

Original Research

Probing Energy-Related CO₂ Emissions in the Beijing-Tianjin-Hebei Region Based on Ridge Regression Considering Population Factors

Lei Wen*, Zhiquan Zhang

Department of Economics and Management, North China Electric Power University, Baoding, China

Received: 30 May 2019

Accepted: 7 July 2019

Abstract

The main driving force for huge energy consumption is population growth and economic development, and many studies have analyzed the factors that influence carbon dioxide emissions. But the influencing factors mainly refer to the economic and social fields. Few studies have looked at population factors, and the extended STIRPAT model and ridge regression method are used to pay attention to the impact of population factors on carbon dioxide emissions in the Beijing-Tianjin-Hebei region. The conclusions drawn are as follows:

1) For Beijing, the urbanization level, population density, per capita disposable income, education level, GDP and energy intensity have a positive impact on CO₂ emissions. However, age structure, family size and industrial structure play negative roles. The improvement of urbanization level has a distinctive positive influence on CO₂ emissions.

2) For Tianjin, most impact factors have a positive effect on CO₂ emissions, except family size and energy intensity. The decrease of family size is the first contributor to CO₂ emissions growth.

3) For Hebei, the urbanization level, population density, per capita disposable income, age structure, GDP and industrial structure, have a positive influence on CO₂ emissions.

Education level, family size and energy intensity have a negative impact on CO₂ emissions, and population density is the most important factor.

Keywords: Beijing-Tianjin-Hebei region, CO₂ emissions, population factors, ridge regression, extended STIRPAT model

*e-mail: wenlei0312@126.com

Introduction

Population growth and economic development have made human survival dependent on huge energy consumption. Consequently, energy shortages, the greenhouse effect and climate change have endangered living environments, which restricts sustainable development and has become a “bottleneck” in national economies. The “greenhouse effect” (GHE) was first proposed by a Swedish scientist and it has proven that GHE is attributed largely to CO₂ emissions [1, 2]. As a result, a global consensus that effectively reduces CO₂ emissions has become a major focus facing the world today.

As the largest developing country, China has been making efforts to respond to climate change and assume its responsibilities. Specifically, the Chinese government has proposed a target that CO₂ emissions per GDP should be cut by 40-45% in 2020 compared with that of 2005 [3]. In order to achieve emission reduction targets, the Chinese government has formulated a series of policy plans.

The Beijing-Tianjin-Hebei region, as one of the new economic support zones, accounts for approximately 20% of CO₂ emissions in China, and therefore it is a large CO₂ emissions area of China and even the world. Besides, the increasing rate of CO₂ emissions in this area is high. The annual growth rate of CO₂ emissions is 7.54% during the period of 2000-2014. Therefore, we studied the influence factors of CO₂ emissions and explored the influence degree of each factor in Beijing, Tianjin and Hebei provinces, which have significance in theory as well as in reality.

There are many aspects to carbon dioxide emissions research. On the one hand are indoors and outdoors, especially cities and parks [4, 6]. This shows that PM2.5 has affected human health. Solar radiation in urban areas affects human health. Indoor plants are affected by solar radiation [7, 8], which leads to climate change on the environment as well as forest, coastal, and urban areas [9, 10]. Especially in developing countries, rapid urbanization and increased energy consumption are seriously damaging to human health [11, 13]. A recent study showed that carbon emissions affect thermal comfort and lead to the climate change problem [14, 15]. On the other hand, the influencing factors mainly refer to the economic and social fields. Thus, in addition to the economic and social factors, this paper aims at finding out the specific demographic influence factors of CO₂ emissions. Meanwhile, we explored the influence degree of each factor of CO₂ emissions in Beijing, Tianjin and Hebei, and propose CO₂ emissions reduction suggestions. Research that mainly focuses on the demographic influence on CO₂ emissions and further extends the demographic factors is less.

Literature Review

At present, influencing factors of CO₂ emissions have been researched by several studies. Research on the impact factors of CO₂ emissions have been in the vanguard of attention and are helpful in CO₂ abatement. Driving factors behind CO₂ emissions in China could be broken down into three main drivers: economic growth, energy structure and CO₂ emission efficiency [16]. Another view proposed that it could also be broken down into energy structure, energy intensity, economic structure, and economic output effect. Especially, economic output effect and energy intensity were the first two main drivers [17]. The relationship between CO₂ emissions and economic growth varied from region to region and there was no universal model fitting every country; government should make policies according to the situation of itself [18]. Specifically, researchers investigated the causal relationships among nuclear energy consumption, CO₂ emissions, renewable energy and real GDP per capita of nine developed countries: Canada, France, Japan, Netherlands, Spain, Sweden, Switzerland, Kingdom and the United States, and the results were different from country to country [19]. In terms of China, scholars have found that the affluence effect and population effect were the first two contributors to the growth of CO₂ emissions in Xinjiang Province [20]. Population, urbanization level, GDP per capita, industrialization level and service level were the main causes of CO₂ emissions growth in Guangdong Province [21]. Other researchers have explored the effect of economic activity change, energy intensity change, and population structure change on CO₂ emissions in Beijing [22].

Li JX et al. [23] used the LMDI method and a modified STIRPAT model to study CO₂ emissions in Kazakhstan from 1992 to 2013, the CO₂ emission trajectory has a U-shaped curve. And using ridge regression estimates to indicate every 1% increase in population size, economic activity, energy intensity and energy carbon structure, there is a subsequent increase in CO₂ emissions of 3.13%, 0.41%, 0.30% and 0.63%, respectively. Moreover, different analytical methods are used to examine the impact factors of CO₂ emissions currently. Some scholars have analyzed the change of aggregated CO₂ in China from 1957 to 2000 based on the logarithmic mean divisia index (LMDI) method and discovered that energy intensity was the main cause of CO₂ emissions [24]. Data envelopment analysis (DEA) was applied to investigate the linkages among CO₂ emissions, GDP growth and energy consumption simultaneously [25]. Fixed effects regression results indicate that worldwide exports and United States exports were positively related to per capita CO₂ emissions [26]. Researchers also adopted the IPAT equation to estimate Chinese population, living standards, technology, and other driving forces behind CO₂ emissions [27].

