Research and Prediction of Carbon Emission Influencing Factors in 30 Provinces of China--Analysis Based on Extended STIRPAT Model

Chaoran Yang[1,a], Ruiqi Li[1,b], Shadan Sun[1,c], Jiacheng Yang[1,d] and Yucheng Zhang[1,e]

[a]2022310215@st.gxu.edu.cn

[b]2022310143@st.gxu.edu.cn

[c]2122310346@st.gxu.edu.cn

[d]2122310308@st.gxu.edu.cn

[e]2122310142@st.gxu.edu.cn

[1]School of Public Administration, Guangxi University, No. 100, Da Xue Road, Nanning 530004, China

Abstract: Global warming and the climate problems it causes have become a common challenge faced by human beings all over the world, especially true for China, which has achieved great development results in recent years and thus brought serious environmental problems. China urgently needs to achieve low-carbon development and reach a peak in carbon emissions in 2030. Owing to China's East-West unbalanced model of development and the background of regional industrial transfer, the carbon emissions of provinces with different development levels are greatly different, and the carbon peak time of each province based on social and economic indicators and carbon emissions is also different.Based on this, this paper divides the 30 provinces in China into the group that carbon dioxide emissions peak ahead of 2030 and the group that carbon dioxide emissions peak in 2030 and select the total population, per capita GDP, amount of foreign direct investment, urbanization rate, energy intensity, and secondary industry structure to explore the difference in the impact of different variables on the total carbon emissions of different groups. Then, predicting whether China can successfully reach carbon emissions peak in 2030 under three different scenarios based on the STIRPAT model.

Keywords: carbon emissions; STIRPAT model; Dual fixed effects model; Regression of ridge.

1. INTRODUCTION

The challenge of global warming has reached a critical point for both the survival of humanity and sustainable development. To tackle the issue of climate change on a global scale and to achieve sustainable, circular and green development, it is crucial to promote low-carbon emissions reduction measures[1, 2]. After a series of international treaties were adopted, such as *The Kyoto Protocol* and *The Paris* Agreement, many countries achieved results on emission reduction commitments[3].

ICIDC 2023, June 02-04, Nanchang, People's Republic of China

DOI 10.4108/eai.2-6-2023.2334659

According to *The Paris* Agreement of 2015, the nationally determined contributions made by countries may not be sufficient to achieve the goal of limiting global temperature rise[4]. Even though all ratifying parties of that agreement fulfill their climate commitments, Global temperature will still warmer than pre-industrial times, in the range of 3°C degrees or more[5]. Given the dire circumstance, greenhouse gases will be severely restricted for a long time to come[6].

Meanwhile, 124 countries have made net-zero emissions pledges ahead of the World Climate Summit to be held in Glasgow (UK) in November 2020[7]. As a responsible country with great potential for development, China is expected to reach peak carbon emissions in 2030 and achieve carbon neutrality in 2060.

China is the world's largest CO_2 emitter (Fig. 1) . The significant increase in carbon dioxide emissions has brought tremendous pressure to Chinese government. As one of the largest victims of global climate, China has committed to taking a series of actions to contribute to reducing carbon dioxide emissions. There are countless factors that affect carbon emissions. Currently, academic research mainly focuses on exploring the relationship between population size[8, 9], per capita GDP[10], urbanization level[11], total energy consumption[12, 13], and energy intensity with carbon emissions[14]. There are differences in CO_2 emissions between the eastern and western regions of China, where approximately 50%, 35%, and 15% of CO_2 Total emissions are calculated by region, all provinces in China are divided into eastern, central and western Region[15]. Eastern region has the advantage of being developed first, concentrates most of the economic output. The western and central regions are far less industrialized and urbanized than the eastern regions. Therefore, it is not easy for countries to reduce high levels of CO_2 emissions. [16].

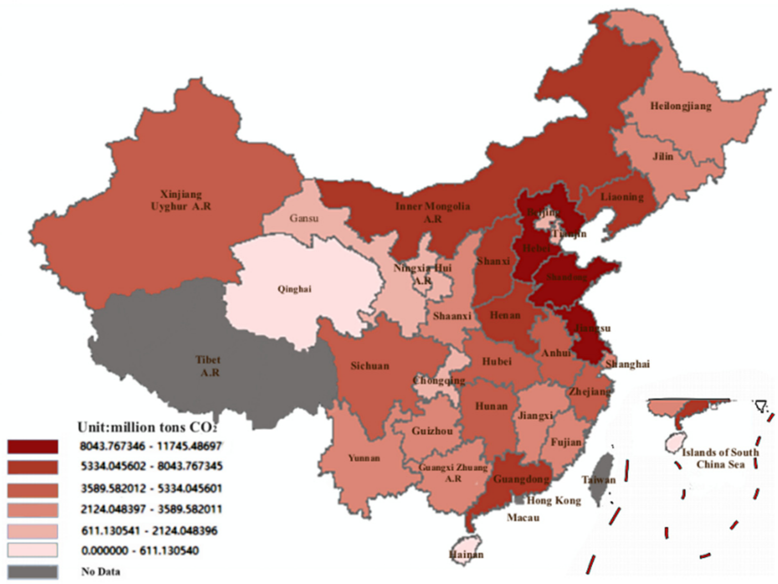

Fig. 1 Accumulated carbon emissions of different provinces from 2005 to 2019 (excluding Macao, Taiwan, Tibet and Hong Kong)

