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Analysis of Factors Influencing Carbon Emissions in Chinese Cities Based on LMDI and Threshold STIRPAT Model

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Abstract

Rapid development of the global economy has led to increasingly prominent environmental issues, particularly carbon emissions. This study analyzed panel data related to carbon emissions and their influencing factors from 284 prefecture-level cities in China from 2004 to 2020. Utilizing the improved Kaya identity and the LMDI model, this study decomposes and identifies the main factors influencing CO_2 emissions: population size, per capita affluence, industrial structure, energy consumption intensity, and energy structure. Subsequently, a threshold-STIRPAT model was established, employing population size and energy consumption intensity as threshold variables to analyze the heterogeneity of population size and the three major economic regions. The findings indicate that from 2004 to 2020, population size, per capita affluence, and energy consumption intensity exhibited a positive driving effect on carbon emissions, whereas industrial structure and energy structure demonstrated a negative inhibiting effect. The threshold-STIRPAT model results reveal that industrial structure has the most significant impact on carbon emissions, whereas population size has the least impact. Furthermore, the impact of population size and energy consumption intensity on carbon emissions is stage-specific. The heterogeneity analysis results demonstrated that the same factor does not uniformly affect carbon emissions under different conditions.

Keywords

Carbon emission; Kaya identity; LMDI model; Threshold-STIRPAT model; Heterogeneity analysis

1. Introduction

Amidst the severe challenges of global climate warming and environmental degradation, carbon emissions, as the primary driver exacerbating the greenhouse effect, have garnered international attention [1]. As the world's largest developing nation and a significant carbon emitter, China's carbon emission trends not only deeply impact the domestic ecological environment and sustainable development but also play a pivotal role in the global climate governance structure [2]. Although the academic community has made certain progress in the field of factors influencing carbon emissions, there remains considerable scope for further research. On the one hand, studies focusing on carbon emissions at the city level are relatively scarce [3], leading to a limited understanding of urban carbon emission characteristics and impact mechanisms. This, in turn, diminishes the precision and efficacy of urban-level emission reduction policies. On the other hand, the majority of studies employ linear models to analyze the factors affecting carbon emissions, which complicates the accurate depiction of the complex nonlinear relationship between economic and social activities and carbon emissions [4].

Furthermore, existing research often overlooks the dynamic shifts in the roles of various factors across different stages of development, especially in varying population sizes. Additionally, they do not fully account for the urban heterogeneity resulting from China's regional economic disparities [5], which imposes evident constraints on the guidance of urban emission reduction practices.

Since its introduction in 1989, the Kaya identity [6] has been widely applied in studies on the decomposition of carbon emission influencing factors. However, due to the complex nonlinear relationship between socioeconomic systems and carbon emissions, the original model struggles to comprehensively capture this dynamic interaction. To address this limitation, scholars have dynamically extended the Kaya identity by incorporating new influencing factors into the analytical framework and integrating it with the LMDI model, thereby significantly enhancing the model's applicability to real-world scenarios. Specifically, Yang et al. (2020) employed the extended Kaya identity and LMDI method to decompose the influencing factors of China's carbon emissions from 1996 to 2016, finding that economic activity had the strongest promoting effect on carbon emissions, while energy intensity exhibited the most significant inhibitory effect [7]. Chen and Li (2021) applied the same methodological framework to analyze the incremental carbon emissions in Sichuan Province, identifying key influencing factors such as energy structure effect, energy intensity effect, industrial structure effect, economic development level effect, and population scale effect [8]. Qi and Li (2024) further extended this approach to the study of carbon emissions in the logistics industry, decomposing factors such as carbon emission intensity, low-carbon technology, industry income level, and workforce size, revealing the inhibitory effect of low-carbon technology on carbon emission efficiency [9]. These studies collectively demonstrate that the combination of the extended Kaya identity and the LMDI model provides an effective tool for refined analysis of carbon emission influencing mechanisms across multiple domains.

To systematically analyze the driving mechanisms of carbon emissions, nonlinear analytical methods such as the STIRPAT model, panel threshold regression model, and threshold-STIRPAT model have been widely applied [10, 11]. The threshold-STIRPAT model, which integrates the STIRPAT model with the threshold regression model, effectively reveals the nonlinear relationships between carbon emissions and their influencing factors. A limited number of studies have employed this model to identify key variables affecting carbon emissions across different research scales [12, 13]. Furthermore, considering the spatiotemporal heterogeneity in the mechanisms influencing carbon emissions [5], scholars have utilized panel threshold regression models to delineate the differential impacts of factors such as trade dependence, urbanization rate, and population aging across various regions by dividing regional economic zones [14, 15].

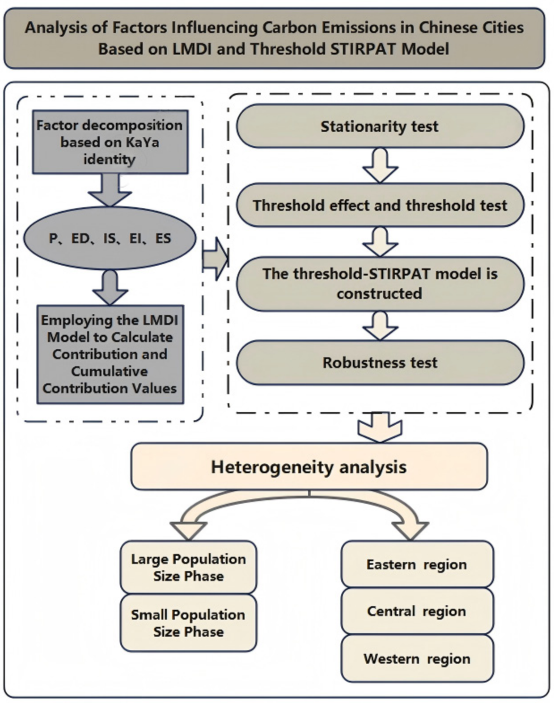

Figure 1. Research framework diagram.

