan, the urbanization rate will reach 70% in 2030, energy consumption per unit of GDP will drop to the national average, and total carbon emissions will steadily decrease after peaking by 2030. |
| **Gansu** | The gross regional product will reach 9016.7 billion yuan in 2020, with a simultaneous growth rate of 3.9 per cent, the urbanization rate will reach about 70 per cent in 2035, and energy consumption per unit of gross product will drop to the national average. |
| **Qinghai** | The average annual growth rate for 2020-2025 will be around 5.5 per cent, the urbanization rate will reach around 62 per cent in 2025, and the reduction of carbon dioxide emissions per unit of gross domestic product will be controlled within the targets set by the State. |
| **Ningxia** | The average annual growth rate of gross regional product in 2020 will be 6.4 per cent, reaching 392.1 billion yuan, per capita GDP will reach US$8,500, the urbanization rate will reach about 60 per cent in 2020, and CO2 emissions per unit of GDP will be reduced and controlled within the targets set by the State. |

The baseline scenario is based on the historical data and relevant policies of the Yellow River Basin at the current stage, and assumes that the Yellow River Basin will develop at the current stage of economic and technological level development trends from 2021 to 2035. The change ratio of each variable set under the baseline scenario is used as a baseline data. Both the low carbon scenario and the technology breakthrough scenario are set at either high or low levels under the baseline data of the baseline scenario. The low-carbon scenario refers to the Yellow River Basin's strategic planning for high-quality development, which attaches great importance to low-carbon development, pays more attention to energy conservation and environmental protection, and strictly controls the implementation of energy conservation and emission reduction initiatives in relevant sectors. It ensures that economic development does not take high speed as the main goal and promotes the Yellow River Basin to maintain high quality economic development. The technology breakthrough scenario is a further optimization under the setting of the baseline scenario and the low-carbon scenario. By constructing a prediction model for each province, it is found that the optimization of energy intensity plays a facilitating role for energy conservation and emission reduction. The energy intensity can basically characterize the level of technological development. Under the technology breakthrough scenario, provincial areas in the Yellow River Basin have encouraged technological innovation and the development of low-carbon, clean and green technologies, and the concept of low-carbon life of residents has been further strengthened. This paper predicts the change of carbon emissions from 2021 to 2035 based on the 2035 visionary target. Combining China's national situation of taking five years as a development stage, the projection period is subdivided into three stages: 2021-2025, 2026-2030 and 2031-2035. The future changes of the five main explanatory variables in the prediction model of the nine provinces in the Yellow River Basin are set separately.

Among them, the setting of future changes in the explanatory variables is based on the evolutionary trends of historical data, existing relevant policies, previous researches and the possible future changes in each explanatory variable. The main references to the relevant policy basis are shown in Table 3.

### *3.2. Influencing factor setting*

#### *3.2.1. Population size setting*

Based on the *14th Five-Year Plan* and the 2035 vision for the nine provinces in the Yellow River Basin, the rate of population change under the three scenarios was developed as shown in Figure 2, with reference to the policy basis for population size in each province in Table 3 and the relevant national policy constraints. Based mainly on *the National Population Development Plan (2016-2030)*, which mentions that the national population will reach its peak in 2030, followed by a negative growth trend, the evolution of the average annual growth rate of each province in the Yellow River Basin is set to decrease sequentially in three stages: 2021-2025, 2026-2030 and 2021-2035. A gap of 0.02% was set for the three scenarios in 2021-2025, and a gap of 0.01% and 0% for 2026-2030 and 2030-2035.

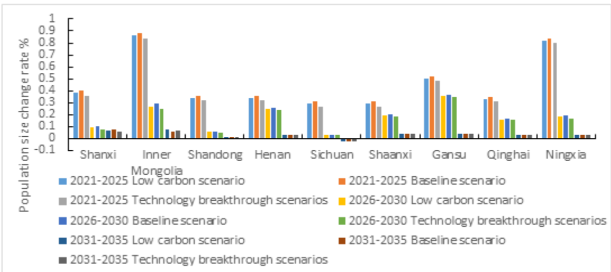



**Figure 2**. Set rate of population size change in nine provinces and districts in the Yellow River Basin

#### *3.2.2. Per capita GDP setting*

In 2020, the GDP growth rate will reach 2.3%. Although the 14th Five-Year Plan does not explicitly put forward the average annual GDP growth target, it proposes that the average annual GDP growth should be kept within a reasonable range, and the expected target will be put forward in each year depending on the situation. Combining the economic and social development of the Yellow River Basin and the national economic and social development bulletin of each province, the future trend of per capita GDP growth rate of each province in the Yellow River Basin is set by calculating the average annual growth rate of per capita GDP in each province during the sample period and then taking its average value, as shown in Figure 3.

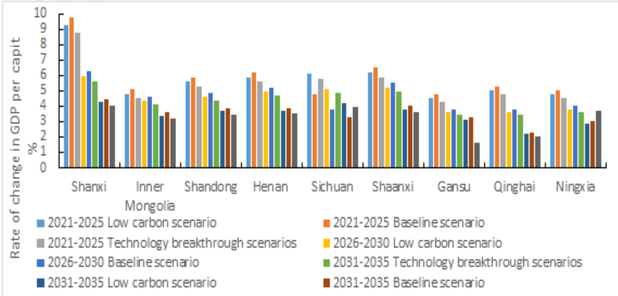



**Figure 3**. Setting the rate of change of per capita GDP in nine provinces and districts in the Yellow River Basin

#### *3.2.3. Energy intensity setting*

The historical data of the Yellow River Basin shows that the energy intensity of the nine provinces has been in a state of gradual decline in Figure 4.