The primary factor behind the divergence in carbon peak policies between China's eastern and western provinces is the unevenness in regional economic development[17]. The reform and opening-up policy has brought a great impact, the eastern region gained an early advantage in development by leveraging its favorable geographical location and policy incentives. State led infrastructure investment, coupled with a sharp increase in foreign investment, has once again made coastal areas the growth center of urban development in China[18]. Compared with underdeveloped provinces, these regions have higher economic value[19], and the carbon emission efficiency of affluent coastal provinces in the eastern region is higher[20]. So, different policies in turn lead impact on carbon emissions between regions.

In summary, the carbon emissions and socio-economic development level of different provinces affect the formulation of carbon peaking policies, and the carbon peaking policies of each province will further affect the future carbon emissions of different provinces. Therefore, it is crucial to conduct differentiated research on provinces with different carbon peak policies.

Furthermore, the transfer of industries has played a significant role in creating disparities in carbon peak policies between China's eastern and western provinces. Imbalance in industrial development remains the main cause of economic imbalance among China's three major regions[21]. The different stages of industrial transfer in China have brought about changes in the inter-regional economic landscape[22]. Industrial transfer has promoted the economic growth of the transferred provinces, but it also poses significant challenges to carbon reduction and environmental protection in these regions. Based on statistics, the western region had the highest increase in per capita carbon emissions (1.83 times) from 2005 to 2015, whereas the eastern region had the lowest increase (1.56 times) [23].

At present, China is confronted with a significant challenge of reducing carbon emissions in an efficient manner without compromising its long-term stable economic growth. In fact, the issue of "energy economy environment" is not only a concern for governments of various countries, but also a focus of academic attention[24]. In terms of calculating carbon emissions, the current academic community mainly uses the IPAT model and its improved STIRPAT model. Some articles have used this model to analyze the future carbon emission peaking in Hebei province as a study [25], while others have studied the environmental impact of population and affluence [26]. Nonetheless, while utilizing the STIRPAT model, Although the secondary sector is the main output sector of carbon emissions, but it is a common mistake to use this data as the value of total carbon emissions.

To sum up, this study classifies 30 provinces in China (excluding Macao and Taiwan, Tibet and Hong Kong), and divides them into 18 provinces that will reach CPA and 12 provinces that will reach CPI according to their different emssion peak targets. Then, the extended STIRPAT model was adopted to obtain the equation of the relationship between carbon emissions and other elements in the two groups. The dual fixed effect model was applied to optimize the model and conduct robustness check. Three scenarios were set, and the carbon emissions of the two groups in the three scenarios were predicted respectively, so as to explore the path of realizing CPA in China.

2. MATERIALS AND METHODS

2.1. Study area and Data sources

The data applied are from the following sections: Carbon emissions data for 30 Chinese provinces for each year from 2005 to 2019, number of resident population, GDP, secondary industry GDP, and total energy consumption data. The China Accounting Database provides data on carbon emissions (https://www.ceads.net.cn/) , other required data from the China Statistical Yearbook, China Annual Statistical Bulletin and provincial statistical yearbooks.

2.2. Data selecting and processing

Table 1 shows the variables selected for the study.

An important part of the increase in carbon emissions is due to the growth in population size[27].

The improvement of urbanization is often accompanied by high carbon emissions and low emission reduction rates, so the changes in urbanization rates profoundly affect the changes in carbon emissions[28].

The level of economic development is the main factor affecting CO_2 emissions, and there are significant discrepancy in carbon emissions generated by regional development and residents' lives under different levels of economic development[29].

As a driving force for global trade and investment, FDI contributes significantly to China's CO2 emissions by acting on the industrial structure[30].

Reducing carbon emissions can be achieved by reducing energy consumption and using renewable energy sources. An increase in energy intensity will be followed by a decrease in carbon emissions [31].

The proportion of secondary industry has a non-negligible impact on the total carbon emissions[32].

Table 1 Description of selected variables

Variable names	Variable explanations	unit	use
CE	Total CO_2 emissions	Million tons CO_2	Into model
POP	Total population	ten thousand people	Into model
URB	Urbanization rate	%	Into model
GDP	gross domestic product	Billion yuan	Into model
$(GDP)^2$	Quadratic term of gross domestic product	(Billion yuan)^2	Into model
EI	energy consumption /GDP	Ton of standard coal / million yuan	Into model
ST	GDP of secondary industry /GDP	%	Into model
FDI	Foreign direct investment	Billion yuan	Into model

EC	total energy consumption	million tons of standard coal	Calculate secondary variable
IND	GDP of secondary industry	Billion yuan	Calculate secondary variable

The industrial structure is also very different，because there are differences in resource endowment and development stages among China's provinces[33], and the carbon transfer that accompanies China's industrial transfer is accelerating[34], so it is necessary to make a distinction when analyzing carbon emissions. According to the carbon dioxide emissions peak policies formulated by different provincial government agencies, 30 provinces are divided into the first group: carbon dioxide emissions peak before 2030(CPB) and carbon dioxide emissions peak in 2030(CPI) (Table 2).