In summary, this study utilizes an extended Kaya identity and LMDI model to analyze five key factors influencing carbon emissions (population, affluence, industrial structure, energy intensity, and energy structure) across 284 Chinese cities (2004-2020). Utilizing threshold-STIRPAT modeling with stationarity and robustness tests, it examines emission heterogeneity by population size and economic region. This research holds significant theoretical and practical implications for accurately understanding the evolution patterns of carbon emissions and for formulating scientific and effective urban emission reduction policies. The analytical framework is presented in Figure 1.

The subsequent sections of this paper are organized as follows: Section 2 delineates the research methodology and data sources. Section 3 presents the empirical results and analyses. Section 4 concludes the study and proposes policy recommendations.

This study provides several potential contributions: (1) based on the panel data of 284 prefectural-level cities in China, we decompose the indicators of influencing factors of carbon emissions using the improved Kaya identity and calculate the contribution values of the influencing factors through the LMDI model, which scientifically quantifies the cumulative contribution effects of the influencing factors; (2) the advantages of combining the STIRPAT model with the threshold regression model are introduced into the study of carbon emissions, and the single threshold-STIRPAT model for population size and the double threshold-STIRPAT model for energy consumption intensity are constructed to explore the potential nonlinear relationship between various influencing factors and carbon emissions; (3) heterogeneity analyses were also conducted for the population size and the three major economic regions to provide a more practical theoretical basis for the implementation of targeted measures in each region.

2. Research Methods and Data

2.1 Improved Kaya identity

In 1989, at the IPCC seminar, the Japanese scholar Kaya proposed the Kaya identity, which was utilized to analyze the influencing factors. Due to the complexity and variety of influencing factors of carbon emissions, the original Kaya identity contains only four influencing factors, which are not in line with the reality of complex environmental phenomena. Therefore, many scholars [16-18] have improved and reused it. Considering that the process of carbon dioxide production from fossil energy combustion mostly occurs during industrial production, some scholars believe that the ratio of industrial added value to regional gross domestic product is also an important factor affecting carbon emissions [19]. Thus, this study introduces the variable industrial value added (IVA) [20] in Kaya identity and extends it as (1):

$$C = P \times \frac{GDP}{P} \times \frac{IVA}{GDP} \times \frac{E}{IVA} \times \frac{C}{E} \tag{1}$$

Where C represents carbon dioxide emissions; P represents population size, that is, the total population at the end of the year; GDP represents gross regional product; IVA represents industrial added value; E represents energy consumption; GDP/P represents per capita affluence, that is, GDP per capita, recorded as ED; IVA/GDP represents industrial structure, that is, the ratio of industrial added value to regional gross regional product, recorded as IS; E/IVA represents energy consumption intensity, that is, the ratio of energy consumption to industrial added value, recorded as EI; C/E represents energy structure, that is, carbon dioxide emissions generated per unit of energy consumption, recorded as ES. Therefore, formula (1) can also be expressed as (2):

$$C = P \times ED \times IS \times EI \times ES \tag{2}$$

2.2 LMDI model

The LMDI model effectively analyzes the factors contributing to changes in energy consumption. This model enables the systematic decomposition of the contribution of each factor to energy consumption variations and is widely applied in the fields of energy [21], environment [22], and related domains. In this study, based on the above improved Kaya identity (2), using the LMDI model, the difference between the total carbon emissions in year t and the base year can be obtained as (3)-(5):

$$\Delta C_{0t} = C_t - C_0 \tag{3}$$

$$= P_t \times ED_t \times IS_t \times EI_t \times ES_t - P_0 \times ED_0 \times IS_0 \times EI_0 \times ES_0 \tag{4}$$

$$= \Delta P_{0t} + \Delta ED_{0t} + \Delta IS_{0t} + \Delta EI_{0t} + \Delta ES_{0t} \tag{5}$$

In the formula (3)-(5): ΔC_{0t} represents the cumulative contribution of various influencing factors to changes in carbon emissions from the base year to the t-th year; C_t represents the total carbon emissions in year t; C_0 represents the total carbon emissions in the base year; $\Delta P_{0t}, \Delta ED_{0t}, \Delta IS_{0t}, \Delta EI_{0t}$, and ΔES_{0t} are the cumulative contributions of population size, per capita wealth, industrial structure, energy consumption intensity, and energy structure to carbon emissions from the base year to the t-th year, respectively.

To reflect the annual contribution value of each factor to carbon emissions more accurately, thereby facilitating a more comprehensive and detailed understanding of the impact of each factor on carbon emissions, this study calculated the annual contribution value using the following formula (6)-(10):

$$\Delta P_{T-1,T} = \frac{C_T - C_{T-1}}{\ln C_T - \ln C_{T-1}} \ln\left(\frac{P_T}{P_{T-1}}\right) \tag{6}$$

$$\Delta ED_{T-1,T} = \frac{C_T - C_{T-1}}{\ln C_T - \ln C_{T-1}} \ln\left(\frac{ED_T}{ED_{T-1}}\right) \tag{7}$$

$$\Delta IS_{T-1,T} = \frac{C_T - C_{T-1}}{\ln C_T - \ln C_{T-1}} \ln\left(\frac{IS_T}{IS_{T-1}}\right) \tag{8}$$

$$EI_{T-1,T} = \frac{C_T - C_{T-1}}{\ln C_T - \ln C_{T-1}} \ln\left(\frac{EI_T}{EI_{T-1}}\right) \tag{9}$$

$$\Delta ES_{T-1,T} = \frac{C_T - C_{T-1}}{\ln C_T - \ln C_{T-1}} \ln\left(\frac{ES_T}{ES_{T-1}}\right) \tag{10}$$

where $\Delta C_{T-1,T}$ denotes the difference between the total carbon emissions in year $T-1$ to year T, and also denotes the value of the contribution of each influencing factor to the change in carbon emissions between year $T-1$ to year T; C_T denotes the total carbon emissions in year T; C_{T-1} denotes the total carbon emissions in year $T-1$; $\Delta P_{T-1,T}, \Delta ED_{T-1,T}, \Delta IS_{T-1,T}, \Delta EI_{T-1,T}$, and $\Delta ES_{T-1,T}$ are the contributions of population size, per capita wealth, industrial structure, energy consumption intensity, and energy structure to carbon emissions from year $T-1$ to year T, respectively.

