[*A PA-LV MODEL FOR THE IMPACT PATH OF FACTORS ON ENERGY-RELATED CARBON EMISSIONS IN CHINA*]

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Abstract: Analysis of the path of China's energy-related carbon emissions is crucial to take effective measures to control carbon emissions. Most existing research used STIRPAT model (stochastic impacts by regression on industrial structure, urbanization, population, affluence and technology) to investigate the direct driving forces of China's CO2 emissions. To overcome the shortcomings of multicollinearity of the variables of STIRPAT model, this paper establishes PA-LV (path analysis with latent variables) model that estimates the direct and indirect effect on China's energy-related carbon emissions. The factors those primarily influence the CO2 emissions in China are population effects (PM) including population (P) and urbanization (URB), industrial structure (IS) which is measured by the second industry proportion (SI) and tertiary industry proportion (TI), energy consumption (EC), energy intensity (EI), economic level (PGDP). The ranking in terms of the size of these factors' total influence on China's CO2 emission is PM> EC> EI> PGDP> IS, that of these factors' direct influence is EC> EI> PGDP and indirect influence is PM> PGDP> EI> EC> IS. Some results different with previous studies are that: (1) the change of economic growth pattern to some extent inhibits the growth rate of CO2 emissions by reducing the energy intensity. (2)The increase of EC has a negative indirect influence on EI so that it exerts a negative influence on CO2 emissions indirectly. (3) The growth of CO2 emissions impacts EC and EI negatively, resulting in a negative impact indirectly on itself. These demonstrate that the transform of China's economic growth mode has played a certain effect on CO2 emissions and China’s energy-saving policies include reduce energy intensity and energy consumption and improve energy efficiency are effective. The Chinese government should further promote the adjustment of industrial structure and improve the technical level to reduce carbon emissions.

Keywords: Energy-related carbon emissions; PA—LV; STIRPAT model; Effect mechanism; Policy Suggestions

1. Introduction

With the rapid development of economy and the progress of technology, the emission of greenhouse gases, especially CO2 which generated by human activities has a big impact on the global environment. China is one of the main energy consuming countries in the world, which has the characteristics of rapid economic development and coal-dominated energy consumption. "World Energy Statistics Report 2014" (BP) shows that in 2013 China's primary energy consumption is 2.8524 billion tons of oil equivalent, accounting for 22.4% of world primary energy consumption; CO2 emissions is 9.524 billion tons with a growth of 4.2 % over 2012, accounting for 27.1% of the world's CO2 emissions. In 2014 China's GDP accounted for 12% of the world, while the energy consumption is 22% of the world and carbon emissions is close to 30%. Since 2007, China has become the largest contributor in the world. (Lin and Du, 2015). China has promised to reduce CO2 emissions of per capita GDP by 40% to 45% in 2020 compared with 2005 and the proportion of non-fossil fuels in primary energy consumption is down to nearly about 15%.

In recent years, the research on the influence factors of carbon emissions from energy consumption has become a hot topic. The related research results are various and the research methods and the object are wide and complex. Representative models include exponential decomposition (Shrestha and Timilsina,1996), IPAT (Ehrlich, 1971), STIRPAT(York et al., 2003) , Laspeyres (Diakoulaki, D., et al, 2006), LMDI (Ang, 2005; Wang, 2005; Ma and Stern, 2008; Zhao et al. (2010)), KAYA (Li et al. , 2014; Li and Ou ,2013), SDA（Lin and Polenske, 1995). Compared with other models, the decomposition results of IPAT and STIRPAT are more easily measured by statistical data and are more convenient for use in policy adjustment. Such as Such as Fan et al. (2006) ,Wang and He (2006),Lin et al. (2009), Wang et al. (2013), Liu et al. (2015), Li and Li (2010) ,Wei (2011), Zhu et al. (2010) employed STIRPAT model to find the key impact factors on the energy-related CO2 emissions in China.