Table 2 The province included in the CPB group and the CPI group

Group:carbon dioxide emissions peak before 2030(CPB)			**Group:carbon dioxide emissions peak in 2030(CPI)**		
Anhui	Shandong	Shanghai	Beijing	Shanxi	Liaoning
Jiangsu	Jiangxi	Jilin	Henan	Guangxi Zhuang A.R	Sichuan
Hunan	Guangdong	Guizhou	Yunnan	Hebei	Fujian
Chongqing	Tianjin	Shaanxi	Zhejiang	Hubei	Gansu
Heilongjiang	Hainan	Qinghai			
Inner Mongolia A.R	Xinjiang Uygur A.R	Ningxia Hui A.R			

2.3. STIRPAT extension model

The debate between Ehrlich and Holdren (1971) and Commoner (1972) on the main causes of environmental impact ultimately led to the concept of the IPAT equation, which corresponds to "environmental impact", "population", "affluence", and "technology", respectively[35, 36].

The IPAT model can be summarized as:

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

In the above equation, I refers to the environmental impact, P stands for population, A stands for affluence, and T stands for technology level.

The disadvantage of traditional IPAT is that the rate of change between the driver and the environmental pressure is consistent. When any driving factor increases or decreases by 1%, the environmental pressure will undergo an accurate 1% change[37]. To address these shortcomings, Dietz and Rosa set a the STIRPAT model based on the IPAT constancy equation[38]. The STIRPAT model can estimate each coefficient as a parameter and decompose each driving factor appropriately. This means that new driving factors can be added to the STIRPAT model according to research needs to statistically model the non proportional impact of variables on the environment.[39, 40]

The STIRPAT model can be summarized as:

$$InI_{it} = a + b(InP_{it}) + c(InA_{it}) + d(InT_{it}) + e_i \quad (2)$$

Among them, P represents population, A represents economic level, T represents technological level, it represents each year, a, b, c, d represents coefficients of each variable, and e represents a random disturbance term.

On the basis of the selected indicators in this study, the model has been improved and the extended model obtained is as follows:

$$InCE = a + b(InPOP) + c(InGDP) + d(InEI) + e(InST) + f((InGDP)^2) + e_i \quad (3)$$

CE stands for carbon emissions, POP stands for population, GDP stands for per capita GNP, EI stands for energy intensity, ST stands for the proportion of secondary industrial structure, a, b, c, d stands for the coefficient of each variable, and e stands for a random disturbance term. Due to the possible inverted U-shaped relationship between economic level and carbon emissions, a variables of quadratic terms containing the GDP quadratic term was added to verify the existence of EKC[41].

3. RESULTS

3.1 Ridge regression estimation

From 2005 to 2019, China's population was still expanding, the economy was growing at a high speed, and a large amount of energy was consumed.

Table 3 Value of variables in CPB group and CPI in 2005-2019

Year	CE		POP		GDP		EI		ST	
	CPB	CPI	CPB	CPI	CPB	CPI	CPB	CPI	CPB	CPI
2005	3054.587975	2512.417396	68854	59470	15848.215064	13405.195897	1.299318	1.526262	0.501761	0.468126
2006	3404.400330	2793.489759	69433	59805	18387.078190	15554.067386	1.227321	1.438941	0.510327	0.476886
2007	3724.754199	3097.515403	70011	60093	22210.238391	19109.896327	1.108801	1.276250	0.507071	0.478483
2008	3993.585610	3211.637439	70617	60525	26152.470368	22325.254027	0.995777	1.138268	0.508908	0.487409
2009	4240.285014	3415.579567	71169	60978	28456.687603	24097.576175	0.966348	1.099276	0.498208	0.479740
2010	4691.839025	3906.849918	71890	61195	33348.908054	28516.757905	0.890998	1.007958	0.505682	0.494857
2011	5287.641493	4216.589633	72715	61663	38954.892388	33658.320224	0.820237	0.915288	0.505251	0.499987
2012	5472.721131	4269.979496	73327	62062	42668.689569	36975.331120	0.783609	0.859747	0.494428	0.491487
2013	5481.631869	4297.321159	73808	62371	46866.328853	40282.422921	0.683722	0.760145	0.476616	0.472143
2014	5597.171345	4310.675985	74323	62769	50628.674838	43186.461470	0.650067	0.720581	0.468168	0.464112
2015	5660.976402	4170.583442	74664	63103	54238.066538	45581.969162	0.610428	0.672899	0.446514	0.436248
2016	5758.429955	4160.027855	75196	63467	58371.814990	48978.508516	0.576615	0.629303	0.431840	0.420101
2017	5937.208149	4234.009568	75626	63804	64028.561606	54310.858253	0.535105	0.578305	0.426000	0.410533
2018	6091.316327	4437.99804	75901	64055	69476.923888	60140.863321	0.507120	0.535454	0.402219	0.392096
2019	6375.540163	4488.869559	76137	64307	74195.686723	64645.994993	0.490438	0.510626	0.394159	0.386917

The commitment to achieve a gradually increasing trend in the annual total carbon emissions of provinces aiming to peak carbon emissions before 2030 has resulted in a downward trend in total carbon emissions from 2015 to 2017, contrary to the initial pledge to peak carbon emissions in 2030. Due to the significant interannual fluctuations in foreign direct investment, it was not included in the process of establishing the prediction model (Table 3) .