2.3 Threshold-STIRPAT models

In 1971, American scholars Ehrlich and Holdren [23] initially proposed the IPAT model in science. Subsequently, in 2003, Dietz and Rosa [24] modified it to a stochastic form and introduced an expandable stochastic environmental impact assessment model, namely the STIRPAT model. Numerous scholars [25-27] have introduced the variables of the LMDI model into the STIRPAT model. This study improves the STIRPAT model by combining the aforementioned LMDI model results. Given that the contribution and cumulative contribution of the energy structure factor were relatively minor from 2004 to 2020, suggesting a limited effect on carbon emissions, this influence was excluded from the model, and only other influences were introduced into the STIRPAT model. By employing regional carbon emissions as a measure of environmental pressure, population size to represent demographic factors, per capita affluence to reflect economic factors, energy consumption intensity, and industrial structure to indicate technological factors, an improved STIRPAT model was developed, whose logarithmic form is more commonly used [28, 29]. See Equation (11).

$$\ln C = \beta_0 + \beta_1 \ln P + \beta_2 \ln ED + \beta_3 \ln IS + \beta_4 \ln EI + \ln \mu \tag{11}$$

The traditional linear regression model assumes that the impact is fixed. However, numerous economic and environmental variables can cause structural changes. Consequently, the impact of these variables may be staged, and the panel threshold model [30] addresses this issue. As the data in this study comprised panel data from 284 cities with significant differences between them, an attempt was made to construct a threshold STIRPAT model based on the aforementioned improved STIRPAT model. If the population size is a single threshold, it can be expressed as (12):

$$\ln C = \beta_0 + \beta_1 \ln IS + \beta_2 \ln ED + \beta_3 \ln EI + \beta_4 \ln P \times I\left(\ln P < \gamma_1\right) + \beta_5 \ln P \times I\left(\ln P \ge \gamma_1\right) + \ln \mu \tag{12}$$

Where $I(\cdot)$ is the indicative function. When the condition in the brackets is met, the indicative function takes the value of 1, otherwise it is 0; γ_1 is the threshold value; μ is the model error term.

2.4 Data sources

The research object of this study comprises panel data pertaining to carbon emissions and the influencing factors of 284 prefecture-level cities in mainland China from 2004 to 2020. The explanatory variables are carbon emissions, while the control variables include population size, per capita affluence, industrial structure, energy consumption intensity, and energy structure. The data for the empirical analysis are primarily derived from the China Urban Statistical Yearbook. Individual index data, such as carbon emissions, were obtained through measurements, and some missing values were interpolated. The measurement of carbon dioxide emission data in this study follows the method of Zhou et al. [31], Han and Xie [32]. Data on the consumption of natural gas, liquefied petroleum gas (LPG), and electricity were obtained from the China Urban Statistical Yearbook, and data on the ratio of coal-powered electricity generation to the total electricity generation were obtained from the China Electricity Yearbook.

2.5 Description of variables

In this study, the improved Kaya identity was used to decompose the influencing factors of carbon emissions into population size, per capita affluence, industrial structure, energy consumption intensity, and energy structure, as shown in Equation (2), with the specific variables described as follows (Table 1):

Table 1. Variable Description

Abridge	Full spelling	Descriptive
C	Carbon dioxide emission	Referring to the practice of scholars such as Zhou et al. [31] and Han and Xie [32] for the measurements
P	Population size	Characterized by the total population of each prefecture-level city at the end of the year
ED	Per capita affluence	Characterized by the ratio of GDP to year-end population of each prefecture-level city.
IS	Industrial structure	Characterized by the ratio of value added of secondary industry to GDP of each prefecture-level city.
El	Energy consumption intensity	Characterized by the ratio of energy consumption to value added of secondary industry by prefecture level city
ES	Energy structure	Characterized by the ratio of carbon dioxide emissions to energy consumption in each prefecture.

3. Results and Analysis

3.1 Calculation of the contribution value based on the LMDI model

Using the LMDI model, the mean value of the contribution of each influencing factor and the mean value of the total contribution from 2004 to 2020 are calculated with reference to equations (6)-(10), and the magnitude and direction of the role of each influencing factor on carbon emissions and the trend of time change are further analyzed. Details are presented in Table 2.

Analysis Table 2 indicates that the annual average and cumulative contributions of the total effect are positive between 2004 and 2020, suggesting that carbon emissions are on the rise. From the perspective of influencing factors, the cumulative contributions of population size, per capita wealth, and energy consumption intensity are positive, serving as the positive drivers of carbon emissions. Specifically, the contribution of population size is positive except for the years 2005 to 2006, albeit with a weak and indecisive influence; the contribution of per capita wealth is consistently positive with a substantial value, indicating a significant driving effect. Conversely, the cumulative contributions of industrial structure and energy structure are negative, acting as inhibitors of carbon emissions. The contribution of the industrial structure is -3.24, which is the strongest inhibitor of carbon emissions, while the contribution of the energy structure is -1.22, exerting the least impact on carbon emissions.

Table 2. Average value of the contribution of influencing factors in prefecture-level cities

Year	Total effect	P	ED	IS	EI	ES
2004-2005	0.66	0.26	0.81	-0.23	-0.16	-0.02
2005-2006	0.75	-0.14	1.02	0.11	-0.30	0.06
2006-2007	0.78	0.10	1.11	0.04	-0.53	0.06
2007-2008	0.37	0.10	1.06	0.06	-0.65	-0.20
2008-2009	0.52	0.06	0.93	-0.29	-0.16	-0.02
2009-2010	0.83	0.11	1.35	0.17	-0.88	0.07
2010-2011	0.82	0.12	1.50	0.05	-1.16	0.30
2011-2012	0.10	0.06	0.96	-0.23	-0.18	-0.50
2012-2013	0.76	0.07	0.82	-0.18	0.10	-0.04
2013-2014	0.02	0.12	0.63	-0.40	0.18	-0.51
2014-2015	0.08	0.01	0.54	-0.52	0.28	-0.23
2015-2016	0.60	0.17	0.49	-0.46	0.67	-0.27
2016-2017	5.04	0.10	0.96	-0.23	3.87	0.35
2017-2018	5.02	0.22	1.05	-0.41	4.05	0.11
2018-2019	0.95	0.27	0.70	-1.51	1.95	-0.46
2019-2020	1.00	0.26	0.36	-0.61	1.23	-0.24
2004-2020	18.30	1.87	17.88	-3.24	3.01	-1.22

3.2 Panel data stationarity test

Before building the model, to effectively avoid pseudo-regression and bias in the model estimation results, the panel data should first be subjected to a unit root test. In this study, the homogeneity unit root test method LLC test, the heterogeneity unit root test method ADF test, and the PP test were used.

