Analysis of Influence Factors of Carbon Emissions during the Process of Urbanization -- Based on STIRPAT Model and Spatial Dobbin Model

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Absteact

The relationship between urbanization and carbon emissions affects economic development, industrial structure, residents' income and the enhancement of comprehensive national strength. It is of great practical significance to study the relationship between urbanization and carbon emissions. At the same time, carbon emissions have increased sharply in recent years. How to reduce carbon emissions while developing urbanization is an urgent problem to be solved. In this paper, the panel data of 30 provinces in China from 2000 to 2019 except Hong Kong, Macao, Taiwan and Tibet were used as samples to construct the static panel STIRPAT model and the spatial Dobbin model. The static panel STIRPAT model shows that both industrial structure and energy intensity variables have a positive impact on carbon emissions. Energy intensity and GDP per capital have the largest impact on carbon emissions, followed by population variables. The spatial Dobbin model shows that both the core explanatory variables and the control variables significantly affect carbon emissions, and the regression coefficients are positive. The analysis of the spatial spillover effect shows that the control variables are significant except for the level of science and technology, and the population variables and per capital GDP have negative spatial spillover effect on the carbon emissions of neighboring areas. There are positive spatial spillover effects of industrial structure and energy structure on carbon emissions in neighboring regions. Finally, according to the empirical results, put forward the targeted suggestions.

Keywords: Urbanization; Carbon Emissions; Static panel STIRPAT model; Spatial Dobbin model

1 Introduction

In recent years, with the rapid development of science and technology, the acceleration of urban construction, enjoying the natural resources and social resources bring convenient at the same time, the shortage of resources, climate change, especially the emergence of global climate warming, extreme weather makes people rethink the importance of protecting the environment, low carbon development, green development, more and more get people's attention. The report of the 19th National Congress of the Communist Party of China proposes to "accelerate the establishment of a legal system and policy guidance for green production and consumption, and establish a sound economic system for green, low-carbon and circular development". Thus, low-carbon and green development has become an important part of the national development strategy.

American geographers divided urbanization into two parts: Urbanization Iand urbanization II: Urbanization I is the process in which non-agricultural population and its activities are concentrated in urban areas; urbanization II is the process in which urban life style, urban life and its values spread to rural areas (Friedmann & Miller, 1965).With rapid urbanization development over the past 40 years of reform and opening up, China is now in a stage of rapid urbanization development, with the urbanization level rising from 17.72% in 1978 to 60.6% in 2019. Along with the rapid development of urbanization, a large number of greenhouse gases have been emitted. Quadrelli and Peterson looked at global carbon dioxide emissions from fossil fuel combustion from 1971 to 2004, and based on that, they found that carbon emissions increased by 1.2Gt in 2003-2004 alone. And carbon emissions mainly come from power generation, heat supply and transportation sectors (Quadrelli & Peterson, 2007). Bosah et al. estimated carbon emissions based on panel data of 15 countries from 1980 to 2017, studied the relationship between energy consumption, economic growth and carbon emissions, and concluded that urbanization has no significant impact on environmental quality, and energy consumption aggravates environmental damage (Bosah, Li, Ampofo & Liu, 2021). Divisia index decomposition method was used to analyze the carbon intensity between industries in the two countries. The results show that the energy intensity of the production sector is the most important factor (Ang & Pandiyan, 1997). There is also a common analysis method, log-mean Dietzmann decomposition (LMDI), which is more suitable for the decomposition of carbon emission influencing factors. Moreover, the residuals after decomposition can be interpreted, and a relatively simple transformation expression can be used (Ang, 2005). STIRPAT model is used to study the carbon emission effect of economic urbanization based on the carbon emission data of 16 emerging countries from 1971 to 2009. The results show that economic growth in the process of urbanization has a continuous positive effect on carbon emission (Sadorsky, 2014; Adem & Untiso, 2021; Adeniyi, 2021).

Urbanization is a process in which rural living habits, customs and systems are transformed into urban lifestyles (Wirth, 2011).Clear the relationship between urbanization and carbon is beneficial to seek to reduce carbon emissions and accelerate the urbanization development of effective measures, most scholars only pay attention to both at home and abroad research in an area, the relationship between the two is from local to explore the relationship between the two, but the spatial econometrics shows that panel data heterogeneity and spatial correlation at the same time, as a result, This study not only explores the impact of urbanization on carbon emissions in local areas, but also studies the impact of urbanization development in neighboring regions on carbon emissions in this region.