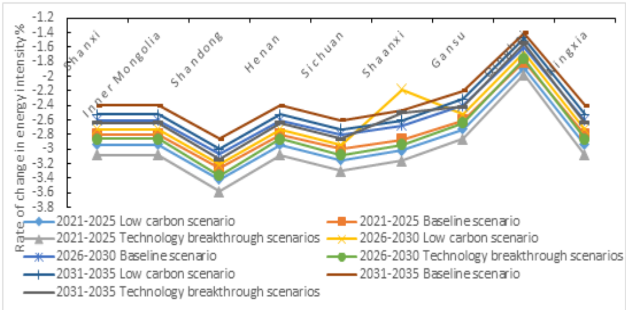



**Figure 4**. Rate of change of energy intensity in nine provinces and districts in the Yellow River Basin

In 2021, China's energy intensity will be reduced by about 3%. Under the carbon peaking and carbon neutrality goals, provinces such as Ningxia and Henan have been optimizing and upgrading their energy structures, setting strict control standards on the consumption of fossil energy such as coal. Therefore, the trend of energy intensity must be gradually reduced in the future planning.

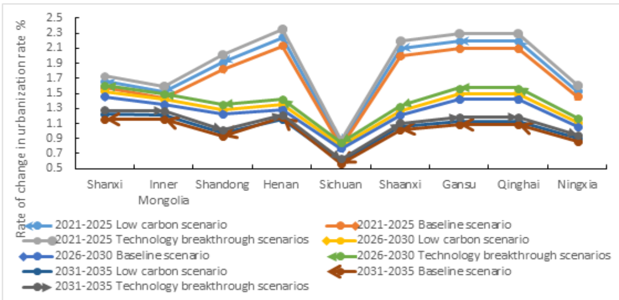



**Figure 5**. Set rate of change of urbanization rate in nine provinces and districts in the Yellow River Basin

#### *3.2.4. Urbanization rate setting*

At present, China's urbanization has been in the middle and late stages of rapid development, and is moving towards a new stage of overall quality improvement. However, the momentum of urbanization development remains strong, and all provinces are more confident in urbanization development, setting their own targets for the *14th Five-Year Plan* for urbanization. We set the growth rates for different scenarios from 2021 to 2035 according to the urbanization rate targets mentioned in the *14th Five-Year Plan* of each province in the Yellow River Basin in Figure 5.

*3.2.5. Industrial structure setting*

This paper characterizes the industrial structure in terms of the proportion of GDP accounted for by the gross domestic product of the secondary industry. From the analysis of China's industrial structure evolution over the years, it can be seen that with the rapid growth of the economic level, the proportion of tertiary industry will increase, while the proportion of industry-based secondary industry will decrease, which is also consistent with the change law of industrial structure optimization and upgrading target. However, there are big differences in the development status of nine provincial areas in the Yellow River Basin, and there are also differences in policy formulation and implementation. This paper sets the changes of secondary industry in nine provincial areas in the Yellow River Basin under the baseline scenario with reference to the *14th Five-Year Plan* of each province, as shown in Table 4.

**Table 4**. Annual average rate of decline in industrial structure in the nine provinces and districts of the Yellow River Basin under the baseline scenario Unit: %

| provinces | 2021-2025 | 2026-2030 | 2031-2035 |
|---|---|---|---|
| Shanxi, Sichuan | 1.0% | 0.8% | 0.6% |
| Henan, Shandong, Ningxia | 0.6% | 0.5% | 0.4% |
| Inner Mongolia, Shaanxi, Qinghai | 1.2% | 1.0% | 0.8% |
| Gansu | 0.6% | 0.5% | 0.4% |

**Table 5.** Probability distribution of risk variables in Shandong Province

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | growth rate | probability | growth rate | probability | growth rate | probability | growth rate | probability | growth rate | probability |
| 2021-2025 | 0.30% | 5% | 5.20% | 5% | -4.19% | 5% | 1.52% | 5% | -1.12% | 5% |
| | 0.34% | 25% | 5.59% | 25% | -3.42% | 25% | 1.92% | 25% | -1.05% | 25% |
| | 0.36% | 40% | 5.88% | 40% | -3.26% | 40% | 1.83% | 40% | -1.00% | 40% |
| | 0.32% | 25% | 5.29% | 25% | -3.58% | 25% | 2.01% | 25% | -1.10% | 25% |
| | 0.38% | 5% | 5.90% | 5% | -2.74% | 5% | 2.12% | 5% | -1.02% | 5% |
| 2025-2030 | 0.05% | 5% | 4.20% | 5% | -3.63% | 5% | 1.21% | 5% | -0.92% | 5% |
| | 0.06% | 25% | 4.65% | 25% | -3.41% | 25% | 1.35% | 25% | -0.84% | 25% |
| | 0.06% | 40% | 4.88% | 40% | -3.06% | 40% | 1.29% | 40% | -0.80% | 40% |
| | 0.05% | 25% | 4.39% | 25% | -3.36% | 25% | 1.42% | 25% | -0.88% | 25% |
| | 0.06% | 5% | 4.90% | 5% | -2.56% | 5% | 1.44% | 5% | -0.79% | 5% |
| 2031-2035 | 0.01% | 5% | 3.20% | 5% | -3.55% | 5% | 0.95% | 5% | -0.68% | 5% |
| | 0.01% | 25% | 3.69% | 25% | -3.00% | 25% | 0.98% | 25% | -0.63% | 25% |
| | 0.01% | 40% | 3.88% | 40% | -2.86% | 40% | 0.93% | 40% | -0.60% | 40% |
| | 0.01% | 25% | 3.49% | 25% | -3.14% | 25% | 1.02% | 25% | -0.66% | 25% |
| | 0.01% | 5% | 3.90% | 5% | -2.68% | 5% | 1.10% | 5% | -0.56% | 5% |

According to the baseline scenario setting criteria, the ratio of future changes in the industrial structure of the Yellow River Basin provinces under the three scenarios is set as shown in Figure 6.