In recent years, the STIRPAT model has been widely used by more researchers. Some articles have applied the STIRPAT model to study the relationships among CO₂ emissions, population, and income levels [28, 30]. One study concluded that population, GDP per capita, industrial structure, energy consumption intensity, and energy consumption structure were the important impact factors of CO₂ emissions through the STIRPAT model [31]. Another article showed that urbanization increased energy consumption and CO₂ emissions in China [32]. Yu et al. [33] used the ridge regression method and the extended STIRPAT model to analyze CO₂ emissions. The results show that population aging, industrial structure and per-capita wealth have a positive impact on the growth of CO₂ emissions, while the impact of energy intensity is negative. At the same time, speeding up construction of the sanatoria industry as well as adjusting the energy and industry structures have been proposed as effective ways to control CO₂ emissions.

It is worth noting that impact factors of CO₂ emissions generally refer to population size, economic level, industrial structure, energy intensity, and so on. The STIRPAT model quite contains these aspects and could be extended to more factors. Thus, it is an appropriate method to explore the impact factors of CO₂ emissions and find the influence degree of each factor through the STIRPAT model.

However, the factors currently focused on are mainly related to economic and social fields. Articles concentrating on detailed demographic influence on CO₂ emissions are not much. This paper not only considers the general impact factors of CO₂ emissions, but also takes specified demographic factors into consideration. Then, based on these and due to the differences among cities and regions, this paper investigates the different influence degrees of each factor to CO₂ emissions in the Beijing, Tianjin and Hebei regions.

Methodology

Measuring CO₂ Emissions

According to the IPCC Guidelines for National Greenhouse Gas Inventories [34], energy-related CO₂ emissions could be calculated by the following formula:

$$CE = \sum_i E_i \times LCV_i \times CEC_i \times COF_i \times \frac{44}{12} \quad (1)$$

... where CE is the total CO₂ emissions (in million tons), i is the i th kind of primary energy, E_i refers to total consumption, LCV_i represents the mean lower calorific value, CEC_i is the CO₂ emissions coefficient, and COF_i indicates the CO₂ oxidation factor. In this article, 8 kinds of primary energy are taken into consideration, including

coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil and natural gas.

STIRPAT Model

In the early 1970s, Ehrlich and Holden first proposed the IPAT equation, which combined environmental impact with population size, affluence and technical level [35, 36]. The equation could be described as follow:

$$I = PAT \quad (2)$$

...where I is the environmental pressure indicator, P is total population, A is affluence and T is technology. IPAT is widely used to analyze the determinants of environmental change.

Since the IPAT equation is an identity, the unity of the units on both sides of the equation is required. More important, the equation in the IPAT model refers to the same ratio between the driving factors and environmental impact, and the application of IPAT can only get the equal proportion of the variables.

To overcome the limitations of IPAT, Dietz et al. established the STIRPAT model, which expressed the IPAT equation in the form of a stochastic model [37]. The model carried out random estimation of environmental impact through statistical regression of population, affluence and technical factors. STIRPAT is expressed as the following equation:

$$I = aP^b A^c T^d e \quad (3)$$

...where I , P , A and T have the same meaning as in IPAT; a is a parameter to be estimated; b , c and d represent the index of population, affluence and technology respectively; and e is the random error. It is obvious that Eq. (3) is the same as Eq. (2) when $a=b=c=d=1$. Hence, IPAT is regarded as a special form of STIRPAT. In empirical study, Eq. (3) could be converted to logarithmic form [38]:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (4)$$

In regression analysis of Eq. (4), regression coefficients reflect the flexible relationship between independent variables and dependent variables. It is when the other independent variables are maintained, the percentage change of the dependent variable caused by the 1% change of one independent variable. The elastic coefficients may be positive (positive effect) or negative (negative effect).

It is worth pointing out that the impact factors of environmental pressure in STIRPAT can also be extended to multiple driving factors. Except for the basic exponents P , A , and T , extra factors could also be considered. Due to its flexibility, the extended STIRPAT model is used in this study to examine the impact

factors of CO₂ emissions in the Beijing-Tianjin-Hebei region in China.

In this paper, considering the specific situation in China, the extended STIRPAT model is built with 9 driving factors to estimate CO₂ emissions. To be noted, besides basic factors, extra driving factors in this study are mainly expanded from population terms.

Extended STIRPAT model in this paper can be expressed as:

$$\ln CE = \ln a + b \ln P_1 + c \ln P_2 + d \ln P_3 + e \ln P_4 + f \ln P_5 + g \ln P_6 + h \ln A + i \ln T_1 + j \ln T_2 \quad (5)$$

Details of variables in Eq. (5) are described in Table 1.

Ridge Regression

A general method to estimate the model parameters in multiple regression is the ordinary least squares (OLS) method. However, if two or more independent variables in a multiple regression model are strongly and linearly related, namely multicollinearity [39], the use of OLS to estimate the parameters of the model will have adverse consequences. Multicollinearity could lead to the generation of large standard errors in parameter estimation. Moreover, the economic meaning of parameter estimation is not reasonable, and the significance test of the variable is meaningless.

These standard errors could be significantly reduced by using a certain method so that the negative consequences of such errors can be effectively eliminated even when multicollinearity remains in the regression model. Ridge regression, which can obtain acceptably biased estimates with smaller mean square errors in independent variables through bias-variance tradeoffs, it is one of the most effective solutions for dealing with multicollinearity.