The most commonly impact factors which selected by scholars are per capita GDP, population, urbanization, energy intensity, industrial structure, and energy consumption. Many scholars have adopted STIRPAT model to analyze and discuss the relationship between these variables and CO2 emissions. Scholars took different approach to solve the multicollinearity problem of the variables. As Wang et al. (2013), Li et al. (2014), Lin et al. (2013) used ridge regression, and Wold et al. (1983), Fan et al. (2006), Jia et al. (2009), Wang et al. (2012), Li et al. (2014) used partial least squares method (PLS) to eliminate collinearity. However, different conclusions have been obtained by using different models and different variables and time span.

Some literatures did not consider the interaction between variables. A large number of nonlinear relationships embodied in economic variables are largely ignored. Granger (1988) points out that the world is almost certainly constituted by nonlinear relationships. The modified STIRPAT model can eliminate the multicollinearity of the variables, but it cannot completely describe the direction and intensity of the interaction between the variables.

Li et al.(2011) was the frist scholar who used Path analysis in CO2 emissions field. Path analysis is a multivariate statistical technique developed by the geneticist Sewall Wright in 1921. Firstly, the path analysis does not require the independent of variables, and it is suitable for the analysis of multiple variables. Secondly, it was developed as a method of decomposing correlations into different pieces for interpretation of effects, enabling people to lucubrate the causal relationship between the cause variables and the outcome variables through the related surface phenomena. (Wright, 1921,Wright, 1934 and Finney, 1972).Additionally, path analysis model can measure the degree of correlation between variables by the correlation coefficient and determine the causal relationship between the variables through analyzing path coefficient. However, the path analysis is only to explore the path coefficient is significant or not and it cannot discuss the goodness-fit test of hypothesis path model, in addition, it also fail to estimate the measurement error effectively.

To address these problems we propose an inferential multivariate statistical methodology framework and develop a path analysis with latent variables (PA-LV) to calculate the driving factors of energy-related CO2 emission in China. PA-LV model contains latent variables and observed variables and combines the path analysis and confirmatory factor analysis, so it has properties between measurement model and structural model. This paper selects the variables from STIRPAT model and establishes the PA-LV model and subsequently computes path coefficients of variables thereby achieving three important goals: (i) estimation of the latent indirect effect and direct effect of the independent variables on CO2 emissions. (ii) ranking of all variables' influence in CO2 emissions in respect to their influential intensity, and (iii) enable Chinese government to establish sustainable development strategy and energy conservation policy. The paper is organized as follows. In the second part we give brief description of the variables and estimate the energy-related CO2 emissions in China. The third part explains econometric methodology and present the model building strategy of preliminary descriptive analysis. Then it subsequently presents the estimation results. In the fourth part we discuss and conclude this study and give some policy suggestions.

2 Data and estimation of CO_2 emissions

Based on the STIRPAT model, this paper chooses industrial structure and population effect variables as latent variables, and establishes the PA-LV model to estimate the total effect, direct and indirect effects of population, industrial structure, energy consumption, energy intensity and PGDP on energy-related CO_2 emissions in china from 1980 to 2013.

2.1 Data and variables

We select IS and PM as latent variables and SI, TI, EC, C, PGDP, P, URB and EI as observational variables to establish the PA-LV model. PM is selected as latent variables, the total population (P) and urbanization level (URB) were used to characterize PM. In addition, SI and TI are the observational variables of IS. The sample data span the period from 1980 to 2013. The data of CO2 emissions is calculated according to the formula of CO2 emissions in the Intergovernmental Panel on Climate Change (IPCC, 2006), the data of which comes from China Energy Statistical Yearbook (1991–2014). Various energy consumption data and the number of population, and the level of urbanization, GDP per capita and GDP in the model were collected from China Statistical Yearbook (CSY, 1992–2014) published by the National Bureau of Statistics of China.

To eliminate the impact of price fluctuations, the GDP was converted into the 1980 price according to the corresponding price. Energy intensity is the value of energy consumption divided by GDP. SI and TI are respectively the second industry and tertiary industry proportion of GDP. The relevant data are given in Table1. In order to eliminate the influence caused by different statistical units, we first carry on normalization preprocessing. The normalization of data processing is scaled so that it falls into a small specific section. In this way, the unit limit of data can be removed, which is transformed into a non-dimensional pure numerical value, which is convenient for different units or the order of magnitude can be compared and weighted.

Table 1 Description of the variables used in the analysis for the period 1980–2013.

