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## emission: Evidence from Beijing city, China

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# An Empirical Research on the Influencing Factors of Regional CO<sub>2</sub> Emission: Evidence from Beijing City, China

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Abstract: In order to further study the realization of carbon intensity target, find the key influencing factors of CO<sub>2</sub> emissions, and explore the path of developing low-carbon economy, this paper empirically studied the influences of urbanization level, economic level, industry proportion, tertiary industry proportion, energy intensity and R&D output on CO<sub>2</sub> emissions in Beijing using improved STIRPAT (stochastic impacts by regression on population, affluence and technology) model. The model is examined using partial least square regression. Results show that urbanization level, economic level and industry proportion positively influence the CO<sub>2</sub> emissions, while tertiary industry proportion, energy intensity and R&D output negatively do. Urbanization level is the main driving factor of CO<sub>2</sub> emissions, and tertiary industry proportion is the main inhibiting factor. In addition, along with the growth of per capita GDP, the increase of CO<sub>2</sub> emissions does not follow the Environmental Kuznets Curve model. Based on these empirical findings and the specific circumstances of Beijing, we provide some policy recommendations on how to reduce carbon intensity. Beijing should pay more attention to tertiary industry and residential energy consumption for carbon emission reduction. It is necessary to establish a comprehensive evaluation index of social development. Investing more capital on carbon emission reduction science and technology, and promoting R&D output is also an efficient way to reduce CO<sub>2</sub> emissions.

Keywords: Carbon dioxide emission; STIRPAT model; Partial least square; Beijing city

### **1. Introduction**

From the United Nations Framework Convention on Climate Change to the Kyoto Protocol, climate issues have long been a concern. It has been shown that the rise of the global temperature is caused by greenhouse gas emissions, mainly CO<sub>2</sub> emissions which are driven up by rapid development of industrialization. As a result, lowering down CO<sub>2</sub> emissions has become a new constraint getting in the way of economic development of the world. China, which is a developing country of the largest population all over the world, is now in the process of fast industrialization and urbanization. Therefore, China is under huge pressure and of great difficulty in controlling greenhouse gas emissions. In order to overcome these difficulties, in November 2009, Chinese government sets a target to reduce the carbon emissions per unit GDP (carbon intensity) by 40%-45% between 2005 and 2020. As a restriction index, this target has been included in the future medium-and-long term plans for national economic and social development. The target is also the vision and goal for China to deal with climate change, energy saving and emission reduction in the future. In addition, "the Outline of National Economy and Social Development Plan in the Twelfth Five-year

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(2011-2015)" explicitly pointed out that energy consumption must be reduced by 16% and  $CO_2$  emissions per unit GDP must be lowered by 17% during the period of the Twelfth Five-year Plan. Moreover, in August 2011, "Beijing Energy-saving and Climate Change responding Plan for the Twelfth Five-year Plan" issued Beijing would reduce its  $CO_2$  emissions by 18% per unit GDP. To realize the emission reduction goals, we need to analysis the existing problems and research the influencing factors of emissions, and then find the appropriate emission reduction path for Beijing.

As the capital of China with approximately 20 million permanent populations, Beijing had achieved the goals of energy saving and emission reduction during the period of the Eleventh Five-year (2006-2010) Plan. However, Beijing is still facing a lot of problems. Firstly, the urban population in Beijing has been increasing rapidly accompany with the corresponding increase of energy use and CO<sub>2</sub> emissions. According to National Bureau of Statistics of China, the urban population in Beijing, by the end of 2010, has reached 16.86 million, which is 59.49% more than that of 2000. Secondly, as the capital of China, the priorities of economic development lead to the result that people in Beijing are getting much wealthier. Based on the latest data, the average monthly salary of residents in Beijing has been over 8000 CNY, which is equivalent to more than 1000 USD. The direct influence of people getting richer is that the life styles of Beijing residents may change. More energy-consuming apparatus may have opportunities to be introduced into the household. Thirdly, due to the gradual completion of the industrial structure adjustment and the service-oriented economic structure tending to be stable, industrial exit and limiting production can no longer achieve the purpose of energy saving and emission reduction. So we need to find the new way to reduce the CO<sub>2</sub> emissions. Lastly, the R&D in Beijing is still not intensive enough compared with that in developed countries. So how can R&D intensity help to reduce the CO<sub>2</sub> emissions still need a deeper research.