Consider the classical multiple linear regression model [40, 41]:

$$Y = \beta X + \varepsilon \quad (6)$$

...where Y is a $(n \times 1)$ matrix of dependent variables and X is a $(n \times m)$ matrix of independent variables. β is a $(m \times 1)$ vector of coefficients and ε denotes the normally distributed random errors. The estimation of β could be carried out as:

$$\hat{\beta} = (X'X)^{-1} X'Y \quad (7)$$

When there is a multicollinearity between the independent variables, the $|X'X|$ matrix is ill-conditioned, $|X'X| \approx 0$. Therefore, the calculation of the $|X'X|^{-1}$ matrix is sensitive to slight variations in the data. The OLS estimation of coefficients becomes unstable and has large variance [42]. Ridge regression assumes to combine the $|X'X|$ matrix with a constant matrix kI ($k > 0$). Thus, the degree of proximity to the singularity of the $|X'X + kI|$ matrix is much smaller than that of the $|X'X|$ matrix. The specified equation of ridge regression could be expressed as:

$$\hat{\beta}(k) = (X'X + kI)^{-1} X'Y \quad (8)$$

Eq. (8) is regarded as the estimation of β by using ridge regression, and the parameter k is called ridge parameter.

Material in Empirical Study

Data Analysis

Panel data covering the period of 1996-2014 are obtained respectively from Beijing, Tianjin, Hebei and

Table 1. Definitions of variables used in this paper.

Symbol	Variable	Definition	Unit
CE	CO ₂ emissions	Total carbon dioxide emissions	million tons
P ₁	Urbanization level	The ratio of urban population over total population	%
P ₂	Population density	Population per unit area	unit/ square kilometer
P ₃	Per capita disposable income	Income that can be used for free disposable	Yuan
P ₄	Age structure	The ratio of population between the ages of 15 and 64 over total population	%
P ₅	Education level	The population size above college degree	million
P ₆	Family size	The ratio of total population over the number of households	units/household
A	GDP	Gross domestic product	billion Yuan
T ₁	Industrial structure	The secondary industry share of GDP	%
T ₂	Energy intensity	Energy consumption per unit of GDP	tons of standard coal/10,000 Yuan

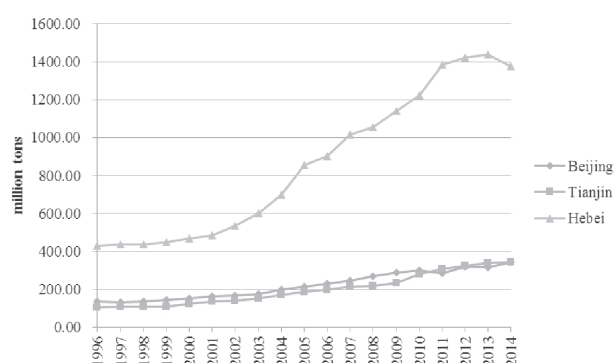


Fig. 1. Total carbon emission changes from 1996 to 2014.

Chinese Statistical Yearbooks, including per capita disposable income, education level, and GDP. Other data are difficult to be acquired directly in references, but they can be figured out through fixed formulas that have already been shown in Table 1.

Energy-Related CO₂ Emissions

Energy-related CO₂ emissions in Beijing, Tianjin and Hebei during 1996–2014 are shown in Fig. 1.

In Beijing, CO₂ emissions had a stable growth trend, which grew 1.51 times from 1996 to 2014. The CO₂ emissions increased from 136.67 million tons in 1996 to 343.35 million tons in 2014, with an annual growth rate of 5.25%. In Tianjin, CO₂ emissions increased from 106.01 million tons to 344.08 million tons during 1996–2014. The annual growth rate was 6.76%, which was slightly higher than that of Beijing.

Compared with Beijing and Tianjin, the growth of CO₂ emissions in Hebei province could be separated into three parts. From 1996 to 2001, there was no obvious growth of CO₂ emissions. However, during 2001–2011, CO₂ emissions increased sharply. It soared from 484.89 million tons to 1384.66 million tons and the annual growth rate was 11.06%. During this period of economic development based on the cost of destroying the environment, because of the only aim to develop economy and low awareness of environment protection. Therefore, the growth of CO₂ emissions was fast from 2011 to 2014. The positive activities of human beings have slowed down the greenhouse effect, and improved the consciousness of energy saving and emission reduction, so the increase of CO₂ emissions tended to slow or even decline.

Population-Related Indicators

As indicated in Fig. 2, urbanization levels of Beijing, Tianjin and Hebei had different trends. Beijing as a highly urbanized city, and though the urbanization level increased, it experienced almost no change. As for Tianjin, as a result of accelerating the opening up of the economy, people have poured in and accelerated the process of urbanization. The urbanization level grew

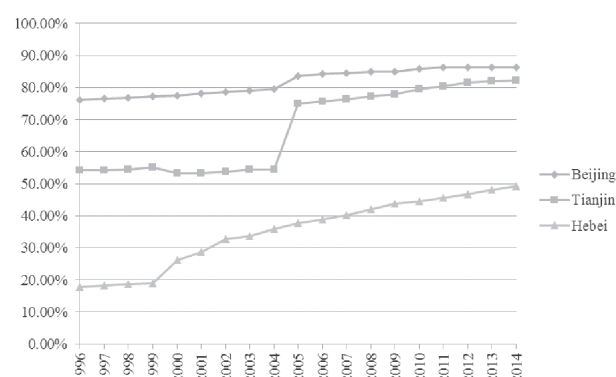


Fig. 2. Changes of urbanization level from 1996 to 2014.

from 54.33% in 2004 to 75.07% in 2005, after which Tianjin became a city with a high level of urbanization. The urbanization process in Hebei province could be divided into two parts. Before 1999, the urbanization level was approximately 20%. Since 1999, the urbanization level has been rising rapidly, which grew from 18.97% in 1999 to 49.32% in 2014 with an annual growth rate of 6.58%. Although there was significant improvement of the urbanization level in Hebei, it was still lower than that of Beijing and Tianjin.