Table 3. Results of stationarity test

Variables	LLC	ADF	PP
InC	-17.8351***	47.5522***	5.2901***
InP	-7.0463***	75.4673***	6.1563***
InED	-16.7419***	42.1640***	28.8107***
InIS	-12.5959***	51.8053***	15.8284***
InEI	-13.2081***	36.3142***	14.1203***

Notes: *, ** and *** represent 10%, 5% and 1% significance levels, respectively.

As indicated by Table 3, all three tests demonstrate that lnC, lnP, lnED, lnIS, and lnEI reject the null hypothesis of the presence of a unit root at the 1% significance level, suggesting that the original series are stationary. Consequently, it is viable to utilize these data to construct the model, thereby avoiding issues such as biased estimation results that can arise from non-smooth data.

3.3 Threshold effect test

Before constructing the threshold effect model, a threshold effect test must be conducted to verify whether the threshold variable is significant and to determine the number of thresholds. Table 4 shows the results of the threshold effect test for population size and energy consumption intensity.

Table 4. Threshold effect test results

Threshold variable	Threshold number	F-value	P-value	1%	5%	10%	Threshold value	95% Confidence interval
InP	Single Threshold	90.07	0.0467	131.4326	82.4850	66.9814	5.6355	[5,6108,5.6409]
	Double Threshold	38.51	0.5233	126.1866	113.0474	94.5737	6.4533	[6,4443,6.4575]
	Triple Threshold	34.62	0.4733	98.2866	82.1637	69.5241	5.3575	[5,3482,5.3677]
InEl	Single Threshold	153.38	0.0000	30.5190	26.0101	21.9595	8.2660	[8.2563,8.2750]
	Double Threshold	50.35	0.0000	28.6607	23.5702	19.2479	6.5874	[6.5572,6.5927]
	Triple Threshold	28.52	0.2767	62.0236	45.3595	38.2063	6.1159	/

In Table 4, following 300 bootstrap samples, using population size as the threshold variable, the p-values for double and triple threshold sampling are 0.5233 and 0.4733, respectively. Consequently, the null hypothesis of no threshold effect cannot be rejected at the 5% significance level. However, the p-value for single threshold sampling is 0.0467, leading to the rejection of the null hypothesis at the 5% significance level. Thus, the threshold-STIRPAT model with a single threshold is selected. When energy consumption intensity serves as the threshold variable, the p-value for triple threshold sampling is 0.2767, and the null hypothesis remains unrejected at the 5% significance level. Conversely, the p-values for double and single threshold sampling are both 0.0000, indicating that the null hypothesis is rejected at the 1% significance level. Therefore, the threshold-STIRPAT model with a double threshold is constructed.

3.4 Threshold-STIRPAT model estimation results

Table 5. Parameter estimation results of threshold -STIRPAT model

Groups	Population size as the threshold variable		Energy consumption intensity as threshold variable	
	Variables	Single threshold mode	Variables	Double threshold model
	InP (InP < 5.6355)	0.811***(0.032)	InP	0.887***(0.030)
	InP (InP ≥ 5.6355)	0.842***(0.031)	InED	0.959***(0.004)
	InED	0.960***(0.004)	InIS	0.988***(0.014)
	InIS	1.016***(0.014)	InEl (InEl < 6.5874)	0.955***(0.006)
	InEI	0.965***(0.004)	InEl (6.5874 ≤ InEI ≤ 8.2660)	0.964***(0.005)
			InEl (InEI > 8.2660)	0.954***(0.005)
	Cons	-10.596***(0.184)	Cons	-10.908***(0.178)

Notes: *, **, and *** indicate 10%, 5% and 1% significance levels, respectively; Values in parentheses are standard errors (The same below).

The single-threshold STIRPAT model with population size as the threshold variable reveals that the coefficients of per capita affluence, industrial structure, energy consumption intensity, and population size are all positive across different population size stages, with more pronounced effects in the larger population stage. Specifically, increased per capita affluence drives carbon emissions by stimulating industrial consumption demand. Industrial structure upgrading, characterized by a higher proportion of secondary industries, leads to elevated energy consumption. The rise in energy consumption intensity directly reflects increased energy use per unit of value added in secondary industries. In the stage with larger population sizes, the coefficients are greater, indicating that cities with larger populations and higher population density—typically more economically developed—exhibit higher per capita carbon emissions. This is particularly evident in megacities such as Chongqing, Beijing, and Shanghai. Overall, the coefficient of industrial structure is the largest, exerting the most significant impact on carbon emissions, whereas the coefficients of population size in both stages are relatively small, suggesting a weaker influence on carbon emissions.

The double threshold-STIRPAT model with energy consumption intensity as the threshold variable reveals that among the three stages of energy consumption intensity, the coefficient in the second stage is the most significant, while the coefficients in the other two stages are relatively similar. Lower energy consumption intensity indicates less energy consumed per unit of added value in the secondary industry, which typically reflects a lower proportion of energy-intensive heavy industries within the secondary sector, resulting in relatively lower carbon emissions. Conversely, higher energy consumption intensity implies greater energy consumption per unit of added value in the secondary industry, which may indicate a higher proportion of energy-intensive heavy industries or lower energy utilization efficiency. However, these cities often have relatively smaller population sizes and lower economic development levels, leading to comparatively lower carbon emissions. Overall, industrial structure remains the most significant factor influencing carbon emissions, whereas the impact of population size on carbon emissions is relatively minor.

3.5 Robustness tests

After building the models, robustness tests were performed to assess the reliability and stability of the results.