Therefore, based on these existing problems, this paper attempts to build an improved STIRPAT (stochastic impacts by regression on population, affluence and technology) model to study the factors influencing CO<sub>2</sub> emissions empirically, and propound some useful policy suggestions for the policy makers. In particular, the study sets focus on the following aspects:

How to improve STIRPAT model to adapt to Beijing;

Find the significant factors influencing CO<sub>2</sub> emissions in Beijing;

Find the appropriate way to reduce the CO<sub>2</sub> emissions and achieve the carbon intensity target.

The innovation and contribution of this research compared with other references mainly lies in the following three aspects. Firstly, factors affecting  $CO_2$  emissions are complex, and studies on different regions with different development stages may have different conclusions. A large number of literatures study influencing factors of  $CO_2$  emissions in macroscopic level, but relevant researches in Chinese city level is less. This paper selects Beijing city as the research object. Secondly, we attempt to introduce R&D output (energy technology related patents) as an index to indicate the technology level. This index is new in the literature, and we find it has a negative influence on  $CO_2$  emissions through an empirical test. Lastly, we draw the conclusion that the key of reducing  $CO_2$  emissions in Beijing is the emissions of tertiary industry and residential energy consumption. It points out the direction and measures for policy makers.

This paper is organized as follows: literature review on the topic of determinants of CO<sub>2</sub> emissions is done in Section 2; in the following section 3, basic STIRTAT model and the modification used in this paper are introduced; data processing and results discussing are presented in Section 4; the conclusions and policy implications are made in Section 5.

#### 2. Literature review

The factors influencing  $CO_2$  emissions are complex. There have been an increasing number of studies on the factors influencing  $CO_2$  emissions during the past few years. Various

determinants analyzing models are used in those studies. The representative models include the input-output model [1], the IPAT model, STIRPAT model [2], Laspeyres method [3], the LMDI method [4], the AWD method, the GFI method, the Kaya Index method [5, 6], provincial cluster analysis [7] and so forth.

A large number of studies indicate that economic growth and technological advancement are the most powerful factors influencing CO<sub>2</sub> emissions. Based on data from 149 countries over the period 1960-1990, Shafik and Bandyopadhyay found a positive relationship between CO<sub>2</sub> emissions and per capita income [8]. Paul and Bhattacharya analyzed the data of main economic departments in India between 1980 and 1996, and found that economic growth was the most fundamental cause of CO<sub>2</sub> emissions [9]. Li et al. tested the relations between carbon emissions and factors using the STIRPAT model, and furthermore, they decomposed the carbon emission influencing factors with the method of LMDI. They found that there was an upside-down U-curve between economic growth and CO<sub>2</sub> emissions [10]. Wang et al. took the LMDI to analyze the data of 1957-2000 in China. They found that energy intensity, which was as the representative of technological variables, was important in reducing CO<sub>2</sub> emissions, whereas economic growth increased CO<sub>2</sub> emissions [11]. Wei and Yang highlighted the impact of technological advancement on CO<sub>2</sub> emissions with the panel data of various Chinese provinces from 1997 to 2007. The findings were that CO<sub>2</sub> emissions were positively related to economic growth, industrialization, and trade liberalization, while independent R&D and technological introduction decreased CO<sub>2</sub> emissions [12]. Cheng et al. [13], Xu et al. [5], Siddiqi [14] and others showed that economic development and technological advancement were the most powerful factors of CO<sub>2</sub> emissions.

Population, urbanization and other social factors have a significant impact on CO2 emissions. Inmaculada and Antonello conducted an empirical study about the impact of urbanization level influencing on CO<sub>2</sub> emissions in developing countries, the results verified an inversed-U-curve relationship between them [15]. Phetkeo and Shinji also found the same results [16]. Salvador et al. use Lotka-Volterra model to discuss the relationships between population, GDP, energy consumption and carbon emissions respectively. The results displayed that the population size was the primary driving factor, and the structure of population also had an impact on carbon emissions [17]. Knapp found there was not a long-term cointegration relationship between population and CO<sub>2</sub> emissions according to the result of Granger causality test, but the global population growth was a stimulative factor of CO<sub>2</sub> emissions increasing [18]. Wei et al. adopted a STIRPAT model to analyze the influencing factors of CO<sub>2</sub> emissions, and found that the population had a significant influence on CO<sub>2</sub> emissions, in particular the proportion of the population aged between 15 and 64 years old. They also used LMDI to decompose the carbon emissions. The results indicated that population growth promoted the increase of CO<sub>2</sub> emissions, and its influence ranking is only second to per capita GDP [19]. Chen and Zhu used a Kaya identity equation to decompose the CO<sub>2</sub> emissions of Fujian Province in China from 2000 to 2009. The results showed that population growth increased CO<sub>2</sub> emissions [20]. Xu and Liu [21], Shi's research showed that the total population had a positive influence on CO<sub>2</sub> emissions [22].