Population density in Beijing, Tianjin and Hebei is described in Fig. 3, which reflected the space intensity of population. Before the 21st century, the population density in Beijing and Tianjin remained constant and was about 800 units per square kilometer. But since entering the 21st century, Beijing and Tianjin have become the two most developed areas in China, attracting a large influx of the floating population. Therefore, the population density in Beijing rose from 830.93 units per square kilometer in 2000 to 1311 units per square kilometer in 2014, with an annual increase rate of 3.31%. In Tianjin, the population density increased from 851 units per square kilometer in 2000 to 1290 units per square kilometer in 2014, with an annual increase rate of 3.02%.

As for Hebei, population density changed little. It was 345.46 units per square kilometer in 1996 and

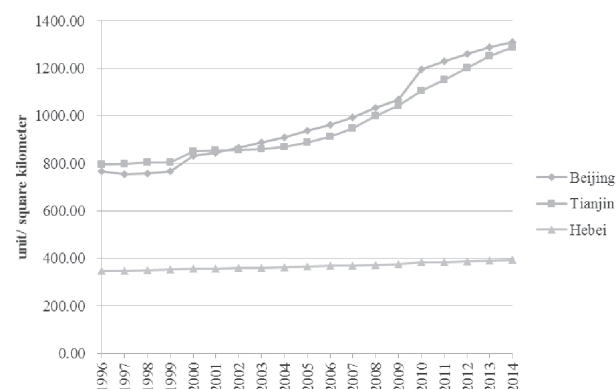


Fig. 3. Changes of population density from 1996 to 2014.

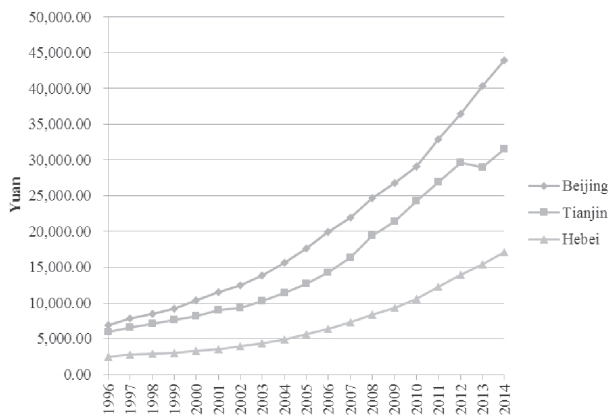


Fig. 4. Changes of per capita disposable income from 1996 to 2014.

393.41 units per square kilometer in 2014, with an annual growth rate of 0.72%. Because the development in Hebei was slower than that of Beijing and Tianjin, there was not much population flow.

Curves in Fig. 4 indicated the changes of per capita disposable income. In Beijing, per capita disposable income has kept rapid growth, from 6885.5 Yuan in 1996 to 43910 Yuan in 2014, for an annual increase rate of 10.84%. In Tianjin, per capita disposable income rose from 5967.71 Yuan in 1996 to 31506 Yuan in 2014, for an annual increase rate of 9.68%. The increase rate of per capita disposable income in Hebei was the fastest, growing from 2476.49 Yuan in 1996 to 17069.22 Yuan in 2014, for an annual increase rate of 11.32%, which indicated the continuous improvement of living levels in Hebei province.

Age structure was the ratio of population between the ages of 15 and 64 over total region population, whose change trends are shown in Fig. 5. To some extent, the number of people between the ages of 15 and 64 represented the labor force in a region.

It could be drawn from Fig. 5 that the ratio of population between the ages of 15 and 64 over total region population in three areas had a trough in the year of 2001. Due to the control of rapid growth of total

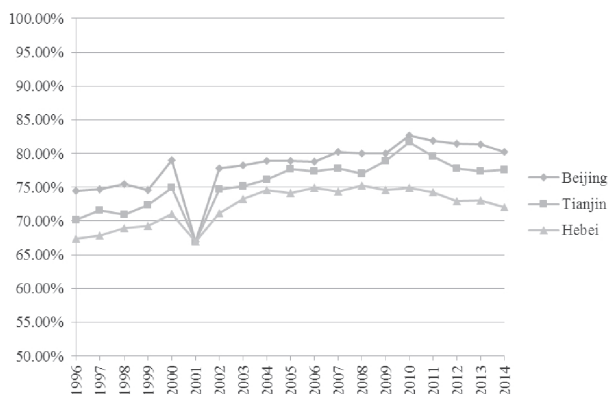


Fig. 5. Changes of age structure from 1996 to 2014.

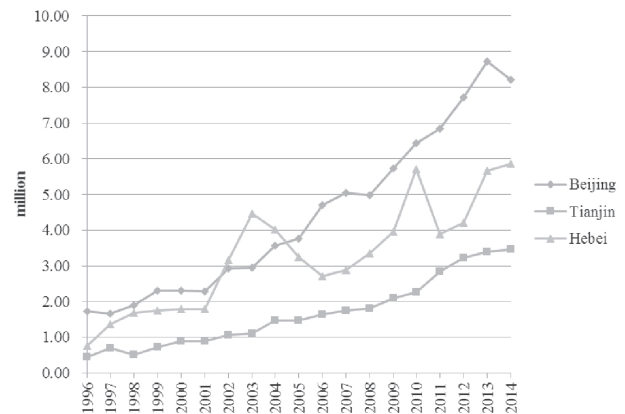


Fig. 6. Changes of education levels from 1996 to 2014.

population, since the beginning of reform and opening up, the Chinese government has maintained a “one-child policy”. The decline in birth rate resulted in less labor force at the beginning of the 21st century. Except for the obvious fall in 2001, the ratio of population between the ages of 15-64 over total region population in three regions during 1996-2014 increased a little with fluctuations. But in general, the ratio kept between 65-85%, which indicated that the age structure in Beijing, Tianjin and Hebei was stable and had an abundant labor force.