In summary, the research on the relationship between urbanization and carbon emissions can be based on STIRPAT model, and the spatial econometric method can be introduced to construct the spatial Dobbin model. In this way, the relationship between urbanization and carbon emissions in this region can be studied, and the relationship between urbanization and carbon emissions in neighboring regions and even the whole country can also be explored.

2. Model setting and variable selection

2.1 Model Setting

2.1.1 Static STIRPAT model

At present, the main models for studying the influencing factors of environmental pollution include IPAT model and STIRPAT model. Two scholars, Ehrlich and Holden, first proposed IPAT model (Ehrlich, Ehrlich & Hurlbut, 1973), this model mainly studies the impact of social, economic and other factors on the natural environment. The significance of this model lies in the fact that the factors causing environmental changes are acted by multiple factors together, rather than occurring alone. The formula of this model is:

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

Where, I represent environmental impact, P represents population size, A represents affluence, and T represents technology level. With the use of the model, people find that the model identifies the relationship between the increase of carbon emissions and the influencing factors as linear, which cannot reflect the influence degree of the change of influencing factors on carbon emissions, and cannot judge the importance of each influencing factor, so there are certain defects in the use of the model. For this reason, Dietz and Rosa extended the model on the basis of retaining the original model variables and proposed the STIRPAT model by assigning different weights to different variables and adding the influence of random variables on carbon emissions (Dietz, T. & Rosa, E.A.,1994), (Dietz, T. & Rosa, E.A.,1997). The formula of this model is:

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}e \quad (2)$$

Where, A is the coefficient of the model, B, C and D are the elastic coefficients of P, A and T respectively, E is the random error, I am the sample individual, and T is the time. STIRPAT model is mainly used to evaluate the impact of human activities on the natural environment. It is a statistical conceptual model. Therefore, the model is nonlinear. Usually, the influence of heteroscedasticity in variables is eliminated by taking pairs of both sides of model (2), and the formula is:

$$\ln I_{it} = a + b\ln P_{it} + c\ln A_{it} + d\ln T_{it} + e \quad (3)$$

2.1.2 Spatial panel Dobbin model

Although the static panel STIRPAT model can describe the relationship between urbanization and carbon emissions to a certain extent, its shortcoming is that it considers each province as an independent object, which is not consistent with the reality. Since carbon emissions are not spatially independent, neighboring provinces have similar growth or decline trends in carbon emissions, which cannot be reflected in the static panel. At the same time, the spatial spillover effect of urbanization exists, that is, the urbanization rate of a province will affect the carbon emissions of neighboring provinces. Therefore, a model more in line with the actual situation should be constructed, and the spatial correlation of carbon emissions and the spatial spillover effect of urbanization should be included in the model to construct the spatial Dobbin model.

Based on the STIRPAT model, this paper constructs the spatial Dobbin model of urbanization and carbon emissions, as follows:

$$ln\, C_{it} = \beta_0 + \rho W\, ln\, C_{it} + \beta_1\, ln\, URB_{it} + \beta_2\, ln\, P_{it} + \beta_3\, ln\, A_{it} + \beta_4\, ln\, T_{it} + \beta_5\, ln\, IS_{it} + \beta_6\, ln\, EI_{it} + \theta_1 W\, ln\, URB_{it} + \theta_2 W\, ln\, P_{it} + \theta_3 W\, ln\, A_{it} + \theta_4 W\, ln\, T_{it} + \theta_5 W\, ln\, IS_{it} + \theta_6 W\, ln\, EI_{it} + \mu_{it} + \varepsilon_{it}$$

(4)

Where, I am the province, t is the time, β0 is a constant, ρ is the spatial regression correlation coefficient, β1, β2, β3, β4, β5, β6 respectively represent the estimated coefficient of urbanization rate, population, per capital GDP, science and technology level, industrial structure and energy intensity. θ1, θ2, θ3, θ4, θ5 and θ6 represent the estimated coefficients of the spatial lag term of six independent variables, namely urbanization rate, population, per capital GDP, science and technology level, industrial structure, and energy intensity, respectively. W represents the spatial economic distance matrix, $?_{it}$ is the individual fixed effect, and $?_{it}$ is the random error.