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observational variable	Definition	Unit	Symbol	Mathematical Symbol
GDP per capita	Gross domestic product divided by population	10^4 yuan	PGDP	x7
Industrial	The share of the secondary industry output value over the total	%	SI	x1

structure	GDP			
	The share of the tertiary industry output value over the total GDP	%	TI	x2
Population	End year population	10^4 units	P	x4
Urbanization rate	The percentage of the urban population in the total population	%	URB	x3
Technology level	The economic output of per unit energy consumption	yuan/tce	EI	x6
Energy consumption	Fossil fuel consumption	10^4tce	EC	x5
CO2 emission	CO2 emissions stem from fossil fuel combustion	10^4 ton	C	x8

Table 2 Latent variables

Latent variables					
Latent development dimensions			Observed indicators		
Description	Symbol	Mathematical Symbol	variables	Symbol	Mathematical Symbol
Industry structure	IS	ξ_1	Second industry proportion	SI	x1
			Tertiary industry proportion	TI	x2
Population effect	PM	ξ_2	Population	P	x4
			Urbanization rate	URB	x3

2.2 Estimation of CO_2 emissions

According to the IPCC Guidelines for National Greenhouse Gas Inventories of 2006, carbon emissions from energy consumption follow the following calculation:

$$C_t = \sum_{i=1}^{3} E_{it} F_i \cdot \frac{11}{3} \qquad (1)$$

where C represents the value of CO2 emissions; 11/3 is the conversion coefficient between carbon and CO2; i is index of fossil fuel, $i = 1, 2, 3$; E_i is the consumption of fossil fuel i; F_i is the carbon emission coefficient of fossil fuel i, representing the carbon content of fuel i (t(C)/t). In this study, the coefficient F_i is assumed to be 0.7329, 0.565 and 0.445 t(C)/t for coal, oil and natural gas respectively, based on the research results of Energy Research Institute. Energy type i is selected from the reference of "China Energy Statistical Yearbook", including coal, oil, and natural gas. (Dai et al., 2009)

3 Method

Path analysis is a multivariate statistical technique developed by the geneticist Sewall Wright in 1921 as a means of investigating the ramifications of various causal models in population genetics and improved constantly by genetic breeding scholars (Wright, 1921, Wright, 1934 and Finney, 1972). Observational variable can be measured directly and represented by a rectangle in the model. Latent variable is estimated by the observational variables and showed by an ellipse. The circle represents the error of variable. The causal relationship between the variables can be represented by the path diagram. The vector shows a causal relationship between variables. Suppose there are two variables x and y, and the vector shows a causal relationship between them. If the vector arrow from x to y, that means x is the cause of y. And there is a correlation between x and y if the vector with two arrows. Each path can be expressed as a regression equation, so the path diagram can be represented as a set of regression equation which contains all of the causal structure.

PA-LV model is based on the assumption of regression analysis, and established by deleted the non-significant path and estimate the residual coefficient through the standard regression path coefficient. The first step we build PA-LV model is finding the causal relationship between the cause variables and the outcome variables. Then we choose suitable method to estimate path coefficient of variables. We conducted some preliminary confirmatory analysis, using chi-square difference approach in GLS estimation of restricted and unrestricted models, to test for the significance of correlations between factors finding that these are highly significant. We choose Generalized Least Squares (GLS) to estimate path coefficient. GLS regression has better results than traditional classical regression especially when the number of variables is more and multiple correlation exists among variables while the number of observation data is less. (Li et al., (2011))

Finally, PA-LV general model is as equation (2) and the diagram of model is shown in Fig. 1. At last, we use statistical software Amos 21 to solve the PA-LV model and obtain the results of path coefficient parameters and result of test and decomposition results of path coefficient. At the same time, we can get the path coefficients model decomposition, which directly affect each variable on carbon emissions, indirect influence and overall impact.