Fig. 6 describes the education level change trends of Beijing, Tianjin and Hebei. Education level was an indicator representing the extent of people receiving higher education. In this article, education level was expressed as the population above college degree.

As the figure indicates, the number of people with more than a college degree in Beijing has grown quickly. Economic development needed more professional and technological people, which accelerated educational development. The number of people increased from 1.72 million in 1996 to 8.21 million in 2014, with an annual growth rate of 9.06%. Similarly, educational development was faced with Tianjin. The amount of the population with more than a college degree had risen

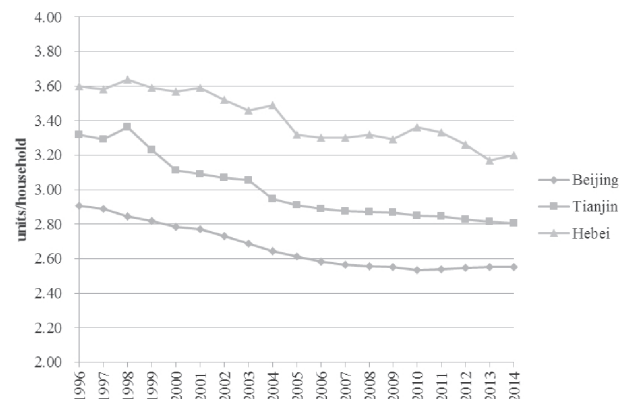


Fig. 7. Changes of family size from 1996 to 2014.

from 0.44 million to 3.47 million between 1996-2014, for an annual increase rate of 12.21%.

In Hebei, the number of people above college degree during 1996-2014 grew sharply with fluctuations. It grew from 0.76 million in 1996 to 5.86 million in 2014, which was a 7.68-times increase, with an annual growth rate of 11.99%. There were two peaks: in the Chinese 10th and 12th Five-Year Plan periods.

Family size used in this paper was the ratio of total population over the number of households, indicating the number of people in a family. As shown in Fig. 7, family sizes in Beijing, Tianjin and Hebei province had a general trend to decline.

Due to the Chinese “one-child policy”, most families have only one child at most. Besides, DINK families, which had shattered the traditional idea of a Chinese family, kept on increasing. In Beijing, the annual decreasing rate of family size was 0.72%. In Tianjin, family size also tended to be reduced. During 1996-2014, it declined with an annual decreasing rate of 0.94%, which was faster than that of Beijing. Family size in Hebei dropped with fluctuations from 3.6 units per household in 1996 to 3.2 units per household in 2014. The annual decreasing rate was 0.65%, which was the lowest in three regions.

Economic Development

In this article, GDP was used as an indicator to reflect the economic development in Beijing, Tianjin and Hebei.

From Fig. 8, we can conclude that GDP in Beijing, Tianjin and Hebei from 1996 to 2014 surged. The economic scale in Beijing grew from 178.92 billion yuan in 1996 to 2133.08 billion yuan in 2014. In Tianjin, the economy developed from 112.19 billion yuan in 1996 to 1572.69 billion yuan in 2014. The economy in Hebei increased from 346.82 billion yuan to 2950.13 billion yuan between the years of 1996 and 2014.

Specifically, economic development during the period of 1996-2014 could be separated into two parts. Before the year of 2000, GDP in three regions developed

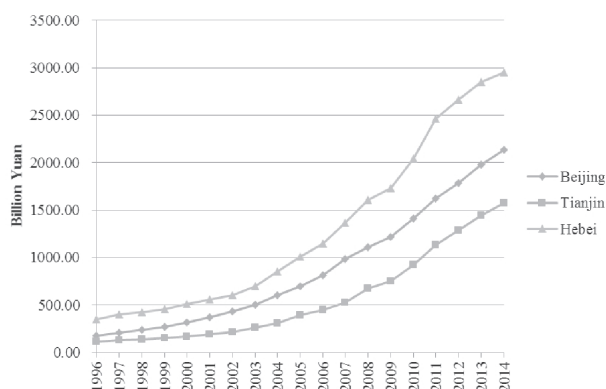


Fig. 8. Changes of GDP from 1996 to 2014.

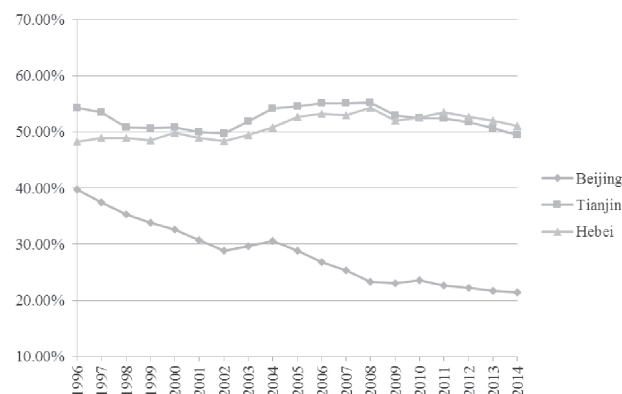


Fig. 9. Changes of industrial structure from 1996 to 2014.

slowly and there was not much improvement. However, since the 21st century, because of the new economic policy and the higher opening-up level, GDP kept increasing rapidly.

Technology-Related Indicators

In this case study, as described in Fig. 9, the changes of the secondary industry share of GDP that characterized the industrial structure behaved as different trends in Beijing, Tianjin and Hebei.

