ISSN 2616-7433 Vol. 5, Issue 11: 109-116, DOI: 10.25236/FSST.2023.051117

An Exploration of the Elements Impacting Provincial Carbon Emissions in China—Based on Two-Way Fixed Effects Regression with Interaction Effects Analysis

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Abstract: *Under China's "Double Carbon" target, analysis of the factors affecting carbon emissions to promote green emissions reduction is paramount. This paper uses theoretical analysis and statistical entropy weighting to screen variables based on panel data of 30 provincial-level regions (excluding Tibet) in China from 2000 to 2020, and constructs a STIRPAT model based on two-way fixed-effects regression and interaction effects for quantitative analysis. A comprehensive analysis, coupled with a fitting diagram, reveals a "Environmental Kuznets Curve" between GDP per capita and total carbon emissions and a negative correlation between industrial structure and total carbon emissions; however, a point cluster is present, suggesting an uneven development of regional industrial institutions. The highway accessibility intensity can be seen to facilitate the transformation and improvement of industrial structures, as well as to coordinate the growth of regional industries. In view of the above results, this paper gives feasible policies and suggestions.*

Keywords: *Carbon Emissions, Bi-directional Fixed Effects, Interaction Effects*

1. Introduction

1.1 Background of the study

As the an Earth-wide temperature boost pattern becomes more dramatic, nations all over the planet understand that efficient power energy improvement has turned into an unavoidable pattern, from the Unified Countries Structure Show on Environmental Change in 1992 to the Kyoto Convention endorsed in 1997 to the Paris Arrangement endorsed by 195 nations in 2015, making it a focal ecological and political errand for every country to cut the rising pace of carbon emissions. While Asian nations like China, India, and Japan still have high levels of carbon emissions, recent policies on green carbon neutrality have also slowed the growth of carbon emissions. This is in contrast to regions like Europe and North America, where the rate of growth of carbon emissions tends to be negative. From the 1970s onwards, the primary justification behind the flood in carbon emissions in Asian nations was the post-war recuperation and financial turn of events, primarily in regards to modern turn of events. The factors that contributed to carbon emissions and the elasticity of their impact on carbon emissions increased with the population, national GDP, and other areas of development. China, a nation with a large population and a strong industrial base, has taken a number of steps to reduce carbon emissions in order to reach carbon neutrality by 2060 and peak carbon emissions by 2030 (the "Double Carbon" target). However, a number of studies have demonstrated that there are still significant regional disparities in China's carbon emissions. This is primarily attributable to the unreasonable industrial structure, the laggard implementation of emission control policies, and the large differences in economic development between regions. To comprehend the variables that impact carbon emissions, it is important to build proper examination objects and economic models to break down and address the issue of carbon emissions.

1.2 Review of the literature

For the qualitative and quantitative analysis of carbon emission data and its possible influencing factors and policy analysis, domestic and international scholars have used different mathematical models to study the problem. For carbon emission scenario analysis, Li Jinchao and Lu Shiqiang used the STIRPAT model and the GA-ELM model to simulate inter-provincial carbon emissions and their peaks

ISSN 2616-7433 Vol. 5, Issue 11: 109-116, DOI: 10.25236/FSST.2023.051117

in China. The results showed that seven regions in China could reach their peaks by 2030 [1]. Pan Siyu and Zhang Meiling used the STIRPAT extended model and based on a BP neural network model to accurately predict and analyse carbon emissions in Gansu Province, assessing the impact of the number of urban residents, economic development and urban and rural consumption on carbon emissions [2]. Mujeeb Sana , Javaid Nadeem Javaid Nadeem prediction and evaluation of carbon emissions based on deep learning principles and quantification of renewable energy sources [3]. Aras Serkan , Hanifi Van M, Hanifi Van M. proposed an interpretable framework based on SHAP values and ML models is proposed for assessing energy consumption and carbon emission projections [4].