Table 6. Threshold effect test results after robustness test

Threshold variable	Threshold number	F-value	P-value	1%	5%	10%	Threshold value	95% Confidence interval
InP	Single Threshold	90.07	0.0467	131.4326	82.4850	66.9814	5.6355	[5.6108,5.6409]
	Double Threshold	38.51	0.5233	126.1865	113.0474	94.5737	6.4533	[6,4443,6.4575]
	Triple Threshold	34.62	0.4733	98.2866	82.1637	69.5241	5.3575	[5,3482,5.3677]
InEI	Single Threshold	153.38	0.0000	30.5190	26.0101	21.9595	8.2660	[8.2660,8.2750]
	Double Threshold	50.35	0.0000	28.6607	23.5702	19.2479	6.5874	[6.5572,6.5927]
	Triple Threshold	28.52	0.2767	62.0236	45.3595	38.2063	6.1159	/

Table 7. Threshold-STIRPAT model after robustness test

Groups	Population size as the threshold variable		Energy consumption intensity as threshold variable	
	Variables	Single threshold mode	Variables	Double threshold model
	InP(lnP < 5.6355)	0.811***(0.083)	InP	0.887***(0.056)
	InP(lnP ≥ 5.6355)	0.842***(0.074)	InED	0.959***(0.008)
	InED	0.960***(0.009)	InIS	0.989***(0.055)
	InIS	1.016***(0.052)	InEl (InEl < 6.5874)	0.955***(0.027)
	InEI	0.965***(0.019)	InEl (6.5874 ≤ InEl ≤ 8.2660)	0.964***(0.024)
			InEl (InEI > 8.2660)	0.954***(0.024)
	Cons	-10.596***(0.489)	Cons	-10.908***(0.378)

Following the robustness test, the data presented in Tables 6 and 7 demonstrate that the threshold effects are statistically significant at both levels. Furthermore, the threshold values and variable coefficients in the model remained consistent and exhibited statistical significance at the level. These findings substantiate the robustness of both the single threshold-STIRPAT model (utilizing population size as the threshold variable) and the double threshold-STIRPAT model (employing energy consumption intensity as the threshold variable) developed in this study.

3.6 Heterogeneity analysis based on different population sizes

In Section 3.4, population size was identified as the single threshold variable with a threshold value of 5.6355. Using this value as the threshold, we further investigated the impact of population size on energy consumption intensity patterns across different stages. Prior to model construction, threshold effect tests were still required.

Table 8. Threshold Effect Test Results

Threshold variable	Threshold number	F-value	P-value	1%	5%	10%	Threshold value	95% Confidence interval
	Single Threshold	95.82	0.0000	36.3490	26.3942	23.8670	7.9901	[7.9523,7.9941]
InEI	Double Threshold	22.64	0.0600	30.3632	23.3673	19.8804	6.8294	[6.7916,6.8324]
	Triple Threshold	27.41	0.3533	71.8372	47.8961	42.1243	6.0820	/
	Single Threshold	45.25	0.0033	31.5769	24.9307	20.2871	8.2482	[8.2770,8.2635]
InEI	Double Threshold	24.52	0.0133	24.6624	20.2575	16.8158	6.2292	[6.2063,6.2461]
	Triple Threshold	12.66	0.5967	52.8316	41.0302	33.8847	7.6475	[7.6081,7.6525]

Table 8 demonstrates that during the stage of larger population size, the single threshold test for energy consumption intensity passes the 1% significance level, with the threshold value being valid. Accordingly, a single-threshold STIRPAT model is established for parameter estimation. In contrast, during the stage of smaller population size, the double threshold test for energy consumption intensity passes the 5% significance level, and the threshold values remain effective. Therefore, a double-threshold STIRPAT model is constructed to conduct parameter estimation.

Table 9. Parameter estimation results of threshold-STIRPAT model

Groups	Stage of larger population size		Smaller population stage	
	Variables	Single threshold mode	Variables	Double threshold model
	lnP	0.716***(0.051)	lnP	1.057***(0.024)
	lnED	0.958*** (0.004)	lnED	0.957*** (0.006)
	lnIS	1.030*** (0.017)	lnIS	1.014*** (0.024)
	lnEI(lnEI < 7.9901)	1.006*** (0.005)	lnEI(lnEI < 6.2292)	0.953*** (0.011)
	lnEI(lnEI ≥ 7.9901)	0.995*** (0.005)	lnEI(6.2292 ≤ lnEI ≤ 8.2482)	0.970*** (0.009)
			lnEI(lnEI > 8.2482)	0.961*** (0.009)
	Cons	-10.079*** (0.322)	Cons	-11.843***(0.253)

Comparing Tables 5 and 9 reveals that under the condition of a larger population size, the coefficient of population size decreases from 0.887 to 0.716, indicating that in the stage of larger population size, the influence of the population effect on carbon emissions decreases. The coefficients of per capita affluence are 0.959 and 0.958, indicating that the influence of per capita affluence on carbon emissions is relatively stable and will not be greatly changed due to the difference in population size. The coefficient of industrial structure increases from 0.989 to 1.030, indicating that the promotion effect on carbon emissions is more significant in cities with larger population sizes. The coefficient of energy consumption intensity changes from a double threshold to a single threshold, and both coefficients increase, indicating that it has a greater promotion effect on carbon emissions when the population size is larger. In summary, in cities with larger population sizes, the factor that has the greatest influence on carbon emissions is industrial structure, and the factor that has the least influence on carbon emissions is population size.

The coefficient of population size increases from 0.887 to 1.057 under the condition of a smaller population size, indicating that the influence of population size on carbon emissions increases when the population size is smaller and becomes the most important factor affecting carbon emissions. The coefficients of per capita affluence are 0.959 and 0.957, respectively, indicating that per capita affluence is not significantly affected by the difference in population size. The coefficient of industrial structure increases from 0.989 to 1.014, indicating that the industrial structure of less populated cities contributes more to carbon emissions, but to a lesser extent than that of more populated cities. Energy consumption intensity continues to show a double threshold: the coefficient for the first stage decreases, whereas the coefficients for the second and third stages increase, indicating that energy consumption intensity also has a slight effect on carbon emissions in cities with smaller populations.