Additional factors have been taken into consideration in further research. Shao et al. examined the role of energy consumption structure and brought in a policy dummy variable [23]. Siddiqi suggested that the increasing of CO<sub>2</sub> emissions kept pace with energy consumption [14]. Li et al. argued that the amount of current CO<sub>2</sub> emissions depended on the amount of the last period (emission inertia) [10]. Paul and Michael found a significant relationship between countries' per capita emissions and their exports to the United States, taking the panel data of 163 countries from 1989 to 2003 as samples [24]. Sun's research supported this result [25].

The previous researches enrich our understanding of the main influencing factors of  $CO_2$  emissions. In summary, the determinants of economic growth, technological advancement, population growth, urbanization level, industrial structure, the structure of energy

consumption, and international trade division are collected. Most of these literatures inclined to analyze the influence mechanism macroscopically. Studies on specific Chinese city are scarce. However, the influencing factors are diversiform because of the different regions [6, 13, 20, 21]. Therefore we selected Beijing as the research object to study the factors influencing  $CO_2$  emissions empirically. And energy technology related patent is innovatively used to measure technical factors in this paper. Hardly any studies have investigated technical factor in this way. The research results will provide some theoretical guidance for the realization of the carbon intensity target.

### 3. Methods and Data

#### 3.1. The STIRPAT model of factors influencing CO<sub>2</sub> emissions

The STIRPAT model is the random form of IPAT equation on environmental stress. The IPAT model was firstly proposed by Ehrlich and Holden [26], and its general form is:

I=PAT

(1)

where I stands for influence of environment, P for population size, A for average affluence, and T for technological level.

This is a widely accepted quantitative model analyzing the impact of human factors on environment. However, it examines only a limited number of variables. Therefore, the research results are generally limited to energy, economy and population factors, and their equal ratio relationship. This is the greatest limitation of the equation [25]. To overcome these shortcomings, some scholars established stochastic models to analyze the non-proportional effect of human factors on the environment. Dietz and Rosa changed the IPAT equation into a random form, creating the STIRPAT model [27]:

$$I=aP^{b}A^{c}T^{d}e$$
(2)

where a is the constant term, b, c, d is the exponential term of P, A and T, e is the error term. In quantitative analysis, the model is often used in logarithmic form:

$$lnI=a+b(lnP)+c(lnA)+d(lnT)+e$$
(3)

The IPAT model is a particular form of the STRIPAT model, when a = b = c = d = e = 1. The STRIPAT model not only retains the multiple relationships between human driving forces of the IPAT model, but also regards such human driving forces as population, affluence, technology as major factors affecting environmental stress change [28]. The STIRPAT model not only allows the estimation of each coefficient as a parameter, but also allows appropriate decomposition of every factor [27]. According to different research purposes and needs, corresponding improvement is often made to the relevant literature based on the original model in order to carry out a variety of empirical researches [23].

Considering the specific situation in Beijing and learning from past research experiences, we carried out corresponding decomposition and improvement on the relevant variables.

(1) Population. In this paper, the variable of population size is replaced by the variable of population structure (urbanization level). Because of the population control in the city of Beijing, the data of Beijing population are relatively stable during the research period. The energy consumption and carbon emission caused by urbanization cannot be reflected by population size. However, urbanization can greatly influences the domestic energy consumption. Energy consumption per capita in urban area is 3.5 or 4 times more than that of rural area. Therefore, in order to correctly describe the energy demand and CO<sub>2</sub> emissions in Beijing, the factor of urbanization must be taken into considerations [29].

(2) Affluence. Affluence is one of the main confirmed factors influencing emissions. A large number of researches on developed countries in Europe and America show that pollution increases with the growth of per capita GDP at low income levels, while at high income levels it declines with GDP growth, that is to say, there exists an environmental Kuznets "inverted U" curve. Relevant study confirms that the Environmental Kuznets Curve (EKC) exists in China,

but many scholars' studies show that the curve does not exist [30] or does not exist in certain regions [31]. To explore whether there is the EKC in Beijing, this paper references the York's method to establish the quadratic model [2]. The economic factor is decomposed into a first power term and square term in the hope of carrying out a more comprehensive empirical study on the relationship between carbon emissions and economic factors.