For model evaluation and analysis of carbon emission factors, Li Chuang, Zhang Zhecong Zhang Zhecong Li Chuang, Zhang Zhecong Wang liping the STIRPAT model was used to conduct a scenario analysis of carbon emissions and carbon peaks in China's transport sector and a policy-oriented study of the factors that play a role in transport-related variables [5]. Ostadzad Ali Hossein A study of renewable energy-related innovation and carbon emissions using fixed effects panel threshold estimation found that energy market-related innovation policies lead to innovation in clean energy and reduction in carbon emissions [6]. Chao-Qun Ma, Jiang-Long Liu, Yi-Shuai Ren and Yong Jiang investigated the effects of economic growth, FDI and energy intensity on China's carbon emissions based on fixed effects regression and quantile modeling of panel data, showing that the intensity of carbon emissions did not decrease significantly with energy intensity, and that there was an energy rebound effect in China's manufacturing sector and a positive effect of FDI on carbon emissions, and that there was still much room for reducing China's overall carbon emissions [7].

After studying and researching the literature, it was found that models such as STIRPAT and panel data regression are commonly used in the analysis of carbon emission factors, using other econometric modelling instruments to improve the accuracy of the calculations. As there may be interactions between explanatory variables on the explained variables in the analysis of factors affecting carbon emissions, the inability of traditional fixed effects regression models to address these inability to accurately determine the effect of explanatory variables on the explained variables due to the presence of interactions may lead to limitations in the validity of policy analysis and produce erroneous results.

The analysis of data on carbon emissions and local economic development in 30 Chinese provinces and municipalities (with the exception of the Tibetan region) from 2000 to 2020, among other things, forms the basis of this paper. Through panel fixed effects regression, the qualitative objective or subjective evaluation and quantitative regression analysis of the variables under study are carried out by applying the statistical entropy weighting method and constructing the STIRPAT model as well as the two-way fixed effects regression model, while introducing the clustering robustness criteria error and interactions between the explanatory variables, selecting significant and insignificant pairs of explanatory variables to be brought into the regression model for significance analysis, and correcting for errors arising from the interaction term factors where possible. The model test is used to conduct an accurate policy analysis, so as to illustrate and analyse the validity of the important factors affecting total carbon emissions, and thus to analyse and assess China's overall total carbon emissions, and to provide strong data support and relevant suggestions for China's overall achievement of the "Double Carbon" target.

2. Variable interpretation and data sources

2.1 Interpretation of variables

An examination of the essential components influencing carbon emissions in relation to the 30 provincial levels of total carbon emissions in China (excluding the Tibetan region) is conducted in this paper, thus furnishing a subjective theoretical elucidation of the aforesaid initial variables.

Total Carbon Emissions, or "C" for short, explained variables in this paper, refers to the amount of carbon dioxide emitted into the atmosphere. The problem of carbon emissions is becoming increasingly serious, and the year-on-year increase in total carbon emissions will be affected by a number of factors under the "Double Carbon" initiative.

GDP Per Capita, or "g" for short, as a measure of a country's average nominal GDP, a country's GDP divided by its total population is the Gross Domestic Product per capita. This variable may have an "U-shaped inverted" relationship with total carbon emissions, i.e. there is an "Environmental Kuznets Curve".

Industrial structure, or "i" for short, refers to the relationship between the primary, secondary and

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tertiary industries in five areas: factors, industries, time, space and levels, i.e. the configuration and coordination between the three major industries. The three major industries in China are agriculture, industry and services. The carbon emissions of the secondary industry far exceed those of the other two industries, while the carbon emissions of the tertiary industry are much smaller than those of the other two industries, and its added value can, to a certain degree, reduce the carbon emissions of the whole industry. The numerical model used in this paper to calculate the industrial structure is the value added of the secondary industry divided by the value added of the tertiary industry.