2.2 Variable Selection

STIRPAT model allows to expand, this article is based on the mechanism of the urbanization process of carbon emissions, in the process of research, not only consider the population scale, affluence and the impact of technology on carbon emissions, but also consider the urbanization level, industrial structure and energy intensity of carbon emissions, the influence of variable selection is as follows (Table 1),

Table. 1 *Explanation of model variables*

Variable	**Variable symbol**	**Indicator Meaning**	**Unit**
Carbon emissions	C	Energy-related carbon dioxide emissions	Ten thousand tons
population	P	Total population of each province at the end of the year	Ten thousand people
GDP per capital	A	The ratio of the total annual GDP of each province to the total population at the end of the year	Ten thousand yuan
scientific and technological level	T	Ratio of R&D expenditure to GDP	percentage
Urbanization rate	URB	The proportion of urban population to total population in that year	percentage
industrial structure	IS	The proportion of output value of secondary industry in GDP	percentage
Energy intensity	EI	Ratio of total energy consumption to GDP	Tons/ten thousand yuan

Explained variables. The explained variable is the carbon emissions of each province in China. There are two main international methods to measure carbon dioxide emissions: one is the field monitoring method to directly monitor carbon dioxide emissions (Kauppi, Mielikainen & Kuusela, 1992). The other method is the IPCC inventory method (Solomon, S., 2007). The carbon emissions data of each province in China come from the carbon dioxide emissions produced by the combustion of eight fossil fuels, and the formula is shown in (5) :

$$C = \sum_{j=1}^{8} S_j * F_j * E_j * \frac{44}{12} \quad (5)$$

Where: C is the total carbon emission, j is the fossil fuel in 8, S is the coefficient of conversion of fossil fuel j to standard coal, F is the carbon emission coefficient of fossil fuel j, and E is the consumption of fossil fuel j. The eight fossil fuels are coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas. The carbon emission coefficients of fossil fuels in 8 are compiled according to China Energy Statistical Yearbook and IPCC National Greenhouse Gas Inventory Guide, as shown in Table 2.

Table. 2 *Carbon emission coefficient of 8 fossil fuels and discount standard coal coefficient*

Energy types	Carbon emission factor (Ten thousand tons carbon/ten thousand tons standard coal)	Discount standard coal coefficient (Ten thousand tons standard coal/ten thousand tons)
coal	0.756	0.714
coke	0.855	0.971
Crude oil	0.586	1.429
gasoline	0.554	1.471
kerosene	0.592	1.457
diesel	0.571	1.471
Fuel oil	0.619	1.429
Natural gas	0.418	1.330（Tons of standard coal / 100 million cubic meters）

(1) Core explanatory variables. The core explanatory variable is the urbanization rate, which is expressed as the ratio of the urban permanent resident population to the permanent resident population of each province.

(2) Control variables. Based on relevant literature and STIRPAT model theory, the control variables were selected for static panel analysis as described above, and the variables of population, economy, science and technology level, industrial structure and energy intensity were introduced.

In this paper, panel data of 30 provinces in China from 2000 to 2019 except Hong Kong, Macao, Taiwan and Tibet are selected as samples. The data are all from: 1) Energy consumption data are from China Energy Statistical Yearbook, and all units are converted into standard coal. 2) Other data are from China Statistical Yearbook and statistical yearbooks of each province, and some data are from China Urban Statistical Yearbook and China Rural Statistical Yearbook. For the few missing values, this paper uses the linear interpolation method and the search statistical annual report method to supplement.

3 Empirical Study

3.1 Empirical analysis of static panel STIRPAT model

3.1.1 Data stationarity test

For long panel data regression, stationary and non-stationary data modeling steps are different, if directly to non-stationary data modeling, easy to appear the phenomenon of spurious regression, therefore generally before long panel data regression, test of panel data, the commonly used method is the unit root test of panel data.

In this paper, LLC test, ADF-Fisher test and PP-Fisher test are adopted to ensure the validity of the test results. The test results are shown in Table 4. The original series is not stationary, and the first difference is taken for each variable. The variable data are stationary. Except for the variable GDP per capital, which shows that the ADF test has unit root, the other two tests all show that the data are stationary.