(3) Technology. Because of the inherent difficulties in measuring what "technology" is, in this research we reference the York's model. York et al. broke technical factors down into industrial structure and energy intensity, and used empirical methods to confirm the influence of these two factors are significant in CO<sub>2</sub> emissions [2]. Scholars have borrowed York's dismantling approach to explore the factors of CO<sub>2</sub>. In their model, they just consider the share of industry to indicate the industrial structure. But in Beijing, the share of tertiary industry is much higher than other provinces', so it is necessary to consider it. As the country's political and cultural center, Beijing has made more investments in technology and advocated less energy consumption in various industries by technological progress. These have led a large number of scientific research achievements and technical patents to emerge. The application of them would inevitably result in improving the quality of production and life, and in reducing energy consumption and CO<sub>2</sub> emissions. Therefore, this article attempts to introduce the R&D output as an index to indicate the technology level. In the aspect of technology level, restricted to the data acquisition, the index of patent data has been frequently used in previous papers to evaluate R&D output. Despite their own flaw, patent data also have three advantages. Firstly, the definition of the patent is closely related to innovation; secondly, patent statistical data is open to public; thirdly, patent can reflect technological innovation to a great extent. As a result, the R&D output is adopted to evaluate technology level [32]. In this analysis, R&D output is measured by the stock of technical patents associated with CO<sub>2</sub> emissions. Using patents related to CO<sub>2</sub> emissions can measure the impact of technology on CO<sub>2</sub> emissions more accurately.

The STIRPAT model is like this after extension:

$$lnI_t = a + blnP_t + c_1 lnA_t + c_2 (lnA_t)^2 + d_1 lnSI_t + d_2 lnST_t + flnE_t + glnT_t + e$$
(4)

where I stands for CO<sub>2</sub> emissions, P for population structure, A for economic level, SI for industry proportion, ST for tertiary industry proportion, E for energy intensity and T for R&D intensity.

#### 3.2. Explanation of variables and data sources

Table 1 shows the explanation of variables in STIRPAT model used in this paper.

Table	1
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Variables	Symbol	Definition Measuring method	Unit of measurement
$CO_2$	Ι	CO <sub>2</sub> emissions stem from fossil fuel combustion	million tons
emissions			
Urbanization	Р	The percentage of the urban population in the	%
level		total population	
Economic	Α	GDP per capita	Constant 2005 RMB Yuan
level			
Industry	SI	The share of the industry sector output value over	%
proportion		the total GDP	
Tertiary	ST	The share of the tertiary industry output value	%
industry		over the total GDP	
proportion			

Energy	E	Energy use per constant 2005 PPP Yuan GDP	kg of coal equivalent per
Intensity			constant 2005 PPP Yuan
R&D output	Т	stock of energy technology related patents	item
*PPP: Purcha	asing Por	wer Parity	

The data on P, A, SI, ST and E are all from the "Beijing Statistical Yearbook(2011)", Since our study period is from 1997 to 2010, a more recent price index maybe more appropriate, thus we use the data of GDP at 2005 price.

In the case of Beijing, since China has not issued direct data on  $CO_2$  emissions, the date on  $CO_2$  emissions of Beijing in 1997-2010 could not be obtained from the Statistical Yearbook. We use the results calculated by Wang et al.[33], in which the data on  $CO_2$  emissions are estimated from the amounts of fossil energy consumption following the Liu et al.'s[34] method.

R&D output variable *T* is measured by the stock of energy technology related patents. Data on energy technology patents were generated from keyword searches on patents titles in the SIPO (State intellectual property office of the P.R.C) patent bibliographic database (SIPO, 2011). The keywords included in the search were as follows: (*oil* or *natural gas* or *coal* or *photovoltaic* or *hydroelectric* or *hydropower* or *nuclear* or *geothermal* or *solar* or *wind*) and (*electric*\* or *energy* or *power* or *generat*\* or *turbine*). The search terms were chosen to yield a broadly defined set of energy technology related patents. The search was performed on titles only to avoid extraneous patents [35].

## 4. Results and discussion

### 4.1. Ordinary least square regression of the model

The correlation analysis of each variable was carried out using SPSS17.0 statistical software; the results are shown in Table 2. lnI had a significant correlation with lnP, lnA,  $(lnA)^2$ , lnSI, lnST, lnE and lnT at the 0.01 significance level.