## 4. Peak prediction of carbon emissions and analysis of peak path

*4.1. Monte Carlo simulation*

This paper introduces a more realistic approach-Monte Carlo simulation for carbon peaking prediction. It is a dynamic simulation method that takes random values of the baseline variables with certain probability, and later, under random combinations, the variables of interest are efficiently computed. The advantage of using Monte Carlo simulation is that it allows scientific forecasting of the relevant variables under changing future scenarios based on historical data of the drivers.

The scenario analysis is static, that is, the rates of change in population size, per capita GDP, energy intensity, urbanization rate and industrial structure are held constant in the scenario analysis. But in fact, the annual average change rate of the above explanatory variables is not constant. In this paper, the risk analysis method is introduced. 300,000 Monte Carlo simulations are conducted using Crystal Ball software. The change rate of carbon emissions is taken as a risk variable, and five discrete values and corresponding probability distributions were set for the change rates of the above five explanatory variables in a period of 5 years. The distribution of the change rate of carbon emissions in the provinces of the Yellow River Basin was calculated, and the maximum probability range of the average annual growth rate of carbon emissions in each province was further determined under each scenario. The discrete values are based on the previous scenario analysis, and the benchmark scenario is set as the highest probability, and the other probability distributions are set symmetrically, and the probability of the maximum and minimum values is set as 5% respectively. The probability values are taken as 5%, 25%, 40%, 25%, and 5%, respectively. Taking Shandong Province as an example, the probability distributions of each explanatory variable are shown in Table 5. The probability distributions of the other eight provincial areas are shown in Appendices 1 to 8.

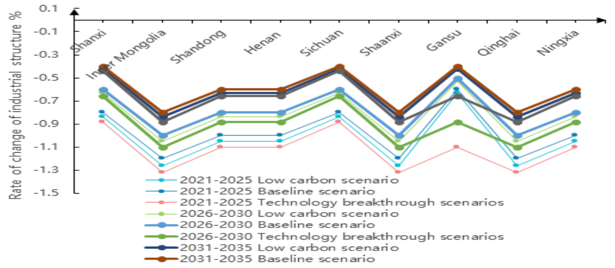



**Figure 6**. Rate of change of industrial structure in nine provinces and districts in the Yellow River Basin

*4.2. Analysis of carbon emission peaking pathways*

Based on the ratio of changes in the above five explanatory variables measured, the future trend of carbon emissions in nine provinces is analyzed by substituting into the carbon emission projection model of each province. The trend of carbon dioxide emissions in the nine provinces in the Yellow River Basin from 2021 to 2035 under the baseline scenario are shown in Figure 7.

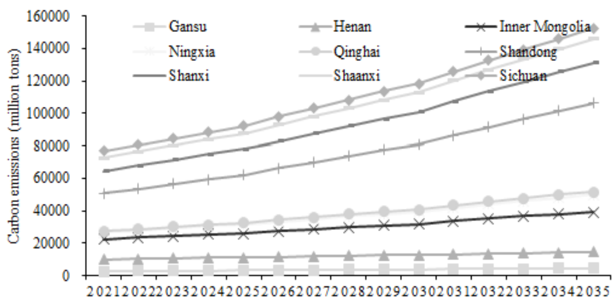



**Figure 7**. Carbon dioxide emissions in the Yellow River Basin under the baseline scenario

According to Figure 7, the carbon emissions of the provincial areas in the Yellow River Basin show a continuous growth trend under the baseline scenario and do not reach a peak in the forecast time, which further indicates that it is difficult to achieve the goal of reaching the peak by 2030 with the existing policies alone.

The growth of carbon emissions in each province tends to slow down significantly under the low-carbon scenario in Figure 8. The total carbon emissions of the provinces in the Yellow River Basin are significantly lower than the baseline scenario. Meanwhile, Gansu, Henan, Inner Mongolia, Shandong, Shaanxi and Sichuan will peak in the low carbon scenario. Gansu, Henan and Shandong will peak in 2029, 2023 and 2029 respectively, and Inner Mongolia, Shaanxi and Sichuan will peak in 2035, 2034 and 2035 respectively. Although Ningxia, Qinghai and Shanxi do not reach their peaks, the carbon emissions are significantly lower than they had been in the baseline scenario.

As can be seen from Figure 9, under the technological breakthrough scenario, carbon dioxide emissions in the nine provinces of the Yellow River Basin will have the slowest trend and the lowest emissions under the three scenarios. Moreover, under the technology breakthrough scenario, the carbon emissions of all the provinces will peak by 2035 except Qinghai. Among them, the carbon emissions of Gansu, Henan, Shandong and Sichuan will peak in 2028, 2023, 2028 and 2025, respectively. The carbon emissions of Inner Mongolia, Ningxia and Shaanxi will all peak in 2034. The carbon emissions of Shanxi province in 2032. The cumulative carbon emission under the technology breakthrough scenario is significantly lower and the peak time is earlier than that under the low-carbon scenario.