Table 4 Stationarity test of panel data

variable	LLC	ADF-Fisher	PP-Fisher
LnC	-2.960*** (0.001)	73.031 (0.120)	54.194 (0.687)
lnP	3.296 (0.999)	47.434 (0.880)	17.603 (1.000)
lnA	-2.709*** (0.003)	58.111 (0.5451)	43.470 (0.947)
lnT	-1.971** (0.024)	121.995*** (0.000)	128.509*** (0.000)
lnURB	4.422 (1.000)	163.655*** (0.000)	351.207*** (0.000)
lnIS	-0.665 (0.253)	46.114 (0.9064)	47.309 (0.883)
lnEI	-0.908 (0.182)	59.020 (0.511)	55.434 (0.643)
D(LnC)	-8.534*** (0.000)	92.627*** (0.004)	458.159*** (0.000)
D(lnP)	-3.953*** (0.000)	1.619* (0.052)	168.320*** (0.000)
D(lnA)	-5.697*** (0.000)	73.448 (0.114)	181.137*** (0.000)
D(lnT)	-6.558*** (0.000)	119.761*** (0.000)	642.945*** (0.000)
D(lnURB)	-18.412*** (0.000)	225.395*** (0.000)	993.243*** (0.000)
D(lnIS)	-5.132*** (0.000)	117.389*** (0.000)	333.784*** (0.000)
D(lnEI)	-6.712*** (0.000)	2.198** (0.014)	297.943*** (0.000)

Note: P values are in parentheses, D(lnC) represents the first-order difference series of variable lnC, and *, ** and *** respectively represent significance at 10%, 5% and 1% levels

3.1.2 Co-integration test

Based on the unit root test of panel data, it can be known that variables are integrated in the first order, but cointegration test is still needed to determine whether there is a long-term stable relationship between variables, so as to ensure the full fitting of the model to a certain extent. The results of co-integration test are shown in Table 5: the T-statistic of Kao test is 3.432, and the P-value is 0.0003; The T-statistic of Pedroni test is 7.009, and the P value is 0.000. Both cointegration test methods reject the null hypothesis at the 1% level, which can indicate that there is a long-term stable relationship between the original variables and can exclude the phenomenon of spury-regression in the model.

Table 5. *Results of panel data co-integration test*

Inspection methods	Statistic	P-value
Kao	3.432	0.0003
Pedroni	7.009	0.000

3.1.3 Selection of panel model

First of all, the fixed effect model or mixed effect model is tested by F-test of the fixed effect model. According to Table 6, the F-statistic of the fixed effect is 53.12, and the probability value is 0.000, which strongly rejects the null hypothesis. Therefore, it is believed that the fixed effect model (FE) is significantly better than the mixed effect model. Secondly, to test whether the model adopts the random effect model or the mixed effect model, the random effect regression is carried out on the model, and then the LM test is carried out to obtain (Ehrlich, Ehrlich & Hurlbut, 1973). According to the LM test results in Table 6, the P-value is 0.000, which strongly rejects the null hypothesis "there is no individual random effect", so the random effect model is considered to be adopted. Finally, Hausman test is commonly used to determine whether the fixed effect model or the random effect model is adopted. The test results are shown in Table 6. The chi-square test value is 26.01, and the P value is 0.0002, which indicates that the null hypothesis is strongly rejected, and the fixed effect model should be used instead of the random effect model.

Table 6. *Test results of model selection*

Inspection methods	Statistic	P-value
F-test	53.12	0.000
LM-test	2670.65	0.000
Hausman-test	26.01	0.0002

3.1.4 Regression analysis of influencing factors of carbon emissions under static panel

Through the above analysis of fixed effect, random effect, mixed effect and correlation test, it is determined that the fixed effect model is selected for the analysis of the influencing factors of carbon emissions under the static panel. Stata software was used for analysis, and the estimated results are shown in Table 7.