The secondary industrial share of GDP in Beijing performed a general declining trend. For Beijing, as one of most developed cities in China, environmental pollution deteriorated as the economy improved. Therefore, Beijing had transferred a part of the second industry and focused on fostering the third industry. The secondary industry share of GDP in Beijing decreased from 39.8% in 1996 to 21.4% in 2014, with an annual declining rate of 3.51%. However, the share of the secondary industry in GDP in Tianjin and Hebei has changed over time. But the proportion was roughly constant. It stayed at around 50 percent, which indicated that the secondary industry was still a significant pillar of economic growth.

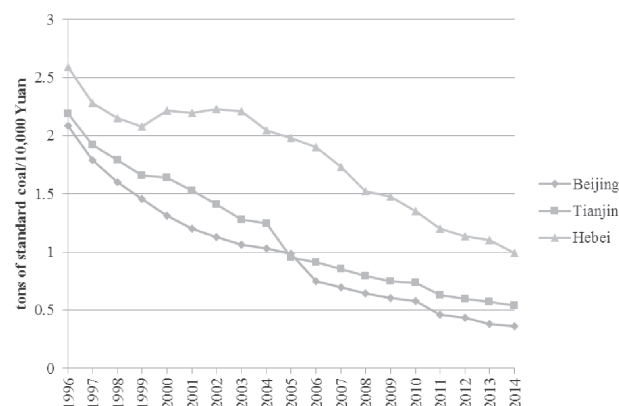


Fig. 10. Changes of energy intensity from 1996 to 2014.

Energy intensity in this paper was the standard coal consumption per unit of gross domestic product, as performed in Fig. 10. It was obvious that the energy intensity in Beijing, Tianjin and Hebei presented an overall decreasing trend.

Technology improvement reduced the energy consumption per unit output value. In Beijing, energy intensity dropped from 2.09 tons of standard coal per 10,000 yuan in 1996 to 0.36 tons of standard coal per 10,000 yuan in 2014, with an average annual

Table 2. Results of correlation test.

	LnCE	LnP1	LnP2	LnP3	LnP4	LnP5	LnP6	LnA	LnT1	LnT2
1.Beijing										
LnCE	1									
LnP1	0.978**	1								
LnP2	0.974**	0.939**	1							
LnP3	0.990**	0.967**	0.984**	1						
LnP4	0.716**	0.727**	0.704**	0.708**	1					
LnP5	0.988**	0.970**	0.978**	0.993**	0.744**	1				
LnP6	-0.958**	-0.965**	-0.902**	-0.951**	-0.736**	-0.955**	1			
LnA	0.991**	0.972**	0.979**	0.998**	0.719**	0.994**	-0.965**	1		
LnT1	-0.972**	-0.952**	-0.954**	-0.981**	-0.677**	-0.973**	0.951**	-0.984**	1	
LnT2	-0.976**	-0.950**	-0.982**	-0.995**	-0.686**	-0.987**	0.929**	-0.990**	0.983**	1
2.Tianjin										
LnCE	1									
LnP1	0.913**	1								
LnP2	0.966**	0.862**	1							
LnP3	0.993**	0.920**	0.970**	1						
LnP4	0.797**	0.795**	0.696**	0.796**	1					
LnP5	0.981**	0.875**	0.935**	0.976**	0.812**	1				
LnP6	-0.936**	-0.864**	-0.837**	-0.925**	-0.829**	-0.961**	1			
LnA	0.996**	0.924**	0.970**	0.998**	0.797**	0.979**	-0.930**	1		
LnT1	0.010	0.227	-0.174	-0.016	0.267	-0.012	-0.150	-0.003	1	
LnT2	-0.987**	-0.939**	-0.945**	-0.991**	-0.811**	-0.980**	0.945**	-0.994**	-0.026	1
3.Hebei										
LnCE	1									
LnP1	0.924**	1								
LnP2	0.967**	0.913**	1							
LnP3	0.983**	0.914**	0.994**	1						
LnP4	0.765**	0.824**	0.665**	0.684**	1					
LnP5	0.817**	0.899**	0.857**	0.840**	0.782**	1				
LnP6	-0.952**	-0.899**	-0.908**	-0.936**	-0.745**	-0.781**	1			
LnA	0.992**	0.928**	0.989**	0.997**	0.726**	0.845**	-0.939**	1		
LnT1	0.854**	0.797**	0.734**	0.769**	0.845**	0.609**	-0.818**	0.810**	1	
LnT2	-0.923**	-0.794**	-0.967**	-0.967**	-0.532*	-0.759**	0.852**	-0.953**	-0.667**	1

Notes: ** and * indicate significance at the 1% and 5% levels

Table 3. Results OLS regression in Beijing.

Variables	Unstandardized coefficients	t-Statistic	Sig.	VIF
Constant	-6.447	-1.256	0.241	
LnP1	0.918	0.860	0.412	30.704
LnP2	0.463	0.900	0.392	105.118
LnP3	1.281	1.574	0.150	2481.131
LnP4	-0.223	-0.657	0.528	3.000
LnP5	0.283	1.407	0.193	133.924
LnP6	-1.121	-0.390	0.706	213.825
LnA	-0.626	-0.818	0.434	4187.145
LnT1	-0.626	-1.602	0.144	63.608
LnT2	0.688	2.340	0.044	269.580
Adjusted R ²	0.985			
F test	132.736			
Sig.	0.000			

decreasing rate of 10.26%. Energy intensity in Tianjin decreased significantly as well, changing from 2.19 tons of standard coal per 10,000 yuan in 1996 to 0.54 tons of standard coal per 10,000 yuan in 2014, with an average annual decreasing rate of 8.11%.

For Beijing and Tianjin, energy intensity in Hebei performed a complicated change trend, which declined with fluctuations. From 1996 to 1999, energy intensity decreased rapidly. After a slight rise, it continued to its present a downward trend. In general, energy intensity in Hebei decreased from 2.59 tons of standard coal per 10,000 yuan in 1996 to 0.99 tons of standard coal per 10,000 yuan in 2014, with an annual decreasing rate of 5.46%.