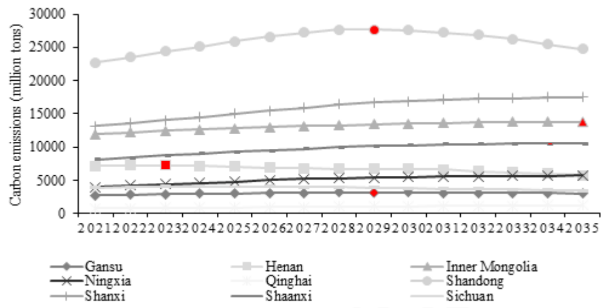



**Figure 8**. Carbon dioxide emissions in the Yellow River Basin under the low-carbon scenario

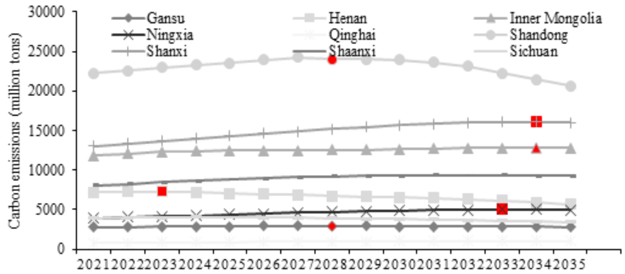



**Figure 9**. Carbon dioxide emissions in the Yellow River Basin under the technological breakthrough scenario

In terms of overall peak attainment, there are provinces that will peak by 2030 in both the low-carbon scenario and the technology breakthrough scenario. Among them, Gansu, Henan and Shandong will peak in 2030, and Sichuan Province will also join the ranks of reaching the peak before 2030 under the technological breakthrough scenario. Under the technology breakthrough scenario, the peak time of carbon emissions in each province is obviously earlier than that under the low-carbon scenario, and the peak time of carbon emissions is also slightly lower than that under the low-carbon scenario. This further illustrates that technological progress plays a significant positive role in carbon emissions. Finally, Qinghai Province does not reach the carbon emission peak in 2035 under the three scenarios, which indicates that Qinghai province has a heavy task to reach the carbon peak and needs to explore more effective emission reduction measures.

## 5. Conclusions and policy recommendations

Based on existing policies and historical data, three scenarios are set, namely the baseline scenario, the low-carbon scenario and the technological breakthrough scenario. Monte Carlo simulations are combined with the scenario settings to calculate the maximum probability distribution range of the change rate of carbon emissions in each province from 2021 to 2035. The change trends of carbon emissions in nine provinces from 2021 to 2035 under the three scenarios are calculated. The main conclusions are as follows:

The explanatory variables have different effects on carbon emissions in different provinces of the Yellow River Basin. There are also differences in the effect mechanism of the same influencing factor on carbon emissions in different provinces. In different regions in different periods or in the same period, the impact of economic growth and industrial structure on carbon emissions has obvious heterogeneity.

The carbon emissions of the provinces in the Yellow River Basin show a continuous growth trend under the baseline scenario and do not reach a peak in the forecast time, which further indicates that it is difficult to achieve the goal of reaching the peak by 2030 with the existing policies alone. The growth of carbon emissions in each province tends to slow down significantly under the low-carbon scenario. The total carbon emissions of the provinces in the Yellow River Basin are significantly lower than the baseline scenario.

Under the technological breakthrough scenario, carbon dioxide emissions in the nine provinces of the Yellow River Basin will have the slowest trend and the lowest emissions. The cumulative carbon emission under the technology breakthrough scenario is significantly lower and the peak time is earlier than that under the low-carbon scenario. Therefore, the technology breakthrough scenario is selected as the optimal peak path. Under the technological breakthrough scenario, the energy use efficiency of nine provinces in the Yellow River Basin is greatly improved, the innovation capacity is significantly enhanced, and the synergistic emission reduction mechanism and related policies between provincial areas are improved. Technological breakthroughs are an important engine to achieve high-quality development in the Yellow River Basin. This further shows that technological progress has a significant positive effect on carbon emissions.

By analyzing the spatial correlation and peak path of emission reduction policies, it is found that per capita GDP, industrial structure and energy intensity in the Yellow River Basin have the greatest impact on carbon emissions. Therefore, the above three variables are the key ideas for the coordinated emission reduction of provinces and regions. The following policy recommendations are proposed:

The Government should strictly implement differentiated emission reduction policies. The Yellow River Basin is a vast area, and there are certain differences in various aspects such as economic development and resource content in different regions, which makes the impact of economic growth and industrial structure on carbon emissions has obvious heterogeneity in different regions at different periods or in the same period. Therefore, the respective emission reduction targets should be clarified and effective policies should be shared together. We should make our best efforts to achieve high-quality development in the Yellow River Basin and the national goal of "carbon peaking and carbon neutrality".

All the provinces should focus on the important "starting point" of coordinated emission reduction, and create demonstration provinces and autonomous regions and healthy competition mode. Local governments should clarify their own emission reduction targets and share effective policies each other.

Focus on technological innovation, increase investment in R&D and create a collaborative innovation model. Combined with the analysis of the carbon peaking path in the Yellow River Basin, it is found that technological breakthroughs and innovation are a key part of promoting provincial and regional peaking as soon as possible. Local governments should support leading enterprises to form innovation consortiums to drive innovation activities of other enterprises. Collaborative innovation is used as a means to build joint prevention and control policies to reach collaborative emission reduction targets and provide ideas for the construction of high-quality development in the whole Yellow River Basin.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**CRediT authorship contribution statement**

**Chuanhui Wang:** Conceptualization, Methodology, Investigation, Writing - original draft, Funding acquisition. **Weifeng Gong:** Validation, Formal analysis, Visualization, Writing - review & editing, Funding acquisition. **Yuyao Wang:** Formal analysis, Data curation. **Zhenyue Fan: Investigation**, Data curation, Writing - review & editing. **Wenwen Li:** Data curation, Software.

**Acknowledgements**

This paper benefited from years of thinking about these issues and the discussion with many colleagues related to economics at that time. In particularly, I would like to thank the chief editor of this journal and the anonymous reviewers for their helpful comments on future drafts.

**Funding**

The research is supported by National Social Science Foundation of China under grants 22BJY174, the National Natural Science Foundation of China under grants 71804089, the Humanities and Social Sciences Youth Foundation, Ministry of Education of the People's Republic of China under grants 19YJC790128 and 18YJCZH034, the Social Science Planning Project of Shandong Province under grants 21CJJJ03, and the Natural Science Foundation of Shandong Province under grants ZR2020QG054.