Table 7. *Estimation results of fixed effects model*

	Estimated coefficient	Std. error	t	p
lnP	0.475***	0.110	4.31	0.000
lnA	1.084***	0.032	34.33	0.000
lnT	0.071**	0.029	2.37	0.018
lnURB	0.091*	0.052	1.75	0.081
lnIS	0.135**	0.058	2.31	0.021
lnEI	1.208***	0.047	25.92	0.000
_cons	3.055***	1.018	3.00	0.003
R-sq	0.9196			

According to the regression results, the goodness-of-fit R2 of the model was 0.9196, the F-statistic of the model was 53.12, and the corresponding P-value was 0.000, indicating that the regression model was well fitted. Variables in the model of population, GDP per capital, energy intensity by examining under 1% significance level, technology level and industrial structure through inspection under 5% significance level, the urbanization rate variable by examining under 10% significance level, there is a long-term equilibrium relationship between each variable, can be seen from the regression model variable population, per capital GDP, science and technology level, the urbanization rate. Both industrial structure and energy intensity variables have positive effects on carbon emissions.

The estimation results of the regression model are:

$$\ln C = 3.055 + 0.475\ln P + 1.084\ln A + 0.071\ln T + 0.091\ln URB + 0.135\ln IS + 1.208\ln EI \quad (6)$$

In the regression equation, energy intensity and per capital GDP have the biggest impact on carbon emissions. Every 1% change of the two variables has a positive impact on carbon emissions by 1.208% and 1.084%. It is not difficult to see from these changes that coal is still the main energy source in China, and the increase of energy consumption brings more carbon emissions. However, the influence of per capita GDP variable representing wealth on carbon emissions is in line with our general expectation, that is, as people live a richer life, they may bring more consumption and travel, and the "low-carbon" life will be weakened, resulting in the increase of carbon emissions. Every 1% change of population variable will positively affect the change of carbon emission by 0.475%. With the increase of population, the construction of infrastructure and housing will be driven to support the change of population structure, which will bring the demand for related services and the continuous increase of vehicle ownership. Changes in population structure will lead directly to increases in carbon emissions. Every 1% growth of industrial structure, carbon emissions will be positive growth of 0.135%, compared with other significant explanatory variables, the industrial structure with a relatively low impact on carbon emissions, but at the same time of rapid economic growth, transformation and upgrading of industrial structure's impact on carbon emissions is also very necessary, should actively promote the development of low carbon industry, reduce the high carbon industry, We will encourage the development of the tertiary industry and vigorously promote the development of emerging industries. Every 1% change in the variables of urbanization rate and science and technology level will positively affect carbon emissions by 0.091% and 0.07%. These two variables promote carbon emissions to a certain extent. Scientific and technological innovation can achieve green technological innovation and low-carbon environmental protection innovation while taking into account resource investment, which reduces carbon emissions to some extent. However, due to the low level of low-carbon technology and the focus of current development is still economic development, the level of science and technology promotes carbon emissions to a certain extent.

3.2 Empirical analysis of Stirpat-space Dobbin model

The static panel STIRPAT model was used to analyze the relationship between urbanization and carbon emissions. Although the relationship between urbanization and carbon emissions can be described to a certain extent, it is not practical to consider each province as an independent individual based on the characteristics of carbon emissions. Therefore, carbon emissions are not spatially independent. The correlation of carbon emissions between neighboring provinces cannot be obtained through the above analysis. At the same time, the existence of spatial spillover effect of carbon emission makes it impossible to realize through traditional econometric model. Therefore, this paper will construct a more realistic model and incorporate the spatial correlation and spatial spillover effect of carbon emissions into the model to construct a spatial econometric model.

3.2.1 Spatial correlation analysis of carbon emissions

Table 8. *Moran's I of carbon emissions of 30 provinces in China from 2000 to 2019*

year	Moran's I	P	Z	year	Moran's I	P	Z
2000	0.260	0.016	2.439	2010	0.306	0.004	2.952
2001	0.285	0.011	2.663	2011	0.305	0.005	2.901
2002	0.276	0.012	2.616	2012	0.286	0.01	2.755
2003	0.261	0.012	2.496	2013	0.281	0.011	2.705
2004	0.300	0.009	2.814	2014	0.272	0.012	2.664
2005	0.327	0.006	3.096	2015	0.272	0.012	2.727
2006	0.317	0.006	3.013	2016	0.252	0.016	2.571
2007	0.312	0.006	3.001	2017	0.243	0.020	2.471
2008	0.321	0.005	3.077	2018	0.249	0.023	2.492
2009	0.305	0.005	2.934	2019	0.232	0.025	2.338