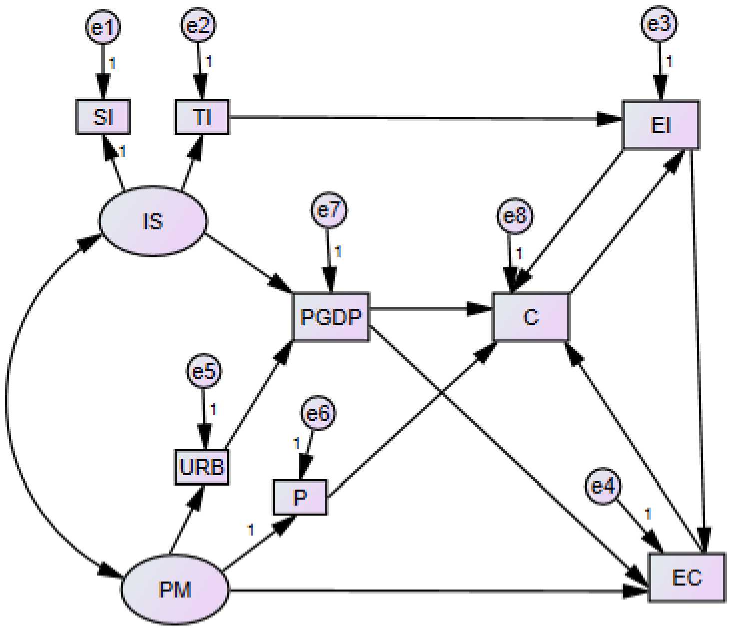

Fig1 Diagram of PA-LV model

This study reveals the interaction path analysis and hierarchical logical relation-ships between various factors. Assume that the path of the variable x_i to the variable x_j is denoted as P_{ji}. The path of the variable ξ_i to the variable x_j is denoted as $\lambda_{ji}\ (i=1,2;\ j=1,2,3,4)$. And $\gamma_{ji}(i=1,2;\ j=5,6,7,8)$ is the path of the variable from ξ_i to x_j.The residual error of $x_i(i=1,2,3,4)$ is δ_i, and the residual error of $x_j(j=5,6,7,8)$ is ε_j.

$$\begin{cases} x_6 = p_{62}x_2 + p_{68}x_8 + \varepsilon_6 \\ x_5 = p_{56}x_6 + p_{57}x_7 + \gamma_{52}\xi_2 + \varepsilon_5 \\ x_8 = p_{85}x_5 + p_{86}x_6 + p_{84}x_4 + \varepsilon_8 \\ x_7 = \gamma_{71}\xi_1 + p_{73}x_3 + \varepsilon_7 \\ x_1 = \lambda_{11}\xi_1 + \delta_1 \\ x_2 = \lambda_{21}\xi_1 + \delta_2 \\ x_3 = \lambda_{32}\xi_2 + \delta_3 \\ x_4 = \lambda_{42}\xi_2 + \delta_4 \end{cases} \quad (2)$$

4. Results

We Use Amos21 statistical software to estimate the degree of influence of factors in CO2 emission. The results be summarized as follows: the path coefficient and their significant test results (Table 3), and the coefficient of covariation variables (Table 4) and decomposition of the path coefficients of the model (Table 5) , and stability and goodness-of-fit test results of the model (Table 6).

4. 1 The results of the path coefficients

Path coefficient are estimated by using GLS. As shown in Table 3, the estimated value (Estimate) is non-standardized regress ion coefficients, and SE is the standard error of estimate. For example, the path regression weight estimate of P to C is.434, has a standard error of about 0.103. When P goes up by 1 standard deviation, C goes up by 0.434 standard deviations. The probability of getting a critical ratio as large as 0.103 in absolute value is less than 0.001. In other words, the regression weight for P in the prediction of C is significantly different from zero at the 0.001 level (two-tailed). It can be derived from Table 1, each path coefficient estimates significant probability corresponding P values is less than the significance level of 5%, which indicate that all of the direct effect of the regression coefficients have reached a significant level.