Foreign trade dependence, or "f" for short, is a nation's dependence on foreign trade as a percentage of its GDP or GNP. The greater the foreign trade dependence, the greater the country's dependence on international trade, and as foreign trade dependence deepens, the literature suggests that it has a significant impact on carbon emissions.

Fiscal expenditure ratio, or "p" for short, as a measure of a country's fiscal expenditure as a proportion of total fiscal revenue and expenditure, the impact of different fiscal policies on carbon emissions is different and their relevance is debatable.

Highway Accessibility Intensity, or "h" for short, is the ratio of the total number of road miles in an area to the area's surface. Highway Accessibility Intensity is a possible explanatory variable, as it can have a dampening or facilitating effect on carbon emissions due to factors such as travel time, fuel consumption and commuting convenience.

The Urbanization Rate, or "u" for short, is the ratio of a region's urban population to its total population. An increase in the urbanization rate may also play an important role in a region's total carbon emissions and, based on previous studies in the literature, it can be considered as a possible explanatory variable.

Proportion Of Deposits And Loans, or "l" for short, is the ratio of a bank's total loans to its total deposits. In terms of economic policy, some banks have introduced green bank loans, which link the ratio of deposits to loans to green emissions.

RD Intensity, or "r" for short, is the ratio of regional GDP to total social expenditures for STI and research. Investment in research and innovation associated with green emissions reduction has a dampening effect on carbon emissions and contributes to the green transformation of carbon emissions and is therefore included as an explanatory variable.

2.2 Data sources

The sources of data used in this paper are the National Bureau of Statistics of China, the China Carbon Accounting Database (CEADs) and the China Multiscale Emissions Inventory Model.

3. Entropy method evaluation index construction and regression model setting

3.1 Study of the variables of the entropy method

In order to visually express the weight of the above eight explanatory variables on the influence of total carbon emissions, this paper uses the entropy method model to construct an indicator evaluation system. The definition of entropy can determine the weight of each variable, the greater the weight the greater the elasticity of the effect of the variable on the explanatory variables. According to the screening rule that the weight is less than or equal to 0.08, this paper eliminates the factors that have a small impact on the overall. The above explanatory variables were first normalized.

$$X^* = \frac{X-MIN(X)}{MAX(X)-MIN(X)} \times 99 + 1 \tag{1}$$

The weights are obtained by normalizing the variables and performing a normalization matrix calculation, denoted as w. The weights are calculated by the formula.

$$w_f = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{2}$$

$$d_j = 1 - e_j \tag{3}$$

$$e_j = -k \sum_{n=1}^{n} (P_{ij} * lnP_{ij}) \tag{4}$$

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$$P_{ij} = \frac{x_{ij}^*}{\sum_{i=1}^{n} x_{ij}^*} \tag{5}$$

The weights of the above eight explanatory variables, as computed through the Stata platform w as shown in Table 1.

Table 1: Weights of explanatory variables w

variables	g	i	f	p	h	u	l	r
Weighting w	.1462411	.1463152	.2211762	.0715044	.1085197	.0681716	.0988968	.1391750

The results obtained $w_f > w_i > w_g > w_r > w_h > w_l > w_p > w_u$. The effect of fiscal expenditure and urbanization rate on total carbon emissions is very small which are less than 0.08. Therefore, fiscal expenditure and urbanization rate are excluded from the model in this paper.

3.2 STIRPAT regression model setup

The six explanatory variables of GDP per capita, industrial structure, foreign trade dependence, highway accessibility intensity, deposit and loan share, and RD intensity are used as the main factors affecting provincial carbon emissions to construct the basic STIRPAT model.

$$C = a \cdot g^{\alpha} \cdot i^{\beta} \cdot f^{\gamma} \cdot h^{\varepsilon} \cdot l^{\theta} \cdot r^{\varphi} \cdot e \tag{6}$$

Multiple linear regression model obtained by logarithmic transformation.

$$\ln C = lna + \alpha lng + \beta lni + \gamma lnf \cdots\cdots \tag{7}$$

4. Empirical analysis

4.1 Descriptive statistics

The resulting data was first cleaned and processed, and the original missing variables were removed by filling in the data using interpolation through the Stata platform to obtain the cleaned data, completing the description of the data to obtain the results in Table 2.