Taking the carbon emission data of 30 provinces in China from 2000 to 2019 as the object, the GeoDA 1.18 software was used to measure the Moran's I (Anselin & Bao,1997) measurement of China's carbon emission, as shown in Table 8. Through the global autocorrelation analysis of carbon emissions in 30 regional provinces in China, it can be concluded that Moran's I is all >0, and at the 95% confidence level, Z values are all >1.96, which have passed the significance test. That is, there is a spatial positive correlation effect of carbon emissions in China's provinces, and Moran's I is between 0.232 and 0.327. The trend of change is not obvious. Through the analysis of the Moran index of carbon emissions, it can be seen that the influence of spatial effect cannot be ignored in the study of carbon emissions within the scope of provinces in China.

3.2.2 Model test

According to the test results in Table 9, LM (lag) test is significant at the 1% level, corresponding LM (error) test is significant at the 5% level, Robust LM (lag) test is significant at the 5% level, but Robust LM(error) test is not significant. This indicates that the spatial lag model is suitable for the description and analysis of data, and also indicates that the variables have spatial correlation. The SDM should be considered, because the SDM is more general than the SAR and the SEM. In order to judge whether the SDM will degenerate into the SAR or the SEM, this paper adopts the LR test based on Lee and Yu (2010). The test results show that the LR test is significant at the 1% level, which rejects the null hypothesis. This article uses the SDM will not degenerate into SAR, or the SEM, the use of space SDM is appropriate, if use SAR, or the SEM estimates of carbon emissions in the process of urbanization of spatial spillover effect may exist error. The Hausman test was conducted in this paper to determine whether the panel model was fixed effect model or random effect model. The Hausman test statistic of the model was 326.47 and the P value was 0.000, which significantly rejected the null hypothesis at the 1% level. Moreover, the LR test concluded that the model should choose the dual fixed effect space Dobbin model.

Table: 9 *Spatial panel data model test results*

test	statistics	P-value	test	statistics	P-value
LM (lag)test	7.621	0.006	LR_spatial_lag	48.77	0.000
Robust LM (lag)test	4.814	0.028	LR_spatial_error	48.10	0.000
LM (error)test	4.345	0.037	LR_both_ind	91.76	0.000
Robust LM (error)test	1.538	0.215	LR_both_time	824.08	0.000
Hausman	326.47	0.000			

Based on the STIRPAT model, this paper constructs the spatial Dobbin model of urbanization and carbon emissions, as follows:

$$\ln C_{it} = \beta_0 + \rho W \ln C_{it} + \beta_1 \ln URB_{it} + \beta_2 \ln P_{it} + \beta_3 \ln A_{it} + \beta_4 \ln T_{it} + \beta_5 \ln IS_{it} + \beta_6 \ln EI_{it}$$
$$+ \theta_1 W \ln URB_{it} + \theta_2 W \ln P_{it} + \theta_3 W \ln A_{it} + \theta_4 W \ln T_{it} + \theta_5 W \ln IS_{it} + \theta_6 W \ln EI_{it} + \mu_{it} + \varepsilon_{it} \quad (7)$$

Where, I am the province, t is the time, β0 is a constant, ρ is the spatial regression correlation coefficient, β1, β2, β3, β4, β5, β6 respectively represent the estimated coefficient of urbanization rate, population, per capital GDP, science and technology level, industrial structure and energy intensity. θ1, θ2, θ3, θ4, θ5 and θ6 represent the estimated coefficients of the spatial lag term of six independent variables, namely urbanization rate, population, per capital GDP, science and technology level, industrial structure and energy intensity, respectively. W represents the spatial economic distance matrix,μit is the individual fixed effect, and εit is the random error.

3.2.3 Spatial panel data estimation results of urbanization on carbon emissions

This paper establishes two sets of regression models to study the impact of urbanization on carbon emissions and the spatial spillover effect, as well as ordinary panel data regression (OLS) and spatial Dobbin model (SDM). The results of two groups of regression models run by STATA16.0 software are shown in Table 10 for comparative analysis.