3.7 Heterogeneity analysis based on the three economic regions

China's economic regions are divided into three main segments: eastern, central, and western, based on the distribution of natural resources and the level of economic and social development. The three major economic regions are quite different in all aspects, so this study explores whether the impact of the five major influencing factors on carbon emissions within different economic regions has changed based on the division of the three major economic regions. Figure 2 shows the division of the three major economic regions for 284 prefecture-level cities in China.

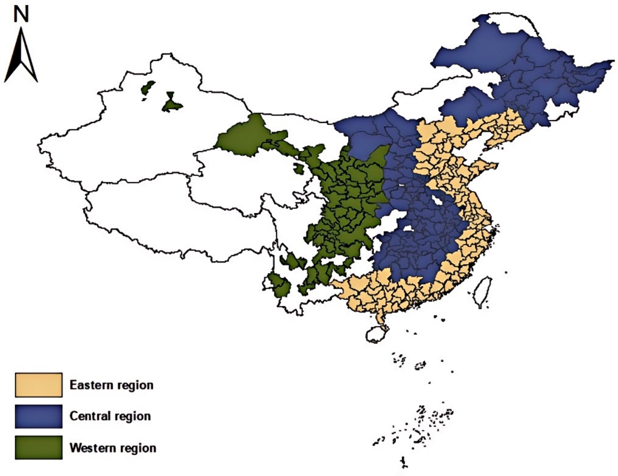

Figure 2. Map of the three economic regions.
(Note: Based on the National Basic Geographic Information Center, the standard map No. GS (2024)0650 downloaded from the Tianditu website is made, and the base map is not modified.)

3.7.1 Eastern region

The test results in Table 10 show that in the sample data of the eastern region, the threshold effect passes the test, and the threshold-STIRPAT model can be established with population size and energy consumption intensity as single thresholds. Table 11 presents the regression results for the two models.

Table 10. Threshold effect test results

Economic regions	Threshold variable	Threshold number	F-value	P-value	1%	5%	10%	Threshold value	95% Confidence interval	Threshold type
Eastern region	InP	Single Threshold	142.07	0.01	142.41	103.02	88.04	5.6062	[5.6046,5.6093]	Single
		Double Threshold	67.49	0.12	129.17	98.17	73.07	6.4533	[6.4496,6.4582]	
		Triple Threshold	21.35	0.85	105.78	83.44	75.72	5.5215	[5.5134,5.5241]	
	InEI	Single Threshold	67.94	0.00	42.39	24.93	20.65	8.2842	[8.2654,8.3006]	Single
		Double Threshold	10.75	0.48	47.08	28.54	19.21	6.8280	[6.7915,6.8319]	
		Triple Threshold	6.08	0.70	30.45	21.98	19.06	6.2814	/	
Central region	InEI	Single Threshold	28.37	0.03	36.86	24.47	20.89	6.6329	[6.5991,6.6449]	Single

Table 10 Continued

Western region		Double Threshold	9.02	0.57	29.97	21.86	19.50	7.9992	[7.9583,8.0045]	
		Triple Threshold	7.94	0.76	31.11	24.98	21.72	7.6534	[7.5964,7.6571]	
	InP	Single Threshold	72.91	0.0567	115.54	74.56	60.83	5.6411	[5.6318,5.6462]	Single
		Double Threshold	52.40	0.1233	98.12	70.27	56.16	6.4378	[6.4103,6.4505]	
		Triple Threshold	47.50	0.1333	157.85	63.01	52.55	5.3578	[5.3485,5.3664]	
	InEI	Single Threshold	52.21	0.0000	32.95	26.78	22.38	6.5009	[6.4283,6.5099]	Single
		Double Threshold	22.36	0.0833	36.83	24.36	21.49	6.5464 5.9121	[6.4993,6.5559] [5.9044,5.9214]	
		Triple Threshold	14.23	0.3067	44.60	30.89	25.43	7.4874	[7.3000,7.4902]	

Table 11. Parameter estimation results of the threshold-STIRPAT model in the eastern region

Groups	InP as a threshold variable		InEl as a threshold variable	
	Variables	Single threshold model	Variables	Single threshold model
	InP (lnP < 5.6062)	0.638***(0.046)	InP	0.857***(0.042)
	InP (lnP ≥ 5.6062)	0.691***(0.044)	InED	0.958*** (0.006)
	InED	0.965***(0.005)	InIS	1.047*** (0.022)
	InIS	1.073***(0.021)	InEl (InEl < 8.2842)	0.959*** (0.007)
	InEI	0.942***(0.006)	InEI (InEI ≥ 8.2842)	0.947***(0.006)
	Cons	-9.395***(0.265)	Cons	-10.587*** (0.253)

According to the results presented in Table 11, it is evident that, within the sample data of the eastern region, the coefficient of industrial structure exhibits the highest value in both models, indicating that industrial structure exerts the greatest influence on carbon emissions. Conversely, the coefficient of population size demonstrated the lowest value in both models, suggesting that population size has a comparatively minimal impact on carbon emissions. This phenomenon may be attributed to the fact that cities in the eastern region generally have larger populations and higher levels of economic development. Consequently, industrial structure has emerged as the primary factor affecting carbon emissions in the region, whereas the influence of population size remains relatively insignificant.

3.7.2 Central region

From Table 10, it can be observed that in the central region, only the energy consumption intensity passed the threshold effect test of a single threshold, and the threshold-STIRPAT model with energy consumption intensity as a single threshold can be established. Table 12 shows the parameter estimation results of the threshold-STIRPAT model.

Table 12 shows that in the central region, industrial structure has the most significant effect on carbon emissions, while the effect of per capita affluence is relatively small. The main reason for this is that heavy industry is more prominent in the central region, and the degree of economic development is slightly less than that in the eastern region.

Table 12. Parameter estimation results of threshold-STIRPAT model in the Central region

Variables	Single threshold model
InP	0.946***(0.033)
InED	0.931***(0.004)
InIS	1.106***(0.017)
InEl (InEI < 6.6329)	1.003***(0.007)
InEI (InEI ≥ 6.6329)	1.011***(0.006)
Cons	-11.483***(0.199)

3.7.3 Western region

Table 10 shows that both population size and energy consumption intensity passed the single threshold test, and both could be modelled as a single threshold-STIRPAT model. The results of the parameter estimation are shown in Table 13.