Variables	lnI	lnP	lnA	lnA^2	lnSI	lnST	lnE	lnT
lnI	1	0.978*	0.984*	0.984*	-0.902*	0.931*	-0.966*	0.935*
lnP	-	1	0.968*	0.969*	-0.904*	0.912*	-0.944*	0.909*
lnA	-	-	1	1.000*	-0.946*	0.970*	-0.993*	0.975*
lnA^2	-	-	-	1	-0.947*	0.968*	-0.993*	0.973*
lnSI	-	-	-	-	1	-0.970*	0.959*	-0.940*
lnST	-	-	-	-	-	1	-0.980*	0.986*
lnE	-	-	-	-	-	-	1	-0.984*
lnT	-	-	-	-	-	-	-	1

Table 2Matrix of correlation between variables

\*. Significant at the 1% level

In Eviews6 software, we used the ordinary least square (OLS) to make a regression analysis of the model. The regression results are shown in Table 3.

Analyzing results of influencing factors of CO<sub>2</sub> emissions by OLS

Variable	Coefficient	Std. Error	t-Statistic	Prob.	VIF
С	29.80228	29.92329	0.995956	0.3577	
lnP	0.494782	0.886097	0.558384	0.5968	30.099
lnA	-8.299387	7.260764	-1.143046	0.2966	222.561
lnA^2	0.415057	0.342982	1.210144	0.2717	148474
lnSI	1.220128	0.653372	1.867432	0.1111	31.500
lnST	3.021804	1.876718	1.610154	0.1585	97.064
lnE	0.065931	0.433187	0.152201	0.8840	182.305
lnT	-0.065081	0.065032	-1.000756	0.3556	98.887
R-squared	0.990911	А	djusted R-squa	ared	0.980306
F-statistic	93.44490	Durbin-Watson stat			2.961112
Prob(F-statistic)	0.000011				

The coefficient of determination of the model was  $R^2=0.99$  and the adjusted coefficient of determination  $R^{2=}0.98$ ; F=93.445, with *p* value close to zero. Thus, the fitting result appeared very good from the overall regression results, but in significant regression coefficient testing, all coefficients couldn't pass the *t*-test. In addition, it can be seen in table 2 that the absolute value of correlation coefficients were both above 0.9 in *lnP*, *lnA*, (*lnA*)<sup>2</sup>, *lnSI*, *lnST*, *lnE* and *lnT*, which means they are highly relevant among the independent variables. Thus, we suspect that variables have the problem of multicollinearity and information overlaps. Therefore, we tested the multicollinearity by calculating Variance Inflation Factor (VIF) (Table 3). VIF is the most commonly used measurement of the multicollinearity. A VIF over 10 often indicates that the multicollinearity may seriously affect the OLS estimate [36]. The VIF values of all variables are much larger than 10, which mean there is a serious multicollinearity among variables. Therefore, this data cannot be modeled using the OLS method. In order to overcome the multicollinearity among variables, we used Partial Least Square (PLS) modeling.

#### 4.2. Partial least square regression of the model

PLS is particularly useful when independent variables have a strong multicollinearity. It overcomes the multicollinearity based on the concept of extracting components and information comprehensively and screening technology [37].

The basic idea of the PLS method is: the latent variables  $t_1$  and  $u_1$  are extracted from the data table of independent variables X and dependent variable Y respectively,  $t_1$ ,  $u_1$  are the linear combination of  $x_1$ ,  $x_2$ , ...,  $x_p$  and  $y_1$ ,  $y_2$ , ...,  $y_p$ .  $t_1$ ,  $u_1$  must meet the following conditions:

(1)  $t_1$  and  $u_1$  should bring as much of their own data variation information as possible in order to represent data tables X and Y better;

(2)  $t_1$  and  $u_1$  should achieve the maximum degree of correlation. This gives  $t_1$  the strongest explanatory power to  $u_1$ .

If the regression equation has reached satisfactory accuracy, the algorithm terminates; otherwise, the residual information of X and Y are extracted again and again, until satisfactory accuracy of results is achieved. Finally, Y will be expressed as the regression equation of X [38].

We use the PLS estimation method to establish the STIRPAT model for population structure, economic level, industrial structure, energy intensity, R&D output and CO<sub>2</sub> emissions in order to avoid the multicollinearity among independent variables.