The VIF values are much larger than 100, so ridge regression is selected. Ridge adopts a regularized loss function to compress the linear regression coefficients resulting in reduced variance.

For the CPB group, when the k value of the model is 0.15, the square of R is 0.979, and the p-value is 0.000. For the CPI group, when the k value of the model is 0.205, the square of R is 0.96, and the p-value is 0.000. The two sets of models show a significant regression relationship, which is stable and can be used for predictive analysis. For each variable in each group, all variables have significant regression analysis with the dependent variable, and all variables can enter the regression prediction equation (Table 4) .

Table 4 Empirical analysis results in Ridge Regression

Group	variable	Beta	t value
CPB	lnPOP	(1.791)***	12.611
	lnGDP	(0.144)***	13.967
	$\ln(GDP)^2$	(0.007)***	14.871
	lnEI	(-0.139)***	-11.660
	lnST	(0.373)**	2.658
	Constant	(-13.569)***	-8.377
CPI	lnPOP	(1.563)***	10.331
	lnGDP	(0.122)***	13.071
	$\ln(GDP)^2$	(0.006)***	13.323
	lnEI	(-0.118)***	-12.405
	lnST	(0.662)***	4.740
	Constant	(-10.397)***	-6.050

Note: *,**,*** means significant at 10%, 5%, and 1% confidence level.

Based on the results of Tikhonov regularization analysis, the equation for the factors of carbon emissions in the CPB group can be obtained：

$$InCE = 1.791 \times InPOP + 0.144 \times InGDP - 0.139 \times InEI + 0.373 \times InST + 0.007 \times (InGDP)^2 - 13.569 \quad (4)$$

Equation of Factors Influencing Carbon Emissions in CPI Group：

$$InCE = 1.563 \times InPOP + 0.122 \times InGDP - 0.118 \times InEI + 0.662 \times lnST + 0.006 \times (InGDP)^2 - 10.397 \quad (5)$$

3.2 Model optimization and robustness testing

The study selects data from different provinces in different years, and panel regression analysis can also be conducted to determine the impact of various influencing factors on carbon emissions by using a dual fixed effects model After removing the indicators with severe collinearity. Foreign direct investment, which is widely believed to have a significant impact on carbon emissions, was included in the inspection. And the total population was replaced by the urbanization rate, and the test results were obtained.

Table 5 Empirical analysis results in dual fixed effects model

variable	Beta	variable	Beta
CPB		CPI	
lnURB	(0.382)***	lnURB	(0.623)***
lnFDI	(0.009)	lnFDI	(-0.034)***
lnGDP	(0.814)***	lnGDP	(0.216)*
lnEI	(0.993)***	lnEI	(0.723)***
lnST	(0.062)	lnST	(0.514)***

After grouping all provinces, it was found that the impact of foreign direct investment on carbon emissions is not entirely significant, the fact that certain considerations should not be directly included in predictive models indicates the rationality of model construction (Table 5) .

3.3 Scenario setting

In the application of IPAT equation, Scenario Analysis has been widely used in emission forecasting in recent years [42]. In order to explore the differences in carbon emissions between the two groups of provinces in China with different levels of socioeconomic development and environmental protection and whether they can reach the peak according to their respective requirements, three different scenarios are set up, namely, the maintenance of the existing policy scenario (MEP) , the extreme environmental protection scenario (EEP) and the extreme economic development scenario (EED). We make different provisions on the inter-annual growth rates of different variables from 2020 to 2030 to predict the total carbon emissions of the two groups of provinces from 2020 to 2030 (fig. 2-5) .

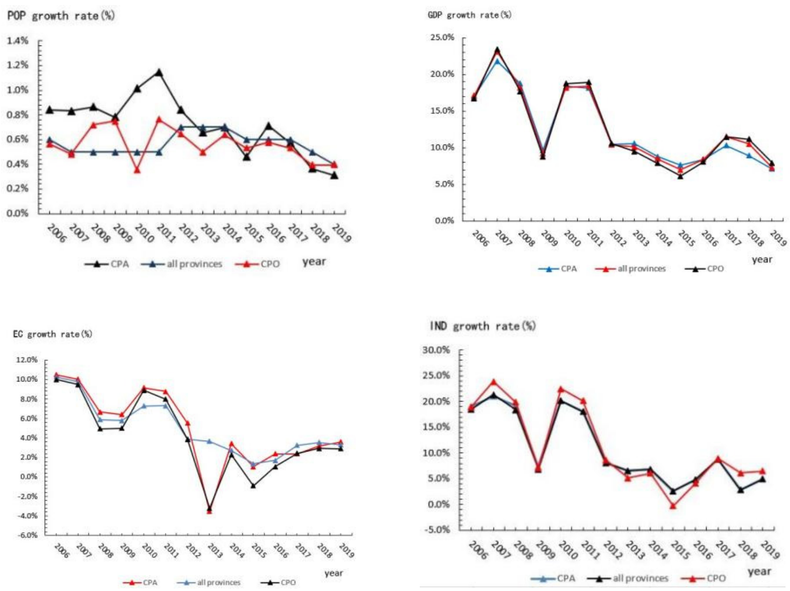

Fig. 2-5 Comparison of growth rate changes among various indices in the CPB group, the CPI group and the group of all provinces from 2006 to 2019

3.3.1 MEP Scenario

The future growth rates of each variable in this scenario are set in accordance with the clear future plans made by the Chinese government for each indicator.