Table 2: Decriptive statistics

VAR-NAME	N	mean	sd	min	max
Total Carbon Emissions	630	33,461	27,149	547.5	155,812
GDP Per Capita	630	36,469	28,762	2,662	164,889
Industrial Structure	630	1.043	0.572	0.494	5.297
Foreign Trade Dependence	630	0.296	0.345	0.00716	1.876
Highway Accessibility Intensity	630	0.744	0.490	0.0208	2.205
Proportion Of Deposits And Loans	630	2.898	1.189	1.282	8.881
RD Intensity	630	0.0140	0.0114	0.00155	0.0741

Converting all descriptive statistical variables into logarithmic form yields $\ln C, lng, lni, lnf, lnh, lnl, lnr$.

Since the number of individuals in this panel data N > time series T there is no need to perform unit root smoothness tests and cointegration series tests, denying the possible existence of pseudo-regressions.

4.2 F-test to jugde fixed or mixed effects

The Stata platform was used to determine whether fixed effects or mixed effects should be used by introducing cluster robust standard errors through the F-test at the same time as the within-group regression. The calculated result is Prob > F = 0.0000 and the original hypothesis should be rejected in favour of a fixed-effects model.

4.3 LM-test to judge mixed or random effects

The LM test gives a p-value = 0.0000, so the original hypothesis of "no individual random effect" is strongly rejected and the alternative hypothesis that a random effect should be selected is accepted. The LM test formula is.

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$$lnC[ID,t] = Xb + u[ID] + e[ID,t] \quad (8)$$

4.4 Hausman-test to judge fixed or random effects

A calculation by a modified Hausman test yields that chi2(8) = (b-B)'[(V_b-V_B)^(-1)] (b-B) = 21.50, Prob > chi2 = 0.0185<0.05, so the original hypothesis is strongly rejected and a fixed effects regression model should be used.

4.5 Construction and results of the fixed effects model

After excluding the explanatory variables, this study conducted a panel data analysis of six explanatory variables, including carbon emissions and GDP per capita, industrial structure, foreign trade dependence, highway accessibility intensity, deposit and loan share, and RD intensity for provincial regions in China by taking logarithms, using time and the individual two-way fixed effects regression and introducing clustering robust standard errors to determine the selection of core explanatory variables, and outputting the results with a high degree of precision through intra-group estimation commands. The model equation is. And the fixed effects estimates are shown in Table 3.

$$y_{it} = \beta x_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \quad (9)$$

Table 3: Two-way fixed effects regression

lnC	Coef.	P>|t|
lng	.381	0.021*
lni	-.307	0.003**
lnf	-.0666	0.326
lnh	-.142	0.421
lnl	.194	0.208
lnr	.189	0.176
_cons	6.314	0.000***

The regression results from the two-way fixed effects show that industrial structure and GDP per capita passed the significance test. Industry structure is the most significant, so it is chosen as the core explanatory variable. Next, To find out how highway accessibility intensity affects total carbon emissions, a two-way fixed effects regression model was added to the interaction between industrial structure and highway accessibility intensity. The results of the two-way fixed regression model with the interaction term are shown in Table 4.

Table 4: Fixed effects regression models with interaction terms

lnC	Coef.	P>|t|
lng	.3439054	0.014*
lni	-.441031	0.000***
lnf	-.0532889	0.386
lnh	-.2337973	0.152
lnl	.0659144	0.649
lnr	.2055127	0.136
lni*lih	-.2158908	0.015**
_cons	6.760678	0.000***

The regression results show that the interaction term has a p-value = 0.015<0.05, which is highly significant, while the results of the fixed effects regression model containing the interaction term are all insignificant when the lni is interacted with the other insignificant explanatory variables in the two-way fixed effects regression by the same interaction, as shown in Table 5.