There are two important tables or plots used to explain the applicability of the PLS Method: the  $t_1/t_2$  scatter plot and  $t_1/u_1$  scatter plot. In the  $t_1/t_2$  scatter plot,  $t_1$  and  $t_2$  are the latent variables extracted from the X variables. If the  $t_1/t_2$  relationship of the sample data is all included in the oval, these sample data are homogeneous and can be accepted perfectly. Obvious, the sample data in this study are acceptable because all points are included in the oval (Fig. 1). Another important plot is the  $t_1/u_1$  scatter plot. If the  $t_1/u_1$  relationship of the sample data is near linear, the PLS regression model is appropriate to the study problem [39]. It is obvious that the  $t_1/u_1$  relationship of the sample data is nearly linear (Fig. 2), thus PLS regression model is reasonable to the study problem of this paper. The results, as calculated by SIMCA-P 11.5(DEMO) Software, are shown in Table 4.



Fig. 2.  $t_1/u_1$  scatter plot

Table	4
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Overview of the PLS regression result

Variable	Unstandardized coefficients	Standardized coefficients	
a(Constant)	2.411	26.447	
lnP	1.878	0.500	
lnA	0.135	0.278	
lnA^2	0.006	0.283	
lnSI	0.168	0.149	

lnST		-0.120	-0.057	
lnE		-0.095	-0.142	
lnT		-0.002	-0.010	
R <sup>2</sup> X(cum)	0.986	R <sup>2</sup> Y(cum)	0.983	
Adjusted R <sup>2</sup>	0.980	$Q^2$ (cum)	0.974	

In Table 4,  $R^2X$  represents the fitting degree of the principal component extracted from *X* variables and the original *X* variables,  $R^2Y$  represents the fitting degree of the principal component extracted from *Y* variables and the original *Y* variables, and  $Q^2$  represents the cross validation. These three indicators increase together with the increase in the number of principal components extracted; the maximum value is 1 [40]. It is generally held that the regression effect is ideal when  $R^2X$  (cum),  $R^2Y$  (cum), and  $Q^2$  (cum) are all larger than 0.8. Table 4 shows  $R^2X$  (cum) = 0.986,  $R^2Y$  (cum) = 0.983,  $Q^2$  (cum) = 0.98 and Adjusted  $R^2$ =0.98, suggesting that the regression results are effective.

The effect of the model can also be observed from the consistency of the predicted value and the observed value. The Observed vs. Predicted Plot used to explain or determine the fitting effect of PLS model. Fig. 3 shows a perfect linear relationship between the predictive value (YPred) and the actual value (YVar). This means the explanation or fitting effect of the results estimated by the PLS method is excellent.



Fig. 3. Observed vs. predicted plot.

From the signs of coefficients, it can be known that urbanization level, economic level and industry proportion positively influence the CO<sub>2</sub> emissions, while tertiary industry proportion, energy intensity and R&D output negatively do. It is consistent with the study of Siddiqi [14], Shi [22] and others. The CO<sub>2</sub> emissions increase along with the rapid urbanization and economic growth of Beijing. The coefficient of  $(lnA)^2$  is positive (Table 4). This means that no Environmental Kuznets Curve (EKC) exists in CO<sub>2</sub> emissions in Beijing with the growth per capita GDP, and with economic growth it has seen a continuous rise according to the existing statistical data. We can explain this result from the following three aspects. Firstly, although Beijing is not an industrial city, the share of secondary industry is still 30% on average in observation period. High emissions of the second industry also play a significant

role on CO<sub>2</sub> emissions. Secondly, with the improvement of people's living standards and the expansion of the scale of the urban population, there will be a steep increase in the tertiary industry and residential energy consumption, which will have a great influence on CO<sub>2</sub> emissions. According to Beijing Bureau of Statistics, residents' energy consumption in year 2010 increased 1.3 times compared with the level in year 2000 which is much higher than growth rate of total energy consumption. The rapid growth of residents' energy consumption brought the accelerated growth of emissions. Thirdly, more attention should be on the indirect emissions of the tertiary industry. The pull effect of tertiary sectoral activities on CO<sub>2</sub> emissions of other sectors cannot be ignored [41]. The traditional tertiary sectoral consumption focus on carbon-intensity sectors, which boosts the CO<sub>2</sub> emissions. The relationship between environment and economic development is a complex issue. It appears to vary due to different regions, different measurement indices and different observation periods. At the same time it is also affected by social and political factors.