China's State Council predicts the population will peak in 2030 at 1.45 billion people. To meet the government's development targets, population growth should be 0.3 per cent between 2020 and 2025 and 0.2 per cent between 2026 and 2030 (Table 6) .

Table 6 The MEP scenario contained groups of all provinces, CPB groups and CPI groups' prediction of the growth rate of the total population from 2020 to 2030

Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Group CPB	0.4%	0.4%	0.4%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%
All Province	0.4%	0.4%	0.4%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%
Group CPI	0.4%	0.4%	0.4%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%

The GDP growth rate is set according to the forecasts of the World Bank and the Development Research Center of The State Council in China in 2030 (Table 7) .

Table 7 The MEP scenario contained groups of all provinces, CPB groups and CPI groups' prediction of the growth rate of gross domestic product from 2020 to 2030.

Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Group CPB	6.0%	5.4%	5.4%	5.2%	5.0%	5.0%	4.8%	4.8%	4.8%	4.6%	4.6%
All Province	6.5%	5.9%	5.9%	5.7%	5.5%	5.5%	5.3%	5.3%	5.3%	5.1%	5.1%
Group CPI	7.0%	6.4%	6.4%	6.2%	6.0%	6.0%	5.8%	5.8%	5.8%	5.6%	5.6%

China National Petroleum Institute of Economics and Technology predicts that China's total energy consumption is expected to reach 6.03 billion tons of standard coal in 2030. According to this target, the growth rate of China's total energy consumption is designed (Table 8) .

Table 8 The MEP scenario contained groups of all provinces, CPB groups and CPI groups' prediction of the growth rate of total energy consumption from 2020 to 2030.

Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Group CPB	3.3%	3.3%	3.3%	2.3%	2.3%	2.3%	1.3%	1.3%	1.3%	1.3%	1.3%
All Province	3%	3%	3%	2%	2%	2%	1%	1%	1%	1%	1%
Group CPI	2.7%	2.7%	2.7%	1.7%	1.7%	1.7%	0.7%	0.7%	0.7%	0.7%	0.7%

The Economic Forecasting Department of the China Information Center predicts that the proportion of China's secondary industry structure will decrease by about 0.5% year by year during the 14th Five-Year Plan period. According to this goal, the growth rate of China's secondary industry structure is designed (Table 9).

Table 9 The MEP scenario contained groups of all provinces, CPB groups and CPI groups' prediction of the growth rate of the proportion of the secondary industry structure from 2020 to 2030.

Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Group CPB	4.7%	4.7%	4.2%	4.2%	4.2%	3.7%	3.7%	3.7%	3.2%	3.2%	3.2%
Group CPI	5.5%	5.5%	5.0%	5.0%	5.0%	4.5%	4.5%	4.5%	4.0%	4.0%	4.0%

Per capita GDP, energy intensity and secondary industry structure are all calculated from the above indicators, and the changing trend of gross population, per capita GDP, energy intensity and secondary industry structure of the two groups of provinces from 2020 to 2030 can be obtained under this scenario. The remaining scenarios are calculated in the same way.

3.3.2. EEP Scenario

In this scenario, the Chinese government attaches great importance to environmental protection, in which the indicators remain at low or even negative growth rates while the transformation of industrial structure is accelerating (Table 10) .

Table 10 The EEP scenario contained groups of all provinces, CPB groups and CPI groups' prediction of growth rates for various indicators from 2020 to 2030

	Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
POP	Group CGA	0.15%	0.15%	0.15%	0.05%	0.05%	0.05%	-0.05%	-0.05%	-0.05%	-0.15%	-0.15%
	Group CGO	0.15%	0.15%	0.15%	0.05%	0.05%	0.05%	-0.05%	-0.05%	-0.05%	-0.15%	-0.15%
GDP	Group CGA	3.0%	2.4%	2.4%	2.2%	2.0%	2.0%	1.8%	1.8%	1.8%	1.6%	1.6%
	Group CGO	4.0%	3.4%	3.4%	3.2%	3.0%	3.0%	2.8%	2.8%	2.8%	2.6%	2.6%
EC	Group CGA	1.8%	1.8%	1.8%	0.8%	0.8%	0.8%	-0.2%	-0.2%	-0.2%	-0.2%	-0.2%
	Group CGO	1.2%	1.2%	1.2%	0.2%	0.2%	0.2%	-0.8%	-0.8%	-0.8%	-0.8%	-0.8%
IND	Group CGA	1.7%	1.7%	1.2%	1.2%	1.2%	0.7%	0.7%	0.7%	0.2%	0.2%	0.2%
	Group CGO	2.5%	2.5%	2.0%	2.0%	2.0%	1.5%	1.5%	1.5%	1.0%	1.0%	1.0%

3.3.3. EED Scenario

In this scenario, the Chinese government hopes to sacrifice environmental protection before 2030 to seek greater social development and economic benefits. All the indicators maintained a higher growth rate than the actual, while the speed of industrial structure transformation slowed down. Moreover, the provinces that promised to peak before 2030 also ignored the target, allowing the growth rate of each indicator to be in line with the provinces that promised to peak in 2030 (Table 11) .