**APPENDIX**

Appendix Table 1 Probability distribution of risk variables in Inner Mongolia

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) |
| 2021-2025 | 0.83% | 5% | 4.16% | 5% | -3.19% | 5% | 1.50% | 5% | -1.42% | 5% |
| | 0.86% | 25% | 4.80% | 25% | -2.94% | 25% | 1.52% | 25% | -1.26% | 25% |
| | 0.88% | 40% | 5.08% | 40% | -2.80% | 40% | 1.45% | 40% | -1.20% | 40% |
| | 0.84% | 25% | 4.57% | 25% | -3.08% | 25% | 1.60% | 25% | -1.32% | 25% |
| | 0.89% | 5% | 5.18% | 5% | -2.74% | 5% | 1.82% | 5% | -1.15% | 5% |
| 2025-2030 | 0.24% | 5% | 4.06% | 5% | -3.63% | 5% | 1.21% | 5% | -1.15% | 5% |
| | 0.27% | 25% | 4.35% | 25% | -2.73% | 25% | 1.42% | 25% | -1.05% | 25% |
| | 0.29% | 40% | 4.58% | 40% | -2.60% | 40% | 1.35% | 40% | -1.00% | 40% |
| | 0.25% | 25% | 4.12% | 25% | -2.86% | 25% | 1.49% | 25% | -1.10% | 25% |
| | 0.30% | 5% | 4.66% | 5% | -2.56% | 5% | 1.64% | 5% | -0.96% | 5% |
| 2031-2035 | 0.05% | 5% | 3.00% | 5% | -2.55% | 5% | 1.14% | 5% | -0.90% | 5% |
| | 0.08% | 25% | 3.40% | 25% | -2.52% | 25% | 1.21% | 25% | -0.84% | 25% |
| | 0.06% | 40% | 3.58% | 40% | -2.40% | 40% | 1.15% | 40% | -0.80% | 40% |
| | 0.07% | 25% | 3.22% | 25% | -2.64% | 25% | 1.27% | 25% | -0.88% | 25% |
| | 0.09% | 5% | 3.86% | 5% | -2.68% | 5% | 1.30% | 5% | -0.76% | 5% |

Appendix Table 2 Probability distribution of risk variables in Shanxi

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) |
| 2021-2025 | 0.34% | 5% | 8.16% | 5% | -3.19% | 5% | 1.52% | 5% | -0.92% | 5% |
| | 0.38% | 25% | 9.26% | 25% | -2.94% | 25% | 1.66% | 25% | -0.84% | 25% |
| | 0.40% | 40% | 9.76% | 40% | -2.80% | 40% | 1.58% | 40% | -0.80% | 40% |
| | 0.36% | 25% | 8.78% | 25% | -3.08% | 25% | 1.74% | 25% | -0.88% | 25% |
| | 0.42% | 5% | 9.88% | 5% | -2.74% | 5% | 1.82% | 5% | -0.79% | 5% |
| 2025-2030 | 0.07% | 5% | 5.56% | 5% | -3.63% | 5% | 1.41% | 5% | -0.67% | 5% |
| | 0.09% | 25% | 5.96% | 25% | -2.73% | 25% | 1.53% | 25% | -0.63% | 25% |
| | 0.10% | 40% | 6.26% | 40% | -2.60% | 40% | 1.46% | 40% | -0.60% | 40% |
| | 0.09% | 25% | 5.63% | 25% | -2.86% | 25% | 1.61% | 25% | -0.66% | 25% |
| | 0.15% | 5% | 6.36% | 5% | -2.56% | 5% | 1.64% | 5% | -0.59% | 5% |
| 2031-2035 | 0.05% | 5% | 4.00% | 5% | -2.55% | 5% | 1.15% | 5% | -0.46% | 5% |
| | 0.08% | 25% | 4.26% | 25% | -2.52% | 25% | 1.22% | 25% | -0.42% | 25% |
| | 0.06% | 40% | 4.46% | 40% | -2.40% | 40% | 1.16% | 40% | -0.40% | 40% |
| | 0.07% | 25% | 4.01% | 25% | -2.64% | 25% | 1.28% | 25% | -0.44% | 25% |
| | 0.09% | 5% | 4.86% | 5% | -2.68% | 5% | 1.30% | 5% | -0.36% | 5% |

Appendix Table 3 Probability distribution of risk variables in Henan

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) |
| 2021-2025 | 0.30% | 5% | 5.50% | 5% | -3.19% | 5% | 2.02% | 5% | -1.12% | 5% |
| | 0.34% | 25% | 5.89% | 25% | -2.94% | 25% | 2.55% | 20% | -1.05% | 25% |
| | 0.36% | 40% | 6.20% | 40% | -2.80% | 40% | 2.14% | 50% | -1.00% | 40% |
| | 0.32% | 25% | 5.58% | 25% | -3.08% | 25% | 2.36% | 20% | -1.10% | 25% |
| | 0.38% | 5% | 5.90% | 5% | -2.74% | 5% | 2.82% | 5% | -1.02% | 5% |
| 2025-2030 | 0.23% | 5% | 4.56% | 5% | -3.63% | 5% | 1.21% | 5% | -0.92% | 5% |
| | 0.25% | 25% | 4.95% | 25% | -2.73% | 25% | 1.35% | 20% | -0.84% | 25% |
| | 0.26% | 40% | 5.20% | 40% | -2.60% | 40% | 1.29% | 50% | -0.80% | 40% |
| | 0.24% | 25% | 4.68% | 25% | -2.86% | 25% | 1.42% | 20% | -0.88% | 25% |
| | 0.26% | 5% | 5.36% | 5% | -2.56% | 5% | 1.45% | 5% | -0.79% | 5% |
| 2031-2035 | 0.03% | 5% | 4.00% | 5% | -2.55% | 5% | 1.15% | 5% | -0.68% | 5% |
| | 0.03% | 25% | 3.71% | 25% | -2.52% | 25% | 1.16% | 25% | -0.63% | 25% |
| | 0.03% | 40% | 3.90% | 40% | -2.40% | 40% | 1.19% | 40% | -0.60% | 40% |
| | 0.03% | 25% | 3.51% | 25% | -2.64% | 25% | 1.20% | 25% | -0.66% | 25% |
| | 0.03% | 5% | 4.86% | 5% | -2.68% | 5% | 1.21% | 5% | -0.56% | 5% |