Table 13. Parameter estimation results of threshold-STIRPAT model in the Western region

Groups	InP as a threshold variable		InEl as a threshold variable	
	Variables	Single threshold model	Variables	Single threshold model
lnP (lnP < 5.6411)	1.102***(0.118)		InP	1.187***(0.117)
lnP (lnP ≥ 5.6411)	1.182***(0.117)		InED	0.995***(0.010)
InED	0.990***(0.010)		InIS	0.804***(0.039)
InIS	0.847***(0.039)		InEl (InEl < 6.5009)	0.850***(0.015)
InEl	0.931***(0.010)		lnEI (InEI ≥ 6.5009)	0.877***(0.012)
Cons	-12.426***(0.664)		Cons	-12.232***(0.666)

Table 13 shows that population size exerts the greatest influence on carbon emissions in the western region, whereas industrial structure has the least impact. This phenomenon can be primarily attributed to the fact that the majority of cities in the western region are characterized by low population density and relatively late development, resulting in a discernible disparity in economic development compared to the eastern and central regions. The regression results presented in Table 13 exhibit substantial similarity to those of the smaller population size stage (Table 9), further corroborating the significant influence of population size on carbon emissions in the western region.

Finally, stability tests were conducted on the constructed models, and the results demonstrated that the established models exhibit robustness. Due to space limitations, the specific results are not presented here.

4. Conclusion

First, through the application of the LMDI model to calculate the contribution value and the cumulative contribution value, it is evident that during the period 2004-2020, population size, per capita affluence, and energy consumption intensity exerted a positive influence on carbon emissions, while industrial structure and energy structure demonstrated a negative inhibitory effect. Among these factors, per capita affluence exhibited the most significant positive driving effect, industrial structure displayed the strongest negative inhibitory effect, and energy structure had the least impact on carbon emissions.

Second, through the construction of a threshold-STIRPAT model based on panel data from 284 prefecture-level cities in China, utilizing population size and energy consumption intensity as threshold variables, it is evident that industrial structure exerts the most significant impact on carbon emissions, whereas population size demonstrates the least influence. Furthermore, the effects of population size and energy consumption intensity on carbon emissions are phased in nature.

Third, through an analysis of the heterogeneity among cities with varying population sizes, it was observed that in cities with large populations, industrial structure exerts the most significant influence on carbon emissions, while population size has the least impact. The effect of energy consumption intensity on carbon emissions exhibited a staged pattern. Conversely, in cities with smaller populations, population size emerges as the primary factor affecting carbon emissions, followed by industrial structure, while the influence of energy consumption intensity remains stage-specific.

Fourth, through the heterogeneity analysis of the three major economic regions, it was observed that in the eastern region, industrial structure exerts the greatest influence on carbon emissions, whereas population size has the least impact, which is in line with the law of cities with larger populations. In the central region, industrial structure demonstrated the most significant effect on carbon emissions, whereas per capita affluence exhibited the smallest impact on carbon emissions. In the western region, population size exhibited the greatest influence on carbon emissions, whereas industrial structure demonstrated the least impact on carbon emissions.

5. Recommendations

In light of the aforementioned conclusions, the following recommendations were proposed:

First, energy structure adjustment: (1) Implementation of policy guidance to gradually reduce the proportion of traditional energy sources in the energy structure, particularly coal, while increasing the proportion of clean energy alternatives. (2) Incorporation of carbon emission targets into the assessment systems of local governments and enterprises to enhance environmental responsibility awareness. (3) Development and implementation of incentive mechanisms such as financial subsidies and tax incentives to support the growth of the clean energy sector. (4) Augmentation of investment in clean energy technology research and development, as well as infrastructure construction, with a focus on renewable energy sources, including wind and solar energy.

Second, high-quality economic development: (1) Facilitates the transformation of the economic growth model from rudimentary to intensive, emphasizing the quality and efficiency of economic growth. (2) Promote the optimization and upgrading of industrial structure, transitioning towards high-end, intelligent, and environmentally sustainable practices. (3) Enhance public awareness of sustainable consumption through educational initiatives and public campaigns, guiding residents to adopt environmentally conscious consumption patterns. For instance, encouraging citizens to utilize energy-efficient appliances and new energy vehicles while reducing the consumption of single-use products.

Third, the optimization of industrial structure: (1) Make industrial structure adjustments and optimize the core strategy for emission reduction, particularly by increasing support for low-energy-consuming and high-value-added industries. (2) Introduce targeted policies to encourage enterprises to adopt advanced production processes and facilitate technological transformation and innovation. (3) Formulate scientific industrial development plans, delineate the development direction and focus of each region and industry, and prevent uncoordinated and unsystematic development. (4) Establish an industrial development information platform to provide enterprises with timely information on markets, technologies, and policies.

Fourth, the relationship between population size and carbon emissions requires careful management. (1) When formulating policies, consideration should be given to the stage-specific characteristics of the relationship between population size and carbon emissions. (2) In cities with large populations, proactive planning should be implemented to address the potential increase in carbon emissions resulting from population growth. For instance, this may involve enhancing public transportation infrastructure and improving the energy efficiency of urban housing. (3) In cities with smaller population sizes, attention should be paid to the possible sharp rise in carbon emissions caused by population growth, and the scale of urban development and industrial layout should be rationally planned to avoid taking the road of sloppy development.

Fifth, regionally differentiated emission reduction strategies. (1) The eastern region should intensify the green transformation of its industries, leverage its economic and technological advantages, and augment its investment in high-tech and modern service industries. For instance, additional scientific and technological research and development centers and financial service centers should be established in developed coastal cities, whereas traditional manufacturing industries with high pollution and energy consumption should be gradually phased out. (2) The central region should prioritize the optimization and upgrading of the industrial structure as the primary means to reduce emissions, enhance the technological transformation of traditional industries, improve energy utilization efficiency, emphasize greening and low-carbon development, and focus on the cultivation and recruitment of professionals in the low-carbon field. (3) Western regions should rationally plan population and industrial development, develop characteristic low-carbon industries, such as eco-agriculture and tourism, and reduce dependence on high-carbon industries. Strengthen the construction of energy infrastructure and improve the stability and efficiency of the energy supply.