Calculation and Results

Multicollinearity Test

Logarithmic processing of each variable is carried out first to eliminate the effect of the variable's dimension before the correlation test. Table 2 presents the results of the correlation test of all variables, which indicates that there are high correlations among the variables used in this article. It is reasonable to assume that multicollinearity among variables could exist.

Next, we use the ordinary least squares (OLS) method to determine whether there is multicollinearity among variables or not. Take Beijing as an example. Table 3 describes the result of the OLS regression model. It is evident that the fitting degree, checked by the adjusted $R^2 = 0.985$, is excellent, and the regression equation is significant, checked by the F-statistic $\text{Sig.} < 0.05$.

Table 4. Results OLS regression in Tianjin.

Variables	Unstandardized coefficients	t-Statistic	Sig.	VIF
Constant	7.888	1.136	0.285	
LnP1	0.201	0.615	0.554	54.080
LnP2	-0.486	-0.541	0.602	282.411
LnP3	-0.443	-1.513	0.165	361.075
LnP4	-0.136	-0.358	0.728	4.713
LnP5	0.112	0.784	0.453	109.039
LnP6	-0.486	-0.575	0.580	35.161
LnA	1.065	2.329	0.045	2224.341
LnT1	-0.326	-0.447	0.666	10.069
LnT2	0.748	1.354	0.209	830.396
Adjusted R ²	0.992			
F test	260.390			
Sig.	0.000			

However, all independent variables are not significant (t -Statistic $\text{Sig.} > 0.05$), except for variable T_2 . Besides, to be noted, the value of variance inflation factor (VIF) characterizes that there is multicollinearity among variables. VIF is the most commonly used criterion of the multicollinearity of independent variables in the regression model [43]. Generally speaking, it could be concluded that multicollinearity among variables does exist when the value of VIF is higher than 10. As Table 3 performed, except variable P_4 , VIF values of all variables are much higher than 10. Thus, the multicollinearity among variables could affect the estimation of OLS, and the regression coefficients of OLS have low credibility. OLS could not well reflect the relationships between the influence factors and the energy-related CO₂ emissions in Beijing.

Similarly, the multicollinearity among variables could also be found in the data of Tianjin and Hebei, as shown in Tables 4 and 5.

Ridge Regression Estimation

To overcome the limitations of OLS regression, ridge regression is done in this part to estimate the coefficients in the STIRPAT model, which could improve the stability and reliability of the regression coefficients and reduce large standard errors among related independent variables [44, 46].

Take Beijing as an example as well. Based on the estimation of Eq. (8), the ridge regression coefficient is selected according to the ridge trace and the relationship between R square and K , shown in Figs 11 and 12. From the curves of ridge trace in Fig. 11, when the value of K is between 0 and 0.02, regression coefficients of independent variables change sensitively. But when the

Table 5. Results OLS regression in Hebei province.

Variables	Unstandardized coefficients	t-Statistic	Sig.	VIF
Constant	7.455	0.647	0.534	
LnP1	-0.480	-3.862	0.004	64.987
LnP2	-1.464	-0.812	0.438	180.570
LnP3	0.094	0.241	0.815	1992.563
LnP4	0.384	0.728	0.485	14.256
LnP5	-0.039	-0.946	0.369	16.751
LnP6	-0.121	-0.184	0.858	28.292
LnA	1.251	4.440	0.002	1419.588
LnT1	-0.496	-0.687	0.509	27.423
LnT2	0.993	3.756	0.005	197.714
Adjusted R ²	0.998			
F test	808.577			
Sig.	0.000			

K value is bigger than 0.02, the coefficients all maintain stability with little change. Fig. 12 indicates that the R square of ridge regression changes with different values of K. It is evident that the R square changes with a high change rate before K = 0.02, but the rate becomes much lower after K = 0.02. Therefore, when K = 0.02, regression coefficients and R square are both stable and it is reasonable to choose 0.02 as the value of K. The fitted ridge regression equation is:

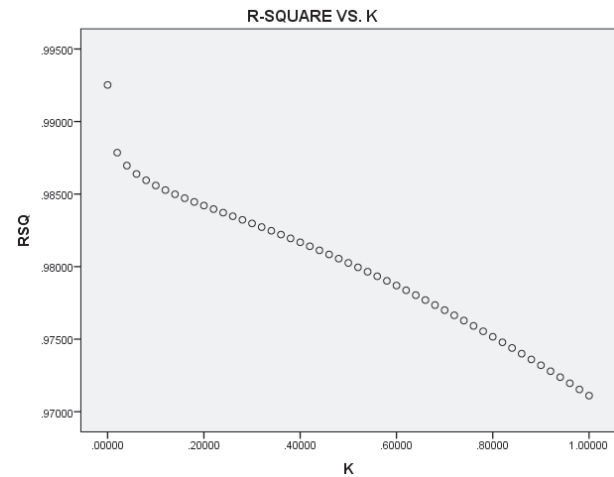


Fig. 12. Changes of RSQ under different K (Beijing).

$$\begin{aligned}
 \text{LnCE} = & -3.7393 + 1.5258\text{LnP1} + 0.3524\text{LnP2} + 0.0955\text{LnP3} \\
 & -0.1082\text{LnP4} + 0.0970\text{LnP5} - 0.6761\text{LnP6} \\
 & + 0.0577\text{LnA} - 0.1049\text{LnT1} + 0.0282\text{LnT2}
 \end{aligned} \quad (9)$$