Table 3 the results of the path coefficients

			Estimate	Standardized Estimate	S.E.	C.R.	P	Label
URB	<---	PM	1.060	.997	.065	16.198	***	par_2
TI	<---	IS	2.459	.838	1.085	2.266	.023	par_1
P	<---	PM	1.000	1.000				

			Estimate	Standardized Estimate	S.E.	C.R.	P	Label
PGDP	<---	URB	.923	.939	.059	15.737	***	par_6
PGDP	<---	IS	.112	.037	.065	1.709	.047	par_12
EI	<---	TI	-.421	-.443	.137	-3.071	.002	par_4
EC	<---	PGDP	.802	.797	.127	6.326	***	par_7
C	<---	P	.458	.434	.103	4.460	***	par_8
EC	<---	PM	.947	.901	.175	5.407	***	par_9
C	<---	PGDP	-.179	-.177	.078	-2.289	.022	par_11
SI	<---	IS	1.000	.354				
C	<---	EC	.931	.928	.080	11.706	***	par_3
EC	<---	EI	.769	.708	.219	3.515	***	par_10
EI	<---	C	-.515	-.562	.138	-3.730	***	par_13
C	<---	EI	.203	.186	.103	1.966	.049	par_14

The covariance estimate is .348, has a standard error of about 1.171. The probability of getting a critical ratio as large as 1.994 in absolute value is 0.046 which is less than 0.05. In other words, the covariance between IS and PM is significantly different from zero at the 0.05 level (two-tailed).

Table 4 the result of covariant variables

	Covariances Estimate	Correlations Estimate	S.E.	C.R.	P	Label
IS <--> PM	.348	1.171	.175	1.994	.046	par_5

4. 2 The results of decomposition of the path coefficients

The results of decomposition of the path coefficients of the model are shown in the Table 5.

(1) The standardized total effect (direct and indirect) of PM on C is 1.219. The standardized total (direct and indirect) effect of PM on URB, PGDP, P, EI and EC is 0.997, 0.936, 1.000, -0.685 and 1.162. This is no any indirect (unmediated) effect that PM may have on PGDP, C and EI. That is, due to direct (unmediated) effect of PM on URB, P and EC, when PM goes up by 1 standard deviation, URB, P and EC go up by 0.997, 1.000 and 0.901 standard deviations indirectly, respectively.

(2) The standardized total (direct and indirect) effect of IS on PGDP, TI, C, EI, EC and SI is 0.037, 0.838, -0.198, -0.26, -0.154 and 0.354. While, the standardized indirect (mediated) effect of IS may have on PGDP, TI and SI is -0.198, -0.26, -0.154. There is no any indirect (unmediated) effect that IS may have on C, EI and EC. The standardized direct (mediated) effect of IS have on them is 0.037, 0.838 and 0.354.

(3) The standardized total (direct and indirect) effect of URB on PGDP, C, EI and EC is 0.939, 0.358, -0.201 and 0.606. While, the standardized direct (unmediated) effect of URB on PGDP is 0.939. This is no any direct (unmediated) effect that URB on C, EI, EC and the indirect effect is 0.358, -0.201 and 0.606.

(4) The standardized total (direct and indirect) effect of PGDP on C, EI and EC is 0.381, -0.215 and 0.645. The standardized direct (mediated) effect of PGDP on C and EC is -0.177 and 0.797, while the indirect effect is 0.559 and -0.152. This is no any direct (unmediated) effect that PGDP on ZEC and the indirect effect is -0.215.

(5) The standardized total (direct and indirect) effect of P on C, EI and EC is 0.294, -0.166 and -0.117. The standardized direct (mediated) effect of P on C is -0.177 and indirect effect is -0.14. This is no any direct (unmediated) effect that P on EI and EC and the indirect effect is -0.166 and -0.117.

(6) The standardized total (direct and indirect) effect of C on C, EI and EC is -0.322, -0.382 and -0.27. The standardized direct (mediated) effect of C on EI is -0.562 and indirect effect is 0.181. This is no any direct (unmediated) effect that P on C and EC and the indirect effect is -0.322 and -0.27.

(7) The standardized total (direct and indirect) effect of EI on C, EI and EC is 0.572, -0.322 and 0.48. The standardized direct (mediated) effect of EI on C and EC is 0.186, 0.708, while the indirect effect is 0.385, -0.228. This is indirect (unmediated) effect that EI on itself is -0.322.

(8) The standardized total (direct and indirect) effect of EC on C, EI and EC is 0.629, -0.354 and -0.25. The standardized direct (mediated) effect of EC on C is 0.928, while the indirect effect is -.298. This is no any direct (unmediated) effect that EC on EI and EC and the indirect effect on them is -0.354 and -0.25.