Appendix Table 4 Probability distribution of risk variables in Sichan

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) |
| 2021-2025 | 0.25% | 5% | 5.50% | 5% | -3.19% | 5% | 0.78% | 5% | -0.92% | 5% |
| | 0.29% | 25% | 6.08% | 25% | -3.15% | 25% | 0.84% | 25% | -0.84% | 25% |
| | 0.31% | 40% | 4.80% | 40% | -3.00% | 40% | 0.80% | 40% | -0.80% | 40% |
| | 0.27% | 25% | 5.76% | 25% | -3.30% | 25% | 0.88% | 25% | -0.88% | 25% |
| | 0.32% | 5% | 6.18% | 5% | -2.74% | 5% | 0.90% | 5% | -0.79% | 5% |
| 2025-2030 | 0.03% | 5% | 3.36% | 5% | -3.23% | 5% | 0.75% | 5% | -0.67% | 5% |
| | 0.03% | 25% | 5.15% | 25% | -2.94% | 25% | 0.81% | 25% | -0.63% | 25% |
| | 0.03% | 40% | 3.80% | 40% | -2.80% | 40% | 0.77% | 40% | -0.60% | 40% |
| | 0.03% | 25% | 4.86% | 25% | -3.08% | 25% | 0.85% | 25% | -0.66% | 25% |
| | 0.03% | 5% | 5.20% | 5% | -2.56% | 5% | 0.86% | 5% | -0.59% | 5% |
| 2031-2035 | 0.01% | 5% | 3.90% | 5% | -2.97% | 5% | 0.50% | 5% | -0.46% | 5% |
| | 0.01% | 25% | 4.18% | 25% | -2.73% | 25% | 0.60% | 25% | -0.42% | 25% |
| | 0.01% | 40% | 3.30% | 40% | -2.60% | 40% | 0.57% | 40% | -0.40% | 40% |
| | 0.01% | 25% | 3.96% | 25% | -2.86% | 25% | 0.63% | 25% | -0.44% | 25% |
| | 0.01% | 5% | 4.26% | 5% | -2.58% | 5% | 0.65% | 5% | -0.36% | 5% |

Appendix Table 5 Probability distribution of risk variables in Shaanxi

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** |
| 2021-2025 | 0.25% | 5% | 6.16% | 5% | -3.19% | 5% | 1.92% | 5% | -1.42% | 5% |
| | 0.29% | 25% | 6.18% | 25% | -3.02% | 25% | 2.10% | 25% | -1.26% | 25% |
| | 0.31% | 40% | 6.50% | 40% | -2.87% | 40% | 2.00% | 40% | -1.20% | 40% |
| | 0.27% | 25% | 5.85% | 25% | -3.16% | 25% | 2.20% | 25% | -1.32% | 25% |
| | 0.32% | 5% | 6.88% | 5% | -2.74% | 5% | 2.30% | 5% | -1.15% | 5% |
| 2025-2030 | 0.17% | 5% | 4.56% | 5% | -3.03% | 5% | 1.11% | 5% | -1.15% | 5% |
| | 0.18% | 25% | 5.23% | 25% | -2.18% | 25% | 1.27% | 25% | -1.05% | 25% |
| | 0.20% | 40% | 5.50% | 40% | -2.67% | 40% | 1.21% | 40% | -1.00% | 40% |
| | 0.19% | 25% | 4.95% | 25% | -2.86% | 25% | 1.33% | 25% | -1.10% | 25% |
| | 0.21% | 5% | 5.52% | 5% | -2.94% | 5% | 1.34% | 5% | -0.96% | 5% |
| 2031-2035 | 0.04% | 5% | 3.20% | 5% | -2.65% | 5% | 1.00% | 5% | -0.90% | 5% |
| | 0.04% | 25% | 3.80% | 25% | -2.60% | 25% | 1.06% | 25% | -0.84% | 25% |
| | 0.04% | 40% | 4.00% | 40% | -2.47% | 40% | 1.01% | 40% | -0.80% | 40% |
| | 0.04% | 25% | 3.60% | 25% | -2.50% | 25% | 1.11% | 25% | -0.88% | 25% |
| | 0.04% | 5% | 4.10% | 5% | -2.38% | 5% | 1.13% | 5% | -0.76% | 5% |