Table 11 The EED scenario contained groups of all provinces, CPB groups and CPI groups' prediction of growth rates for various indicators from 2020 to 2030.

	Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
POP	Group CGA	0.6%	0.6%	0.6%	0.5%	0.5%	0.5%	0.4%	0.4%	0.4%	0.3%	0.3%
	Group CGO	0.6%	0.6%	0.6%	0.5%	0.5%	0.5%	0.4%	0.4%	0.4%	0.3%	0.3%
GDP	Group	8.0%	7.4%	7.4%	7.2%	7.0%	7.0%	6.8%	6.8%	6.8%	6.6%	6.6%

	CGA											
	Group CGO	8.0%	7.4%	7.4%	7.2%	7.0%	7.0%	6.8%	6.8%	6.8%	6.6%	6.6%
EC	Group CGA	4.3%	4.3%	4.3%	3.3%	3.3%	3.3%	2.3%	2.3%	2.3%	2.3%	2.3%
	Group CGO	4.3%	4.3%	4.3%	3.3%	3.3%	3.3%	2.3%	2.3%	2.3%	2.3%	2.3%
IND	Group CGA	6.5%	6.5%	6.0%	6.0%	6.0%	5.5%	5.5%	5.5%	5.0%	5.0%	5.0%
	Group CGO	6.5%	6.5%	6.0%	6.0%	6.0%	5.5%	5.5%	5.5%	5.0%	5.0%	5.0%

4. DISCUSSION

4.1. Carbon emission projections for two groups and all provinces in MEP Scenario

China's emissions will not peak by 2030 if indicators follow Chinese government goal. For the two different groups, neither CPB nor CPI has peaked. Obviously, if China wants to achieve social development and environmental protection goals such as population growth, economic development, industrial structure transformation, green technology progress and resource conservation, it will not be able to reach the peak in 2030 as promised (fig. 6-8) .

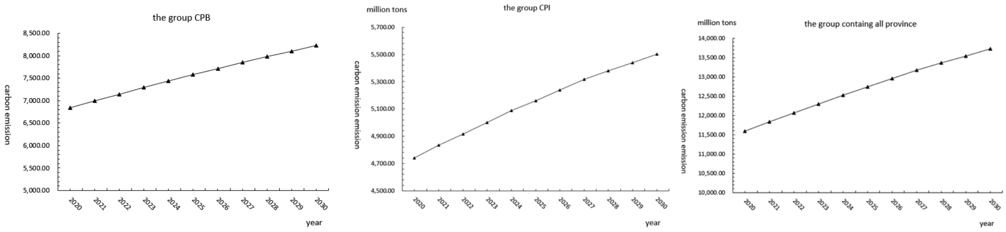

Fig. 6-8 Carbon emission projections for the group CPB, group CPI and group containing all provinces in 2020-2030 in MEP Scenario

4.2. Carbon emission projections for two groups and all provinces in EEP Scenario

If the Chinese government implements strict environmental protection policies, limits population growth, accelerates industrial transformation, even willing to sacrifice GDP growth for environmental protection, so as to fulfill the solemn commitment of emission peak in 2030. Then China will reach the peak carbon emissions in 2028. Among them, the provinces that promised to peak in 2030 will peak their carbon emissions in 2028, while those that promised to peak in 2030 will peak their carbon emissions in 2027. This shows that if the use of environmental protection policies to excessively restrict the development of each province, rather than taking measures to adapt to local conditions, it is likely to harm the social and economic development of some provinces (fig. 9-11) .

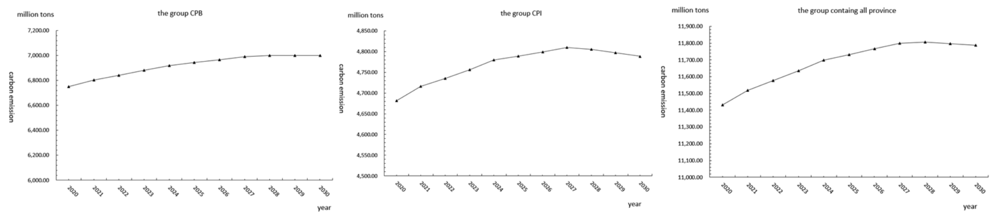

Fig. 9-11 Carbon emission projections for the group CPB, group CPI and group containing all provinces in 2020-2030 in EEP Scenario

4.3. Carbon emission projections for two groups and all provinces in EED Scenario

If the Chinese government wants to achieve a more successful phase of development before reaching emission peak, it will have to adopt policies that allow the growth rate of indicators to be much higher than previously planned. Since China is still in an immature stage of development and has not yet reached the inflection point of the EKC curve. Rapid socioeconomic development will only lead to a surge in carbon emissions, rather than an inverted U-shaped trend due to advances in environmental protection technology. This is also the same as previous studies (fig. 12-14) .