Table 5: Interaction regression results of other insignificant explanatory variables with lni

Interaction term for explanatory variables	Coef.	P>|t|
lni*lnf	.0364192	0.547
lni*lnl	-.3194595	0.120
lni*lnr	-.2214556	0.142

It can be shown that there is an interaction effect between industrial structure, highway accessibility intensity and total carbon emissions, so that the non-significant highway accessibility intensity in the

ISSN 2616-7433 Vol. 5, Issue 11: 109-116, DOI: 10.25236/FSST.2023.051117

original two-way fixed effects regression results can be explained in an economically meaningful way. The data were visualised through the Stata platform and logarithmic scatter plots and quadratic fitted curves of total carbon emissions, GDP per capita and total carbon emissions, and industrial structure and total carbon emissions are presented in Figures 1 and 2 respectively to better illustrate the spatial and quantitative relationships between them.

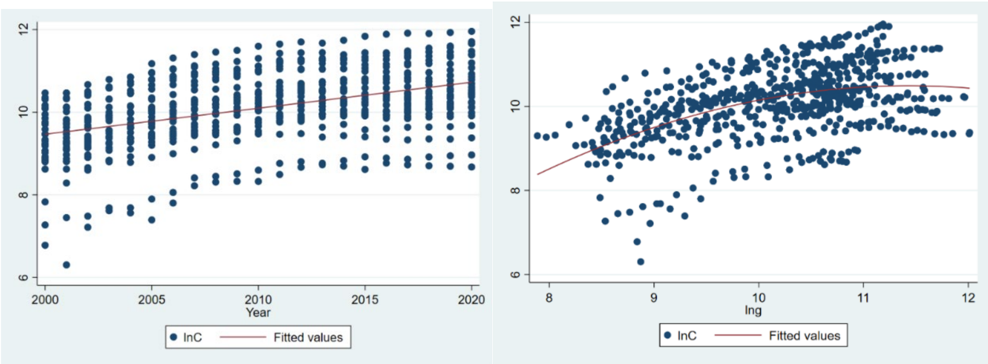

Figure 1: (a) Scatter fit of the logarithm of Total Carbon Emissions (b) Logarithmic fit of GDP Per Capita to Total Carbon Emissions

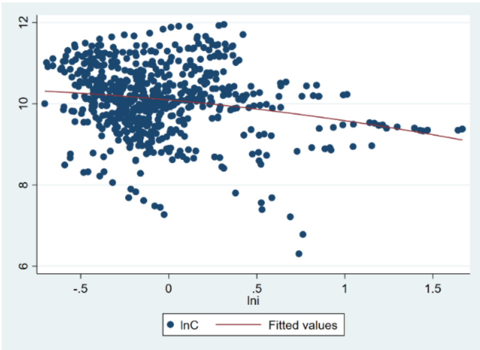

Figure 2: Logarithmic fit of Industry Structure to Total Carbon Emissions

Firstly, for GDP per capita, the graphical and significant two-way fixed effects regression results show that GDP per capita and total carbon emissions always move in the same direction, and from the two-fixed effects regression model it can be concluded that for every 1% increase in GDP per capita, total carbon emissions increase by an average of 0.381%. Furthermore, Figure 2 clearly shows that there is an "U-shaped inverted" trend between GDP per capita and total carbon emissions, indicating that there is indeed an 'Environmental Kuznets Curve' between GDP per capita and total carbon emissions. As GDP per capita increases, the slope of the curve flattens out and then tends to decline. For the 30 provincial regions of China as a whole, although there is a decreasing trend in total carbon emissions as GDP per capita increases, the overall trend may be biased by outliers in individual provinces, i.e. uneven economic development between regions.