Table 10. *Regression results of ordinary panel model and spatial Dobbin model*

statistics	OLS	SDM
ln*URB*	0.308*** (0.066)	0.186*** (0.048)
ln*P*	1.081*** (0.019)	0.612*** (0.124)
ln*A*	1.038*** (0.026)	1.059*** (0.069)
ln*T*	-0.074*** (0.022)	0.102*** (0.029)
ln*IS*	0.342*** (0.054)	0.150** (0.074)
ln*EI*	1.201*** (0.029)	1.159*** (0.045)
W*ln*URB*		0.073 (0.074)
W*ln*P*		-0.501*** (0.159)
W*ln*A*		-0.604*** (0.087)
W*ln*T*		-0.027 (0.036)
W*ln*IS*		0.331*** (0.117)
W*ln*EI*		0.288*** (0.085)
ρ		-0.061* (0.035)
R^2	0.927	0.482

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively; Standard errors in parentheses.

Table 10 shows that spatial autoregressive coefficients rho under the 10% level significantly negative, negative carbon emissions are the spatial correlation and spatial correlation with panel data, so using common panel regression model already can't satisfy the basic assumptions, the conditions of using normal panel regression coefficient of parameter estimation will cause deviation. Therefore, the above analysis is verified, and the spatial econometric model is needed for parameter estimation.

According to the regression results of spatial Dobbin model (SDM), the values of β1, β2, β3, β4, β5 and β6 are 0.186, 0.612, 1.059, 0.102, 0.150 and 1.159, respectively. The urbanization rate of the core explanatory variable is significant at the 1% level, indicating that urbanization level does affect China's carbon emission level. Except for the industrial structure, which is significant at the 5% level, all the other control variables have passed the 1% significance level test. The specific analysis is as follows:

(1) The core explanatory variable urbanization level is significantly positively correlated with carbon emissions. Every 1% increase in urbanization level leads to a corresponding 0.186% increase in carbon emissions, indicating that urbanization level will increase carbon emissions. The main reason is that the development of urbanization level will bring about changes in population structure, economic structure, social structure and spatial structure. First from the analysis of the development of urbanization population structure will affect the age structure change of human society, which affect the change of carbon emissions, second from the economic and social structure analysis, rises with the level of urbanization, population transfer to the high-centralized industry gradually, and in the process of the change patterns of economic activity, production energy consumption will also increase, finally from the spatial structure analysis, With the migration of agricultural population to urban population, it is necessary to build a large number of infrastructure and urban housing to meet the continuous increase of urban population, and the accompanying changes in the process of population migration will also increase carbon emissions.

(2) The control variable population is significantly positively correlated with carbon emissions. Every 1% increase in population variable leads to a corresponding increase of 0.612% in carbon emissions, indicating that the increase in population will increase carbon emissions. The main reason is that population variables mainly affect carbon emissions from three aspects: population age structure, family number and family size. In terms of age structure, with the worsening of population aging, the pressure of carbon emission reduction will also increase, and even increase carbon emissions; With the development of urbanization, the number of households keeps increasing, which brings more carbon emissions; However, the family size is mainly affected by economic and fertility policies. More and more "small family" family size forms lead to the dispersion of energy resources, which is easy to cause the waste of resources, and eventually bring more carbon emissions.

(3) The economic variable of the control variable is per capital GDP, and per capital GDP is significantly positively correlated with carbon emissions. With the increase of per capital GDP by 1%, carbon emissions will increase by 1.059%. With the increase of per capital income of urban residents, people's consumption level will also increase, which requires the increase of a large number of commercial buildings and the corresponding demand for related services. All these changes will bring about the increase of carbon emissions. At the same time, the increase of residents' consumption level will also increase the purchase behavior of commodities, and the production and sales process of commodities will increase accordingly, which indirectly leads to the increase of carbon emissions.

(4) The variable of science and technology level is positively correlated with carbon emissions. A 1% increase in the level of science and technology will increase carbon emissions by 0.102%. The impact of science and technology level on carbon emission is long-term and lasting. It is difficult for a certain technology to change its impact on carbon emission in a short period of time when it is applied to urbanization development, so it will increase carbon emission in the short term.

(5) The variable of industrial structure is significantly positively correlated with carbon emissions. For every 1% increase in industrial structure, carbon emissions will increase by 0.150%, that is, industrial structure will positively affect carbon emissions. It is found that the industrial structure has an important effect on the carbon emission of a certain region. In the second industry, energy consumption in industrial production is the main source of energy consumption in the third industry and carbon emissions. At present, the proportion of the second industry is still very large. The development of the second industry is more conducive to the development advantage of our country, leading to the increase of carbon emissions.