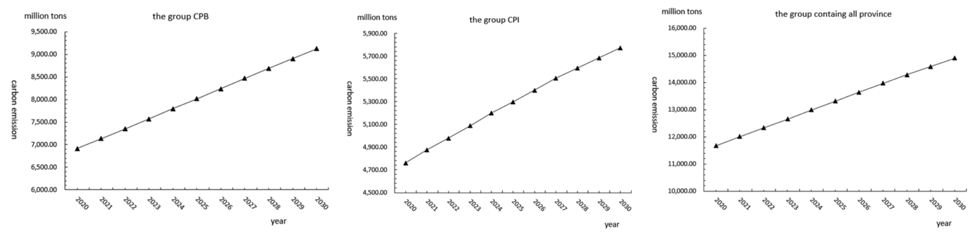

Fig. 12-14 Carbon emission projections for the group CPB, group CPI and group containing all provinces in 2020-2030 in EED Scenario

5. CONCLUSIONS

Based on the STIRPAT model, this article uses ridge regression to build a prediction model for China's future carbon emissions, and uses the double fixed effect model to verify the robustness of the model. The results indicate that only under the EEP Scenario can China achieve carbon peaking in 2030, but this will come at a heavy cost of sacrificing social and economic development and exacerbating imbalanced development among different provinces. According to China's current policies, achieving carbon peak in 2030 is very difficult. The model shows that controlling the population growth rate, making the expected population peak earlier than the carbon emission peak, and promoting the use of clean energy to reduce energy consumption intensity are feasible and effective policy measures.

REFERENCES

[1]Wang, S.J.; Xie, Z.H.; Wang, Z.H. The spatiotemporal pattern evolution and influencing factors of CO2 emissions at the county level of China. Acta Geographica Sinica 2021, 76, 3103–3118.
[2]Fan, F.; Lian, H.; Liu, X. Can environmental regulation promote urban green innovation Efficiency? An empirical study based on Chinese cities. J. Clean. Prod. 2020, 287, 125060.
[3]Zhang Penghui, Liu Hui. Jointly cope with climate change challenges [N]. People's Daily, 2021-08-24 (017) DOI: 10.28655 / n.c. Nki NRMRB. 2021.008977.
[4] Special Report IPCC. Global warming of 1.5℃. Report. Cambridge: Report.
Cambridge University Press; 2018.
[5]Wei YM, Han R, Wang C, Yu B, Liang QM, Yuan XC, et al. Self-preservation strategy for approaching global warming targets in the post-Paris Agreement era. Nat Commun 2020;11:1624.
[6]Dai Yande, Zhu Yuezhong, Bai Quan. China's low-carbon development path in 2050: Energy demand and carbon emission scenario analysis [J]. Reference in economic research, 2010, No. 2298 (26) : 2-22 + 33.DOI:10.16110/j.carol carroll nki issn2095-3151.2010.26.002.
[7] Black R, Cullen K, Fay B, Hale T, Lang J, Mahmood S, et al. Taking stock: a global assessment of net zero targets. Report. London: Energy & Climate Intelligence
Unit and Oxford Net Zero; 2021.
[8]Qin Zhu;;Xizhe Peng.The impacts of population change on carbon emissions in China during 1978–2008[J]. Environmental Impact Assessment Review,2012
[9]A. K. Misra;Anjali Jha.Modeling the effect of population pressure on the dynamics of carbon dioxide gas [J]. Journal of Applied Mathematics and Computing,2021(prep)
[10]Shiwei Yu;;Junjie Zhang;;Shuhong Zheng;;Han Sun.Provincial carbon intensity abatement potential estimation in China: A PSO–GA-optimized multi-factor environmental learning curve method [J].Energy Policy,2015
[11]Liu T J. The relationship between urbanization and carbon dioxide emissions in China: An analysis based on provincial panel data. Shanxi agricultural economy, 2020, No. 267 (3) : 80-81. The DOI: 10.16675 / j.carol carroll nki cn14-1065 / f 2020.03.040.
[12]Mousavi B, Lopez NSA, Biona JBM, Chiu ASF, Blesl M. Driving forces of Iran’s CO2 emissions from energy consumption: an LMDI decomposition approach. Applied Energy 2017;206:804–14.
[13]Wang Z G, Hoffmann T, Six J, et.Humaninduced erosion has offset carbon emissions from landcoverchange. Nature Climate Change, 2017
[14]Obas J E, Anthony J I. Decomposition analysis of CO2 emission intensity between oil-producing and non-oil-producing sub-Saharan African countries. Energy Policy, 2006, 34(18): 3599-3611.
[15]Liu D, Xiao B . Can China achieve its carbon emission peaking? A scenario analysis based on STIRPAT and system dynamics model[J]. Ecological Indicators, 2018, 93(OCT.):647-657.
[16]Liu Z C. An empirical analysis of regional differences of carbon dioxide emissions in China and their influencing factors [D]. Jinan University,2013.
[17]Zhang Y, Yu Z, Zhang J . Research on carbon emission differences decomposition and spatial heterogeneity pattern of China's eight economic regions[J]. Environmental Science and Pollution Research, 2022, 29(20):29976-29992.
[18]Chaolin G U, Lingqian H U , Cook I G . China's urbanization in 1949–2015: Processes and driving forces[J]. Chinese Geographical Science, 2017, 27(006):847-859.
[19]Kang P, Song G, Chen D , et al. Characterizing the generation and spatial patterns of carbon emissions from urban express delivery service in China[J]. Environmental Impact Assesment Review, 2020, 80(Jan.):106336.1-106336.10.