Appendix Table 6 Probability distribution of risk variables in Gansu

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** | **growth rate (esp. in economics)** | **probability (math.)** |
| 2021-2025 | 0.47% | 5% | 4.30% | 5% | -3.19% | 5% | 2.00% | 5% | -1.12% | 5% |
| | 0.50% | 25% | 4.56% | 25% | -2.73% | 25% | 2.20% | 25% | -0.63% | 25% |
| | 0.52% | 40% | 4.80% | 40% | -2.60% | 40% | 2.10% | 40% | -0.60% | 40% |
| | 0.48% | 25% | 4.32% | 25% | -2.86% | 25% | 2.30% | 25% | -1.10% | 25% |
| | 0.52% | 5% | 4.88% | 5% | -2.74% | 5% | 2.40% | 5% | -0.58% | 5% |
| 2025-2030 | 0.35% | 5% | 3.40% | 5% | -3.63% | 5% | 1.41% | 5% | -0.90% | 5% |
| | 0.36% | 25% | 3.61% | 25% | -2.52% | 25% | 1.50% | 25% | -0.53% | 25% |
| | 0.37% | 40% | 3.80% | 40% | -2.64% | 40% | 1.43% | 40% | -0.50% | 40% |
| | 0.38% | 25% | 3.42% | 25% | -2.46% | 25% | 1.57% | 25% | -0.88% | 25% |
| | 0.39% | 5% | 3.82% | 5% | -2.56% | 5% | 1.60% | 5% | -0.49% | 5% |
| 2031-2035 | 0.04% | 5% | 1.60% | 5% | -2.55% | 5% | 1.02% | 5% | -0.76% | 5% |
| | 0.04% | 25% | 3.14% | 25% | -2.31% | 25% | 1.13% | 25% | -0.42% | 25% |
| | 0.04% | 40% | 3.30% | 40% | -2.20% | 40% | 1.08% | 40% | -0.40% | 40% |
| | 0.04% | 25% | 1.62% | 25% | -2.42% | 25% | 1.19% | 25% | -0.66% | 25% |
| | 0.04% | 5% | 3.32% | 5% | -2.18% | 5% | 1.20% | 5% | -0.36% | 5% |

Appendix Table 7 Probability distribution of risk variables in Qinghai

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) |
| 2021-2025 | 0.30% | 5% | 4.70% | 5% | -2.19% | 5% | 2.00% | 5% | -1.42% | 5% |
| | 0.33% | 25% | 5.05% | 25% | -1.89% | 25% | 2.20% | 25% | -1.26% | 25% |
| | 0.38% | 40% | 5.30% | 40% | -1.80% | 40% | 2.10% | 40% | -1.20% | 40% |
| | 0.31% | 25% | 4.77% | 25% | -1.98% | 25% | 2.30% | 25% | -1.32% | 25% |
| | 0.42% | 5% | 5.35% | 5% | -1.74% | 5% | 2.40% | 5% | -1.15% | 5% |
| 2025-2030 | 0.16% | 5% | 3.40% | 5% | -2.63% | 5% | 1.41% | 5% | -1.15% | 5% |
| | 0.16% | 25% | 3.61% | 25% | -1.68% | 25% | 1.50% | 25% | -1.05% | 25% |
| | 0.17% | 40% | 3.80% | 40% | -1.60% | 40% | 1.43% | 40% | -1.00% | 40% |
| | 0.16% | 25% | 3.42% | 25% | -1.76% | 25% | 1.57% | 25% | -1.10% | 25% |
| | 0.18% | 5% | 3.82% | 5% | -1.56% | 5% | 1.60% | 5% | -0.96% | 5% |
| 2031-2035 | 0.03% | 5% | 4.00% | 5% | -1.55% | 5% | 1.02% | 5% | -0.90% | 5% |
| | 0.03% | 25% | 2.05% | 25% | -1.47% | 25% | 1.13% | 25% | -0.84% | 25% |
| | 0.03% | 40% | 2.30% | 40% | -1.40% | 40% | 1.08% | 40% | -0.80% | 40% |
| | 0.03% | 25% | 2.07% | 25% | -1.54% | 25% | 1.19% | 25% | -0.88% | 25% |
| | 0.03% | 5% | 2.32% | 5% | -1.38% | 5% | 1.20% | 5% | -0.76% | 5% |

Appendix Table 8 Probability distribution of risk variables in Ningxia

| year | population | | per capita GDP | | energy intensity | | urbanization | | industrial structure | |
|---|---|---|---|---|---|---|---|---|---|---|
| | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) | growth rate (esp. in economics) | probability (math.) |
| 2021-2025 | 0.80% | 5% | 4.40% | 5% | -3.19% | 5% | 1.45% | 5% | -1.12% | 5% |
| | 0.82% | 25% | 4.75% | 25% | -2.94% | 25% | 1.53% | 25% | -1.05% | 25% |
| | 0.84% | 40% | 5.00% | 40% | -2.80% | 40% | 1.46% | 40% | -1.00% | 40% |
| | 0.80% | 25% | 4.50% | 25% | -3.08% | 25% | 1.61% | 25% | -1.10% | 25% |
| | 0.86% | 5% | 5.10% | 5% | -2.74% | 5% | 1.62% | 5% | -1.02% | 5% |
| 2025-2030 | 0.15% | 5% | 3.50% | 5% | -3.63% | 5% | 1.01% | 5% | -0.92% | 5% |
| | 0.18% | 25% | 3.80% | 25% | -2.73% | 25% | 1.11% | 25% | -0.84% | 25% |
| | 0.19% | 40% | 4.00% | 40% | -2.60% | 40% | 1.06% | 40% | -0.80% | 40% |
| | 0.17% | 25% | 3.60% | 25% | -2.86% | 25% | 1.17% | 25% | -0.88% | 25% |
| | 0.20% | 5% | 4.20% | 5% | -2.56% | 5% | 1.24% | 5% | -0.79% | 5% |
| 2031-2035 | 0.03% | 5% | 2.70% | 5% | -2.55% | 5% | 0.85% | 5% | -0.68% | 5% |
| | 0.03% | 25% | 2.85% | 25% | -2.52% | 25% | 0.90% | 25% | -0.63% | 25% |
| | 0.03% | 40% | 3.00% | 40% | -2.40% | 40% | 0.86% | 40% | -0.60% | 40% |
| | 0.03% | 25% | 3.70% | 25% | -2.64% | 25% | 0.95% | 25% | -0.66% | 25% |
| | 0.03% | 5% | 4.00% | 5% | -2.68% | 5% | 0.96% | 5% | -0.56% | 5% |

**References**


Ang B.W. and Pandiyan G. (1997). Decomposition of Energy-induced CO2 Emissions in Manufacturing. Energy Economics, **19** (3), 363–374.