Energy intensity is negatively correlated with  $CO_2$  emissions of Beijing. The elasticity is -0.095, which means that  $CO_2$  emissions will increase 0.095% when energy intensity decreases by 1%. This conclusion is consistent with results of Zhu et al. (2012) [42]. In the period of 1997-2010, the economy of Beijing increased rapidly, at the same time, the population increased almost by 50% and GDP per capita increased by 170%. However, the energy intensity decreased only by 55%. It means that energy intensity decreasing can barely offset  $CO_2$  emissions increase, because  $CO_2$  emissions cut is refilled by  $CO_2$  emissions increment caused by other reasons. The negative coefficient reflects the rebound effect of energy intensity. It means that although energy intensity has decreased align with industrial structure adjustment and technological progress, the increasing of  $CO_2$  emissions cannot be offsetted because of the rapid energy consumption. It is relative to the economic and technological developing stage of China. In the future, the positive effect of energy intensity on decreasing the  $CO_2$  emissions will emerge abreast with industrial upgrade and labor promotion.

#### 4.3. Variable importance analysis

For in-depth analysis of each variable's interpretative ability, we used the software to calculate the Variable Importance in Projection (VIP) of each variable. VIP shows the importance of every independent variable when explaining the dependent variable. It can be expressed as the following formula:

$$VIP_{j} = \sqrt{\frac{p}{Rd(y;t_{1},\dots,t_{m})}} \sum_{h=1}^{m} Rd(y;t_{h}) \omega_{hj}^{2}$$

$$\tag{5}$$

Here,  $VIP_j$  is the VIP of  $x_j$ ; p is the number of independent variables;  $t_1$ , ...,  $t_m$  are components extracted in the variable X;  $Rd(y; t_1, ..., t_m) = \sum_{h=1}^m Rd(y; t_h)$  is the accumulative explanation capability;  $\omega_{hj}$  is No. j component of  $\omega_h$  which is measured by the marginal contribution of  $x_j$  for constitution  $t_h$ , and for any h=1, 2, ..., m,  $\sum_{j}^p \omega_{hj}^2 = \omega_h \omega_h = 1$  [19]. The definition of VIP is based on the following principle: the interpretation of  $x_j$  to Y is shown by  $t_h$ , if  $t_h$  has a strong explanatory power to Y, and  $x_j$  plays an important role in the structure of  $t_h$ , the interpretative ability of  $x_j$  in the interpretation of Y is great [43]. If the VIP value of some variables is less than 0.8, because of relatively weak interpretative ability, they should be removed.

The VIP value of each variable is shown in Fig.4. All VIP values of variables are larger than 0.9, so each independent variable plays an important role in explaining the growth of CO<sub>2</sub> emissions. Among them, urbanization level has the greatest interpretative ability, followed by economic level, energy intensity, tertiary industry proportion and R&D output, while industry proportion has the least interpretative ability. The influence of urbanization on

carbon emissions is more obvious. Firstly, rapid urbanization brings more and more urban residents who tend to consume high-carbon products for enjoying. Secondly, expansion of urban area boosts city infrastructure construction, increases the number of housing heating and refrigeration systems, and thus increases the energy consumption and CO<sub>2</sub> emissions. Thirdly, the reduction of forestland caused by urbanization also indirectly leads to CO<sub>2</sub> emissions increase. Economic level is also an important factor driving CO<sub>2</sub> emissions. The government paid much attention to economic growth and excessively pursued the single goal of high-speed GDP growth, and lacked awareness of energy saving and emission reduction work in the past. Thus, the economy growth is at the cost of a considerable amount of energy consumption and high, intensive carbon emissions. The emissions of industry are generally high, but industry proportion is relatively small in Beijing. It has reduced 11% in year 1997-2010, and its proportion is only 19.6% in year 2010. Therefore the influence of industry proportion on overall CO<sub>2</sub> emissions is weak. With the improvement of people's living standards and the expansion of the scale of the urban population, there will be a steep increase in the tertiary industry and residential energy consumption, which will have a greater influence on CO<sub>2</sub> emissions.



Fig. 4. The VIP histogram of each variable

### 5. Conclusions and policy implications

In this paper, the improved STIRPAT model is applied to analyze the impact of CO<sub>2</sub> emissions in Beijing quantitatively using factors such as urbanization level, economic level, industry proportion, tertiary industry proportion, energy intensity and R&D output. Energy technology related patent is innovatively used as an index to measure technical factors in this paper. We used the method of PLS to analyze the data selected from 1997-2010 in order to overcome the multicollinearity among variables, and used VIP index to study the importance of each factor.