[20]Yan D, Lei Y, Li L, et al. Carbon emission efficiency and spatial clustering analyses in China's thermal power industry: Evidence from the provincial level[J]. Journal of Cleaner Production, 2017, 156(jul.10):518-527.
[21]Min-Na L I , Cai S , Zhang H R , et al. FACTOR ENDOWMENTS AND THE ECONOMIC SPATIAL DISSIMILARITY IN THE YELLOW RIVER VALLEY[J]. Economic Geography, 2011.
[22]Ding Fanlin. Reflection on the Path of China's Industrial Carbon Peak under the Background of Industrial Transfer [J/OL]. Contemporary Economic Management: 1-10, 2023.
[23]Li C , Li H , Qin X . Spatial Heterogeneity of Carbon Emissions and Its Inluencing Factors in China: Evidence from 286 Prefecture-Level Cities[J]. International journal of environmental research and public health, 2022, 19(3).
[24]Guo,Yudong. Comprehensive Evaluation of Energy-EconomyEnvironment Harmonious Rate in Chang-Zhu-Tan[C]// 2013 International Conference on Education,Management and Social Science(ICEMSS 2013). 0.
[25]Li W , Du L . Assessment Framework of Provincial Carbon Emission Peak Prediction in China: An Empirical Analysis of Hebei Province[J]. Polish Journal of Environmental Studies, 2019, 28(5).
[26]Wei T . What STIRPAT Tells About Effects of Population and Affluence on Environmental Impact?. 2010.
[27]Xiaoyan Li.Study on the impact of energy rebound effect on carbon emission reduction at different stages of urbanization in China [J]. Ecological Indicators, 2021
[28]Lin Boqiang, Liu Xiying. Carbon emissions during China's urbanization phase: influencing factors and emission reduction strategies [J]. Economic Research, 2010,45 (08): 66-78.
[29]Wei YM, Han R, Wang C, Yu B, Liang QM, Yuan XC, et al. Self-preservation strategy for approaching global warming targets in the post-Paris Agreement era. Nat Commun 2020;11:1624.
[30]Xiao Y, Gao K and Sun R (2022) Modeling the Impact of Foreign Direct Investment on China's Carbon Emissions: An Economic and Environmental Paradigm. Front. Environ. Sci. 10:922208.
[31]Wang, Z., Lu, Q., & Lv, Z. (2018). Evaluation on the Effect of Energy Intensity Reduction of Thermal Power Enterprise in Four Provinces of China. Journal of Cleaner Production, 191, 469-481.
[32] Ehrlich, Paul, R, et al. IMPACT OF POPULATION GROWTH[J]. Obstetrical & Gynecological Survey, 1971.
[33]Bo C A , Hz A , Wei L A , et al. Research on provincial carbon quota allocation under the background of carbon neutralization[J]. Energy Reports, 2022, 8:903-915.
[34]Xu J , Zhang M , Zhou M , et al. An empirical study on the dynamic effect of regional industrial carbon transfer in China[J]. Ecological Indicators, 2017, 73:1-10.
[35] EHRLICH, PAUL, R, et al. IMPACT OF POPULATION GROWTH[J]. Obstetrical & Gynecological Survey, 1971.
[36]Ridker R G . Population, resources, and the environment /[M]. Commission on Population Growth and the American Future, 1972.
[37]Sun W, Ren C . Short-term prediction of carbon emissions based on the EEMD-PSOBP model[J]. Environmental Science and Pollution Research, 2021:1-15.
[38]Dietz T , Rosa E A . Rethinking the environmental impacts of population, Affluence and technology. 1994.
[39]Wu, S, & Gao, C (2017). Analysis of urbanization rate projections in China. Development Studies, 11(2017), 4 (in Chinese).
[40]York R , Rosa E A , Dietz T . STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts[J]. Ecological Economics, 2003, 46(3):351-365.
[41]Liu D, Xiao B. Can China achieve its carbon emission peaking? A scenario analysis based on

STIRPAT and system dynamics model[J]. Ecological Indicators, 2018, 93(OCT.):647-657.
[42]Guo X，Huang Y，Zhao D Q，et al. Analysis and dynamic prediction of building energy consumption and GHG emission in Guangdong Province based on scenario analysis method[J].Environmental Science & Technology，2015,（12)：305-310.