Cramer J.C. (1997). A demographic perspective on air quality: Conceptual issues surrounding environmental impacts of population growth. *Human Ecology Review*, **3**, 191–196.

Chen X. and Zhou P. (2020). An empirical study on the level of carbon emissions from China's (FDI-dependent) participation in international industrial transfer. *Ecological Economics*, **36**(07), 51-60+146.

Fu H., Li G.P., and Zhu T. (2021). Carbon emissions from manufacturing industries in China: decomposition of industry differences and drivers. *Reform*, **327**(05), 38–52.

Gong W.F., Wang C.H., Fan Z. Y, and Xu, Y. (2022). Drivers of the peaking and decoupling between co2 emissions and economic growth around 2030 in China. Environmental Science and Pollution Research, **29**(3): 3864–3878.

Hu M.F., Zheng Y.B., and Li Y.H. (2022). Research on the peak carbon emission projection of transportation in Hubei Province under multiple scenarios. *Journal of Environmental Science*, **42**(04), 464–472.

Hu J.B., Luo Z.P., and Li F. (2022). Forecasting China's carbon emission intensity under the "carbon peak" target: an analysis based on LSTM and ARIMA-BP models. *Finance and Economics Science*, **407**(02), 89–101.

Tiawon H, Irawan â, and Miar â. (2020). Empirical Assessment for Driving Forces of $CO_2$ Emissions: Application of STIRPART Model on the Leading ASEAN Countries. *Contemporary Economics*, **14**(04), 453–465.

Hao Y., Chen H., and Zhang Q.X. (2016). Will income inequality affect environmental quality? Analysis based on China's provincial panel data. *Ecological Indicators*, **67**(08), 533–542.

Hu Y., Zhang X.W., and Li J. (2019). Export trade, geographical features and air pollution. *China Industrial Economy*, **378**(09), 98–116.

Lin B.Q., and Jiang Z.J. (2009). Environmental Kuznets curve prediction of carbon dioxide in China and analysis of influencing factors. *Management World*, (04), 27–36.

Lin C.C., He R.X., and Liu W.Y. (2018). Considering Multiple Factors to Forecast $CO_2$ Emissions: A Hybrid Multivariable Grey Forecasting and Genetic Programming Approach. *Energies*, **11**(12), 3432.

Luo Y.L., Zeng W.L., Hu X.B., Yang H. and Shao L. (2021). Coupling the driving forces of urban $CO_2$ emission in Shanghai with logarithmic mean Divisia index method and Granger causality inference - ScienceDirect. *Journal of Cleaner Production*, **298**,126843.

Li X. M., and Zhang Q. (2019). Factors influencing carbon emissions of energy consumption and its scenario prediction in Tianjin. *Arid Zone Research*, **36**(04), 997–1004.

Shi J.R., Cai H.L., Tang L., and Yu L.A. (2015). Impacts of Carbon Emission Trading on China:Based on CGE Model.*Chinese Journal of Management Science*, **23**(S1):801–806.

Tang S., Fu J.W., and Wu J.L. (2021). Analysis of factors influencing carbon emissions in typical Chinese cities. *Statistics and Decision Making*, **37**(23), 59–63.

Wang L.D., Wu L.Y., Chen Y.L., Ma X.Z., and Du M.N. (2021). Timing and peak levels of carbon attainment in relevant provinces and regions of the Yellow River Basin under steady economic growth. *Resource Science*, **43**(11), 2331–2341.

Wang Q., Su M., and Li R.R. (2018). Toward to economic growth without emission growth: The role of urbanization and industrialization in China and India. . *Journal of Cleaner Production*, **205**(12), 499–511.

Wang S.J., Mo H.B., and Fang C.L. (2022). Simulation of urban carbon emission dynamics and carbon peaking in the Pearl River Delta urban agglomeration. *Science Bulletin,* **67**(07), 670–684.

Wang Y.Z., and Ma L.P. (2016). Analysis and prediction of factors influencing carbon emissions related to energy consumption in Jilin Province-Based on grey correlation analysis and GM(1,1) model. *Ecological Economy*, **32**(11), 65–70.

Wang Z., Zhao Z., and Wang C. (2021). Random forest analysis of factors affecting urban carbon emissions in cities within the Yangtze River Economic Belt. *PloS one*, **16**(06), e0252337.

Yang Y.W., Wu A.L., and Zhu Y. Y. (2020). Decomposition of carbon emission drivers and dynamic simulation: an example of Inner Mongolia Autonomous Region. *Statistics and Decision Making*, **36**(12), 76–80.

Yin Y., Jiang Z., Liu Y., and Yu Z. (2019). Factors Affecting Carbon Emission Trading Price: Evidence from China.*Emerging Markets Finance&Trade*, **55**(15), 3433–3451.

Yoichi Kaya. Impact of Carbon Dioxide Emission on GNP Growth: Interpretation of Proposed Scenarios[R]. Presentation to the Energy and Industry Subgroup, Response Strategies Working Group, IPCC, Paris, 1989.

York R., Rosa E.A., and Dieta T. (2003). STIRPAT, IPAT and IMPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, (03), 351–365.

Zhou Y.N., Yang Y., Cheng B., and Huang J.X. (2020). Regional differences in the canoupling relationship between economic growth and carbon emissions in China based on decoupling index and LMDI. *Journal of the University of Chinese Academy of Sciences*, **37**(03), 295–307.

Zhuang Y. and Xia B. (2017). Accounting for transportation carbon emissions in Guangdong Province and analysis of influencing factors. *Environmental Science Research*, **30**(07), 1154–1162.