(9) It is apparent that the sequence of the size of factors' direct influence on CO2 emission is EC>P>EI>PGDP, while total influence of them is in the order of PM>EC>EI>PGDP>URB>C>P>TI>IS (in absolute value), and indirect influence of them is in the order of PM>PGDP>EI>URB>C>EC>TI>IS>P. Both the correlation coefficients and path coefficients of PGDP are statistically significant and its direct path coefficients are relatively small, indicating that the major influence of PGDP on China's CO2 emission are from its indirect effect. The main influence of PGDP is realized indirectly, because its total indirect path coefficient is positive and bigger than its direct path coefficient, which is negative. Both EC and EI influence China's CO2 emission through both direct and indirect ways.

(10) Carbon emissions has a negative effect on itself indirectly. Firstly, the increasing carbon emissions will encourage the government to practice new policies to save energy consumption. At the same time, the enterprise will take measures to improve energy efficiency and reduce energy intensity by improving the technical level. Such negative effect on energy intensity can contribute to reducing CO2 emissions, because the energy intensity has significant positive impact on carbon emissions, which to some extent inhibited the growth of carbon emissions. Secondly, Carbon emissions can reduce the growth rate of energy consumption to a certain extent by lowing the energy intensity due to significant positive impact which energy consumption exerts carbon emissions. Through the above two ways, the increase of carbon emissions to a certain extent inhibits the degree of growth of itself.

Table 5 the results of decomposition of the path coefficients

Causal variable	Results variable	Standardized Total Effects	Standardized Direct Effects	Standardized Indirect Effects

PM	URB	0.997	0.997	.000
	PGDP	0.936	.000	0.936
	P	1.001	1.001	.000
	C	1.219	.000	1.219
	EI	-0.685	.000	-0.685
	EC	1.162	0.901	0.261
IS	PGDP	0.037	0.037	.000
	TI	0.838	0.838	.000
	C	-0.198	.000	-0.198
	EI	-0.26	.000	-0.26
	EC	-0.154	.000	-0.154
	SI	0.354	0.354	.000
URB	PGDP	0.939	0.939	.000
	C	0.358	.000	0.358
	EI	-0.201	.000	-0.201
	EC	0.606	.000	0.606
PGDP	C	0.381	-0.177	0.559
	EI	-0.215	.000	-0.215
	EC	0.645	0.797	-0.152
P	C	0.294	0.434	-0.14
	EI	-0.166	.000	-0.166
	EC	0.117	.000	0.117
TI	C	-0.253	.000	-0.253
	EI	-0.301	-0.443	0.143
	EC	-0.213	.000	-0.213
C	C	-0.322	.000	-0.322
	EI	-0.382	-0.562	0.181
	EC	-0.27	.0000	-0.27
EI	C	0.572	0.186	.385
	EI	-0.322	.000	-.322
	EC	0.48	0.708	-.228
EC	C	.629	.928	-.298
	EI	-.354	.000	-.354
	EC	-.250	.000	-.250

4.3 Test of model

4.3.1The stability test of model

Stability index for the following variables C, EC and EI is .552.The above list of variables constitutes a 'nonrecursive subset' of the variables in the model. That is, in the path diagram of the model, it is possible to start at any one of the variables in the subset, and, by following a path of single-headed arrows, return to the original variable while never leaving the subset. Suppose there are *k* variables in the nonrecursive subset and consider the *k* by *k* matrix that gives the direct effects of these *k* variables on each other. Then .552 is the modulus of the largest eigenvalue of that matrix. If there is only one nonrecursive subset in the model, the stability index displayed here is identical to the stability index described by Fox (1980) and Bentler and Freeman (1983). If any stability index is one or greater, the system is called 'unstable'. A recursive model contains no nonrecursive subsets, and the associated linear system is stable. The stability index is .552 which is smaller than 1 that indicate this model is stable.

4.3.2 The goodness-of-fit of model

Table 6 the results of goodness-of-fit of model

Statistic	Standard of adaptation	Values	Evaluation results
Chi-square = 20.917	Probability level P>0.05	Probability level = .053	Yes
GFI	>0.9	0.910	Yes
RMR	<0.05	0.012	Yes
NCP	The smaller the better	0.001	Yes

If the appropriate distributional assumptions are met and if the specified model is correct, then the value of probability level is the approximate probability of getting a chi-square statistic as large as the chi-square statistic obtained from the current set of data. For example, if the value is .05 or less, the departure of the data from the model is significant at the .05 level. In this model, the value is 0.053 and bigger than 0.05, which indicates that this model is appropriate with sample data. It can be seen from the table 4, all evaluation indexes of the model conform to its evaluation standard, so we can judge that this model has a good adaptation degree with the actual data.