(6) Energy intensity is positively correlated with carbon emissions. Every 1% increase in energy intensity will lead to a corresponding increase of 1.159% in carbon emissions, indicating that the increase in energy consumption per unit of GDP will lead to an increase in carbon emissions. At present, the overall energy utilization is relatively low in the process of urbanization, and there is still a long way to go to realize low carbon urbanization.

In terms of spatial effect test, θ1, θ2, θ3, θ4, θ5 and θ6 were 0.073, -0.501, -0.604, -0.027, 0.331 and 0.288, respectively. The spatial response coefficient of urbanization on carbon emission is 0.073, but it is not significant. The control variables are all significant at the 1% level except the level of science and technology. Population variables and per capital GDP have a significant negative impact on the carbon emissions of neighboring areas, and there is a negative spatial spillover effect. Industrial structure and energy structure have a significant positive impact on the carbon emissions of neighboring areas at the 1% level, and there is a positive spatial spillover effect. When spatial econometric analysis is used for panel data with spatial factors, it is necessary to consider not only the influence of the change of local independent variables on the dependent variable of the region, but also the influence of neighborhood related variables on the dependent variable of the region, that is, the direct effect and indirect effect (spillover effect) caused by spatial effects. This can effectively avoid the problem of biased point estimation in spatial regression model.

4 Conclusions and recommendations

This paper takes provincial panel data as sample data and studies the relationship between urbanization and carbon emissions by building a static panel model and a spatial panel model. The static panel STIRPAT model studies the effects of urbanization rate, population, economy, science and technology level, industrial structure and energy intensity on carbon emissions. The main conclusions are as follows: population variables, per capital GDP, science and technology level, and urbanization rate. Both industrial structure and energy intensity variables have positive impacts on carbon emissions. Energy intensity and GDP per capital have the largest impact on carbon emissions, followed by population. After analyzing the shortcomings of the static panel model, the STIRPAT model of the spatial panel was constructed, and the results showed that: Both the core explanatory variables and control variables significantly affect carbon emissions, and the regression coefficients are positive, indicating that carbon emissions are positively correlated with these factors, and the magnitude of the impact is energy intensity, per capital GDP, population, urbanization rate, industrial structure and science and technology level. To analyze its spatial spillover effect display control variables in addition to the level of science and technology are significant at the 1% level, population variables and GDP per capital of carbon emissions in the neighborhood have a significant negative impact, there exists negative spatial spillover effects, industrial structure and energy structure at the 1% level of adjacent areas have significant positive influence on carbon emissions, there is spatial spillover effects.

In view of the above conclusions, combined with the economic development level of each province and the goal requirements of improving the quality of urbanization development, the following low-carbon emission reduction suggestions are put forward:

First, we need to stick to a low-carbon development strategy. China is in the stage of rapid urbanization development. We should follow the national policies and guidelines to take a good path of low-carbon urbanization development.

Second, accelerate industrial restructuring. At the same time of economic development, the transformation and upgrading of industrial structure is also very necessary to curb CO_2 emissions. It is necessary to actively promote the development of low-carbon industries, reduce or limit the development of high-carbon industries, and accelerate the "adjustment and promotion". We will encourage the development of the tertiary industry and vigorously develop strategic emerging industries.

Third, improve energy efficiency. To reduce the energy consumption per unit GDP of the city, alleviate the energy structure of current is given priority to with coal pressure of high carbon, it is necessary to improve the efficiency of energy use, give play to the role of driving force of technological innovation, developing circular economy, we will increase support strategic emerging industries projects, such as new energy, new materials, Internet of things, such as biotechnology.

Fourth, establish a carbon emissions trading system. A sound carbon emission accounting standard will be established, a carbon emission testing and certification system will be established, a carbon emission account management system will be established, and relevant trials of carbon emission will be actively carried out.

At present, our country is in the carbon emission growing stage, effective control carbon emission is urgent. Starting from the influencing factors of carbon emission and according to the actual situation of carbon emission in each province, various measures for low-carbon development can be formulated to reasonably improve the low-carbon level and promote the continuous improvement of urbanization quality.

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