We find that urbanization level, economic level, industry proportion, tertiary industry proportion, energy intensity and R&D output are the influencing factors of Beijing CO<sub>2</sub> emissions. Of these, urbanization level, economic level and industry proportion positively influence CO<sub>2</sub> emissions, while tertiary industry proportion, energy intensity and R&D output negatively do. It means that along with the rapid urbanization process and economic growth of Beijing, the CO<sub>2</sub> emissions increase accordingly. However, if tertiary industry proportion is expanded or technological upgrade is accelerated, CO<sub>2</sub> emissions in China would decrease accordingly. As the urbanization level has reached a high level of approximately 86% in 2010, urbanization is more difficult and its driving force on CO<sub>2</sub> emissions became smaller in

further. Moreover, steady and fast economic growth is always an important goal of Chinese government. The government also promised emissions reduction targets with economic development, characterized by GDP, as the prerequisite. Therefore, it isn't the most feasible method to reduce  $CO_2$  emissions at the cost of sacrificing economic growth in future. Adjusting the industrial structure, increasing R&D investment and improving energy efficiency may be more effective ways to reduce  $CO_2$  emissions in Beijing.

Industry proportion has the least explanatory ability compare with other factors considered in this paper. The change of industrial structure has a weak influence on CO<sub>2</sub> emissions in Beijing. Tertiary industry proportion plays a significant role in restraining CO<sub>2</sub> emissions. Furthermore, urbanization level is the main driving force in inducing CO<sub>2</sub> emissions. The development of urbanization produces high CO<sub>2</sub> emissions largely because urban residents consume more fossil energy than the rural ones. Therefore, in the Twelfth Five-year Plan period, Beijing cannot excessively depend on industrial exiting and limiting production to promote energy conservation and emission reduction, but should focus on tertiary industry and residential energy consumption. To reduce CO<sub>2</sub> emissions of tertiary industry, it is important to shift the focus of tertiary industry from carbon-intensive sectors to non-carbon-intensive sectors. In addition, reducing the carbon emissions intensity of carbon-intensive sectors is also conducive to reduce emissions of the tertiary industry. To reduce CO<sub>2</sub> emissions from the residential energy consumption, the government should increases subsidies and promotes the adoption of high efficiency and energy-saving household appliances, automobiles, motors, lighting products, etc. They need to advocate green-healthy lifestyles and consumption patterns, and continuously enhance society's awareness of environmental protection.

R&D output is considered in this paper and we find it has a negative influence on CO<sub>2</sub> emissions. Therefore, investing more capital on carbon emissions reduction science and technology, and promoting R&D output is an efficient way to reduce CO<sub>2</sub> emissions. Technical progress has become the main pattern in limiting carbon emissions under the premise of city developing and economic growth. Energy conservation technology plays a significant role in city's management and continuous improvement of energy efficiency. Yet improvements in energy efficiency mean producing the same economic output with reduced energy consumption, which will indirectly reduce CO<sub>2</sub> emissions. Therefore, the government should makes full use of its function by promoting research and development, strengthening enterprises' research and development abilities, improving the ability of independent innovation, and perfecting technology patent system. Concretely, Beijing could establish and perfect the industry cluster technology service system, give full rein to research institutions, provide reasonable guides to the transfer and expansion of technology patents, construct intellectual property management and protection system, drive energy conservation and consumption reduction with technological progress in each industry, and so on. They should give full play to the advantages of intelligence and science in Beijing, accelerate changing the economic development mode, and improve economic development's reliance on scientific and technological progress.

Along with the growth of per capita GDP, there is no EKC in the variation of  $CO_2$  emissions in Beijing, and there is a continuous rise. Therefore, in order to conserve energy, reduce energy consumption and  $CO_2$  emissions, we must give up the old pattern of high pollution and energy consumption in exchange for economic growth, change the sole measuring method of economic and social development level, which uses GDP, and coordinate development of the environment and the economy. Beijing also should establish a comprehensive evaluation index of social development which weaken the GDP index and strengthen the improvement of people's living environment.

Ultimately, perfecting the laws and regulations is necessary to guarantee the implementation of these measures. While ensuring the constant development of the economy, through controlling the urbanization level within a reasonable size, optimizing the industrial

structure, strengthening R&D output and improving energy efficiency, Beijing can restrain CO<sub>2</sub> emissions, slowdown and then gradually decrease CO<sub>2</sub> emissions growth.

The conclusion drawn by this study has an important reference value for the government to adopt relative strategies, and also has an important academic value in terms of enriching the low carbon economy research system in China. However, the research is still preliminary, and many aspects are worthy of further study. For example, policy modeling and pathway choice for the realization of carbon intensity target are valuable, and the government and academia should also pay close attention to these issues.

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