5. Discuss and conclusions

Many scholars have studied the influence factors of China's carbon emissions of energy consumption, this paper uses the PA-LV method to analyze the driving factors. Some of our results confirm previous conclusions, include The results obtained in this paper are that the energy intensity has a significant total positive effect on the carbon emissions and energy consumption; The population has the most significant effect positive impact on carbon emissions, which the expansion of population scale and improvement of the level of urbanization both lead to the increase of energy consumption and resulting in carbon emissions. The adjustment of industrial structure has a certain inhibition effect on carbon emissions. The mechanism is that improving the third industries to reduce energy intensity and improving the technical level to reduce energy intensity. Reduce energy intensity will lead to a reduction of total energy consumption and suppress a substantial increase carbon emissions. Some results contain new discoveries.

5.1 Discuss

(1) The growth of the economic

The conclusions about the relation between carbon emissions and economic growth are various. Researchers generally believe that with continuous growth in the overall economy, consumption will continue to rise and increase the CO_2 emissions. The results obtained in this paper are that increase of

GDP per capita will increase the total energy consumption and CO_2 emissions, but the improvement of the economic can inhibit the growth of carbon emissions to a certain extent.

The result of this paper is that when PGDP goes up by 1 standard deviation, C goes up by -0.177 deviations directly and 0.559 deviations indirectly, while the total deviations of C is 0.381. The development of economy at the price of energy consumption. This paper draws the conclusion that the total intensity of the effect of PGDP on energy consumption is 0.645. When PGDP goes up by 1 standard deviation, EC goes up by -0.177 deviations indirectly. In another way, PGDP has a negative effect on EI and EI goes up by -0.215 deviations when PGDP goes up by 1 standard deviation. On the other hand, the change of China's economic growth mode makes the economic growth rate higher than the energy consumption, which makes energy intensity decrease and inhibits the increase rate of carbon emissions.

In recent years, growth rate of China's GDP is downswing, but the amount of energy consumed per unit of GDP is declining. Although China is the world's largest carbon emissions country, the energy intensity is reducing from 12.826 (tons / million) in 1980 to 3.297(tons / million) in 2013. During the “Twelfth Five Year Plan”, China continues to adjust industrial structure and advance the competitiveness of industry. Promote steadily and deeply the fusion between informatization and industrialization, and China’s enterprises persist in enhancing its capability of independent innovation. Growth mode of China's economic shift from extensive growth mode to intensive growth mode.

(2) The feedback effect of carbon emissions
On one hand the standardized direct (mediated) effect of C on EI is -0.562 and indirect effect is 0.181. It means that when C goes up by 1 standard deviation, EI goes up by -0.382 deviations totally. On the other hand, EC goes up by -0.27 deviations indirectly when C goes up by 1 standard deviation. Carbon emissions have a negative impact on the energy intensity, which indirectly reduces the growth rate of the total energy consumption, and in a certain extent inhibit the increase of carbon emissions with forming a positive feedback effect.
First, the Chinese government has issued a series of energy-saving policies to reduce carbon emissions through improving energy utilization efficiency. In order to accelerate the progress of energy-saving technology and promote the popularization of energy-saving technology, government guide companies adopt new equipment and technology to promote energy conservation and strength energy efficiency and ease environmental pressure. Industry is the largest carbon emissions. Industry as energy consumption and CO_2 emissions of major industries rely mainly on technological progress to promote the reduction of carbon emissions. Industrial consumption in 1980 accounted for 78.51% of the total energy consumption, emissions of carbon dioxide accounted for 81.2% of China, while the two data points are 69.79% and 73.5% in 2012.