In the industrial structure, a more accurate economic relationship can be derived from the double fixed effects regression model and the fitted curves of industrial organization and total carbon emissions. On average, total carbon emissions decrease by 0.307% for every 1% increase in the ratio of tertiary sector to secondary sector value added, which may indicate that the shift from the industrial structure to the secondary sector has a suppressive effect on the increase in total carbon emissions. However, the growth of the industrial structure, as seen from the logarithmic scatter plot, appears to be aggregated, and considering the uneven development of China's provincial regions, this indicates an imbalance in the regional development of the industrial structure and a sure irregularity between the change and overhauling of the industrial structure and the "Double Carbon" strategy.

Secondly, the interaction term between industrial structure and highway accessibility intensity was analysed. The negative coefficient of the connection term demonstrates that highway accessibility intensity strengthens the negative correlation between industrial structure and total carbon emissions, i.e. highway accessibility intensity can promote the negative correlation between industrial structure and total carbon emissions, i.e. as highway accessibility intensity increases, the more the impact of industrial structure on total carbon emissions is suppressed. It can be further explained that highway accessibility

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intensity promotes a shift in industrial structure from the secondary sector, which is very high in carbon emissions, to the tertiary sector, which is green and reduces carbon emissions, thus promoting CO2 emission reduction.

5. Conclusions and recommendations

5.1 Conclusion

This paper uses panel data for 30 provincial-level regions in China (excluding Tibet) from 2000 to 2020 to derive the effects of GDP per capita, industrial structure and highway accessibility intensity on carbon emissions using statistical qualitative analysis and quantitative analysis of two-way fixed effects regression and interaction effects based on the STIRPAT model.

1) From 2000 to 2020, China's overall total carbon emissions grow year by year, but the overall growth rate decreases year by year and tends to be stable.

2) The "U-shaped inverted" trend that exists between GDP per capita and total carbon emissions suggests that carbon emissions will initially rise with economic development, and then decrease as society becomes more aware of green emission reduction and environmental protection policies are implemented, but overall, GDP per capita growth is still not completely decoupled from carbon emissions, and regional economic development is uneven.

3) Industrial structure has a significant negative correlation with total carbon emissions, i.e. the transformation and upgrading of industrial structure has a very obvious effect on curbing carbon emissions. However, according to the logarithmic fit graph of industrial structure and total carbon emissions, it tends to be seen that there is as yet an enormous hole in the improvement of industrial institutions in different locales.

4) Highway accessibility intensity has a significant contribution to the effect of industrial structure in curbing carbon emissions. It may be due to the fact that the deepening of road development will improve commuting efficiency and enhance inter-regional communication and cooperation on green emission reduction.

5.2 Recommendations

1) Adjust macroeconomic policies and improve the resource allocation system. For the adjustment of policies, macroeconomic policies need to be adjusted and the government should strengthen the economic regulation of individual regions where the synergy between GDP per capita and total carbon emissions is still high, so that they can smoothly transition to the peak of the "Environmental Kuznets Curve", while adjusting the allocation of factor resources in a timely manner to bridge the gap of uneven economic development between regions.

2) Strengthen the implementation of environmental policies and develop "environmental taxes". Efforts to promote green emissions are rooted in environmental policy itself. With the introduction of the "double carbon" target, the emerging policy of "environmental tax" has gained importance as an effective way to monitor and control pollutant emissions. Relevant government departments should further expand the scope of environmental taxes and strengthen the regulation of the emission of relevant pollutants, while relevant regulations should be further improved to ensure accurate implementation.

3) Strengthen the highway accessibility intensity and promote industrial restructuring. Starting from the five aspects of road safety, convenience, efficiency, greenness and economy, we will ensure safe travel and improve the construction of transport facilities to ensure wide road coverage, fast and smooth transport networks, and intelligent and efficient comprehensive transport. Promote the coordination and timeliness of inter-regional exchanges, allowing areas that have completed industrial transformation and upgrading first to drive areas that have not, and ensuring that the gap in industrial structure between regions is narrowed.

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