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References

[1] IPCC. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva: IPCC; 2014.

[2] Yuan J, Xu Y, Hu Z, Zhao C, Xiong M, Guo J. Peak energy consumption and CO2 emissions in China. Energy Policy. 2014;68:508-23.

[3] Huiling G, Bowen S, Guangming R. Regional differences, dynamic distribution and evolution trends of carbon emission intensity in urban agglomerations in China. China Price J. 2024;(1):113-8.

[4] Chen J, Weng S, Tao W, Song M, Zhang L. Measuring carbon neutrality and exploring the threshold effects of its driving factors: Evidence from China. Appl Energy. 2024;373:123824.

[5] Sufeng W, Jiantao H, Huafu L. Spatial and temporal heterogeneity of factors influencing carbon emissions from energy consumption in Chinese cities. World Reg Stud. 2024;33(8):102-16.

[6] Kaya Y. Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. Geneva: IPCC Response Strategies Working Group; 1989.

[7] Yang J, Cai W, Ma M, Li L, Liu C, Ma X, et al. Driving forces of China's CO2 emissions from energy consumption based on Kaya-LMDI methods. Sci Total Environ. 2020;711:133-8.

[8] Junhua C, Qiaochu L. Research on the influencing factors of energy consumption carbon emission in Sichuan Province under the background of the construction of Chengdu-Chongqing Double City Economic Circle: from the perspective of LMDI method. Ecol Econ. 2021;37(12):30-6.

[9] Yu Q, Yan L. Research on influencing factors and development path of carbon emission of China's logistics industry under the carbon peaking and carbon neutrality goals: based on the extended Kaya identity and LMDI model. Times Econ Trade. 2024;21(2):41-5.

[10] Chun-Ran J, Qing-Juan X, Ting S. Influential factors and scenario prediction of carbon emissions in China's coal producing areas: based on LMDI model and threshold-STIRPAT model. J Nanning Norm Univ (Nat Sci Ed). 2023;40(1):32-42.

[11] Ning W, Chengyu H, Yang Z, Zhaolin G. Regional carbon emission peaking based on threshold-stirpat extension model: a case study on east China. Environ Eng. 2024;42(5):154-62.

[12] Lin B, Li Z. Is more use of electricity leading to less carbon emission growth? An analysis with a panel threshold model. Energy Policy. 2020;137:111121-8.

[13] Yong W, Ziyi X, Yaxin Z. Influencing factors and combined scenario prediction of carbon emission peaks in megacities in China: based on threshold-STIRPAT model. Acta Sci Circumstantiae. 2019;39(12):4284-92.

[14] Liang Y, Mazlan NS, Mohamed AB, Mhd Bani NYB, Liang B. Regional impact of aging population on economic development in China: evidence from panel threshold regression (PTR). PLoS One. 2023;18(3):e0282913.

[15] Liang Y, Xinping H, Mazlan NS, Liang B, Ting L. Regional impact of aging population on carbon dioxide emissions in China: evidence from panel threshold regression (PTR). PLoS One. 2023;18(9):158-82.

[16] Chen P, Shantong L, Qiang L. Driving forces of Chinese provincial CO2 emissions from the perspective of consumption. Econ Manag. 2022;36(3):58-66.

[17] Lei W, Zhemin L. Analysis on the scale evolution characteristics and driving factors of rural homestead: based on extended Kaya identity and LMDI. Agric Outlook. 2021;17(9):10-6.

[18] Xuankai D. Research on influencing factors of land use carbon emission in Wuhan City: based on extended Kaya equation and LMDI decomposition method. Agric Technol. 2021;41(20):104-9.

[19] Jiangyuan L, Tao D. Driving factors for the growth of China's carbon emissions based on LMDI model. Coal Econ Res. 2020;40(6):47-56.

[20] Yuheng F. Research on influencing factors of carbon emissions in China's coal production areas: based on the improved LMDI model. Coal Econ Res. 2020;40(12):40-5.

[21] YuXin G, Liang X. Calculation and analysis of transportation carbon emission in Yangtze River Delta. Logist Eng Manag. 2022;44(10):85-8.

[22] Yan Z, YuShu B, KangDe W, XiaoHong J. Carbon emission efficiency evaluation and driving factors analysis of logistics enterprises. J Transp Syst Eng Inf Technol. 2023;23(2):11-21.

[23] Ehrlich PR, Holdren JP. Impact of population growth: complacency concerning this component of man's predicament is unjustified and counterproductive. Science. 1971;171(3977):1212-7.

[24] Dietz T, Rosa EA. Rethinking the environmental impacts of population, affluence and technology. Hum Ecol Rev. 1994;1(2):277-300.

[25] Gungyu T. The impact of population aging on green innovation: analysis based on STIRPAT model and threshold effect. Rev Financ Technol Econ. 2023;(1):102-19.

[26] Li J, Chen Y, Li Z, Liu Z. Quantitative analysis of the impact factors of conventional energy carbon emissions in Kazakhstan based on LMDI decomposition and STIRPAT model. J Geogr Sci. 2018;28(7):1001-19.

[27] Xinwei G, Yuan Z. Do research inputs constrain carbon emission from carbon emission factors based on LMDI model and STIRPAT model? Resour Ind. 2020;22(6):37-45.

[28] Qinglong W, Jianming W, Pibin G. Peak regional carbon emissions based on open STIRPAT modeling in an energy-producing region of Shanxi. Resour Sci. 2018;40(5):1051-62.

[29] Shen-Ning Q, Chao-Xian G. Forecast of China's carbon emissions based on STIRPAT model. China Popul Resour Environ. 2010;20(12):10-5.

[30] Hansen BE. Threshold effects in non-dynamic panels: estimation, testing, and inference. J Econom. 1999;93(2):345-68.

[31] Di Z, Fengnian Z, Xueqin W. Impact of low-carbon pilot policy on the performance of urban carbon emissions and its mechanism. Resour Sci. 2019;41(3):546-56.

[32] Feng H, Rui X. Does the agglomeration of producer services reduce carbon emissions? J Quant Tech Econ. 2017;34(3):40-58.