Secondly, the introduction of the adjustment of the industrial structure and adjust the guide directory, the third industry accounted for 21.6% from 1980 to 46.1% in 2013, more than second industry accounted for 43.9%, the tertiary industry has developed into the leading industry of our national economy. Compared with the second industries of high energy consumption and high emissions, the energy consumption of tertiary industry is more efficient and the energy intensity is lower.

5.2 Conclusions

(1) Economic growth has a positive impact on carbon emissions totally, but China's economic growth mode shift from the consumption mode to the efficiency one. The change of mode of economic growth can reduce the energy intensity, thereby indirectly inhibit the growth rate of carbon emissions.

(2)The increase of EC has a negative indirect influence on EI so that it exerts a negative influence on carbon emissions indirectly. The growth of carbon emissions impacts EC and EI negatively, resulting in a negative impact indirectly on itself. Thought the growth of energy consumption has a positive effect on energy intensity totally, it can reduce the energy intensity to some extent indirectly. That is energy consumption and carbon emissions can play a positive feedback effect on carbon emissions and control the growth rate of themselves through improving energy efficiency.

(3)The reduction of energy intensity and adjustment of industrial structure, especially the growth of proportion of the tertiary industry inhibited the increase of carbon emissions to some extent. Population, urbanization, and energy consumption drive the positive effect on carbon emissions; some results different with previous studies are that the change of economic growth pattern to some extent inhibited the growth rate of carbon emissions by reducing the energy intensity.

(4) It is apparent that the sequence of the size of factors' direct influence on CO2 emission is EC>P>EI>PGDP, while total influence of them is in the order of PM>EC>EI>PGDP>URB>C>P>TI>IS (in absolute value), and indirect influence of them is in the order of PM>PGDP>EI>URB>C>EC>TI>IS>P.

6 Policy recommendations

(1) Transform the mode of economic development and adjust industrial structure.

To control carbon emissions in the process of economic development, China should first change the mode of economic development and divert attention from extensive growth mode to intensive growth mode. Adjust the industrial structure and accelerate industrial restructuring, optimization, transformation and upgrading. In the process of economic development, vigorously develop the low consumption industries, reduce or limit the development of high energy consuming industries, optimally allocate the proportion of the tertiary industry. The Chinese government should upgrade the industry through the relevant policies, such as tax relief or tax rebates, etc.

(2) Develop clean energy and adjust the energy structure.
Since the reform and opening-up, coal accounts for energy production and consumption more than 66%, and fossil energy consumption is more than 90%. Improve energy consumption structure and develop clean energy is the main task. Therefore, positively constructing a diverse, safe, clean, and efficient energy supply and consumption system, promoting the application and popularization of low-carbon energy such as solar, wind, nuclear and tidal, and achieving the substitution of traditional fossil energy, will further ease China's carbon emissions. In addition, to strengthen the adjustment of the energy structure, the government should provide support in the forms of tax incentives, capital, technologies, markets and other aspects of environmental protection, create a good environment for the development of clean energy, and reduce the emission of greenhouse gases from the source and

production processes. In the future, the enterprises should also use advanced technology to improve management level, lower energy intensity, improve energy efficiency, and reduce carbon emissions.

(3) Reduce energy intensity and improve the efficiency of energy use.

Improving energy efficiency is a well-known method for reducing carbon emissions. In our analysis, energy intensity and energy efficiency are the most important factors to restrain carbon dioxide emissions. There is still certain space for decreasing carbon emissions by increasing energy efficiency. Technological progress drives the energy efficiency. It is necessary to increase investment in advanced energy-saving technology and encourage the development and promotion of the technology, and promote innovation in the aspects of energy production, conversion and utilization. At the same time, we should guarantee the improvement of energy efficiency from the aspects of laws and regulations and implement correctly and increase appropriately the intensity of environmental regulations.

(4) Appropriately control population scale.

Population growth and urbanization also promote the growth of carbon emissions to a certain extent. The increasing population will place greater pressure on the environment. The rise in carbon dioxide does parallel the growth rate of urbanization. Therefore, in the process of urbanization, the government should improve the existing household registration system, rationally distribute the population, actively guide and arrange migrant workers to the urban areas, pay attention to optimizing the structure and the quality of population, and control the population to a scale in harmony with environmental capacity. In order to low the carbon emissions, we should vigorously promote the concept of low-carbon consumption and green consumption.

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