Similarly, according to Figs 13-16, the most advisable value of K in the ridge regression of energy-related CO₂ emissions and its influence factors in Tianjin is 0.03, and as well in Hebei. The fitted ridge regression equation in Tianjin is shown as Eq. (10) and in Hebei is described as Eq. (11):

$$\begin{aligned}
 \text{LnCE} = & -2.5367 + 0.0048\text{LnP1} + 0.7061\text{LnP2} + 0.1199\text{LnP3} \\
 & + 0.0498\text{LnP4} + 0.0917\text{LnP5} - 0.7630\text{LnP6} \\
 & + 0.1012\text{LnA} + 0.4399\text{LnT1} - 0.0992\text{LnT2}
 \end{aligned} \quad (10)$$

$$\begin{aligned}
 \text{LnCE} = & -13.7975 + 0.0612\text{LnP1} + 1.5661\text{LnP2} + 0.1594\text{LnP3} \\
 & + 1.0954\text{LnP4} - 0.0600\text{LnP5} - 1.4592\text{LnP6} \\
 & + 0.1649\text{LnA} + 1.4554\text{LnT1} - 0.1612\text{LnT2}
 \end{aligned} \quad (11)$$

Discussion

Analysis of Ridge Regression Results in Beijing

According to the signs of coefficients in Eq. (9), it is apparent that urbanization level, population density, per capita disposable income, education level, GDP and energy intensity have positive impacts on CO₂ emissions in Beijing. However, age structure, family size and industrial structure play negative roles. The influence degree of each factor, no matter whether the impact is positive or negative, could be represented by the absolute value of its elastic coefficient in decreasing order as: urbanization level, family size, population

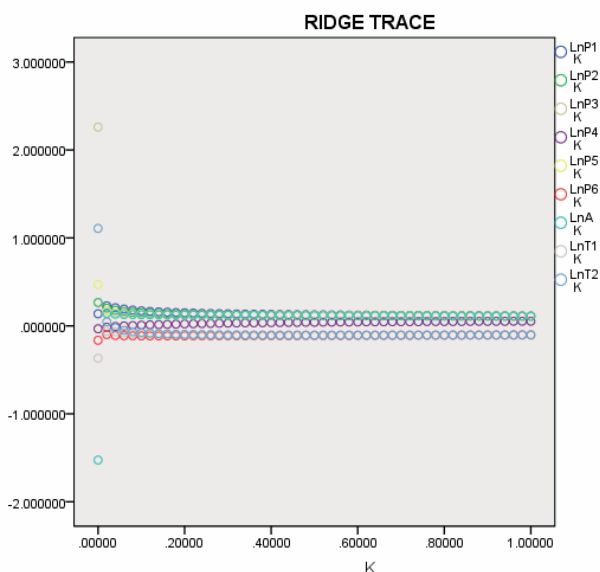


Fig. 11. Curves of ridge trace (Beijing).

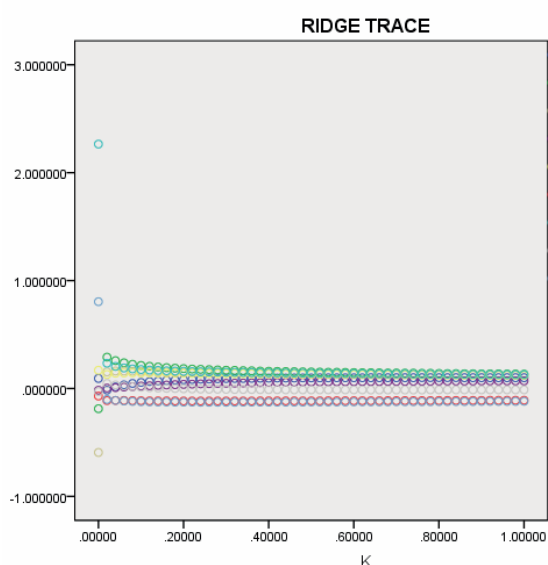


Fig. 13. Curves of ridge trace (Tianjin).

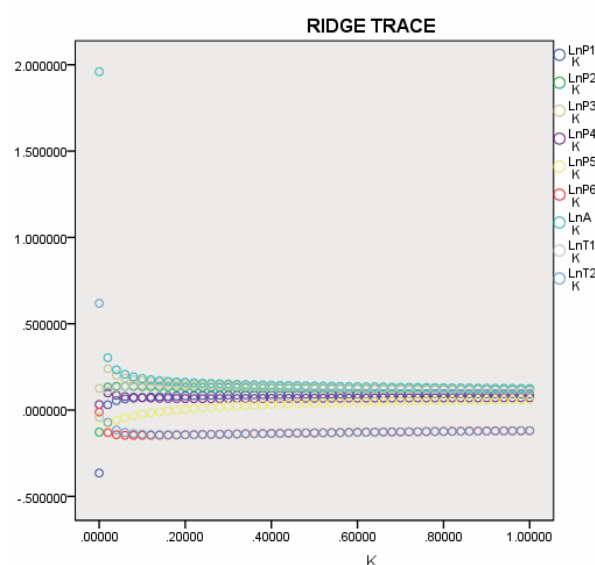


Fig. 15. Curves of ridge trace (Hebei).

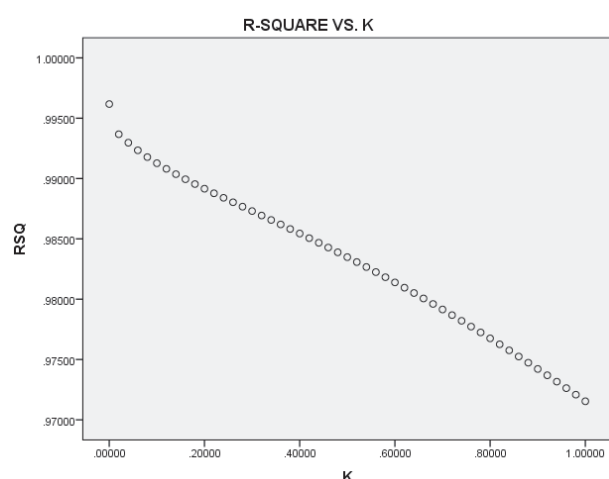


Fig. 14. Changes of RSQ under different K (Tianjin).

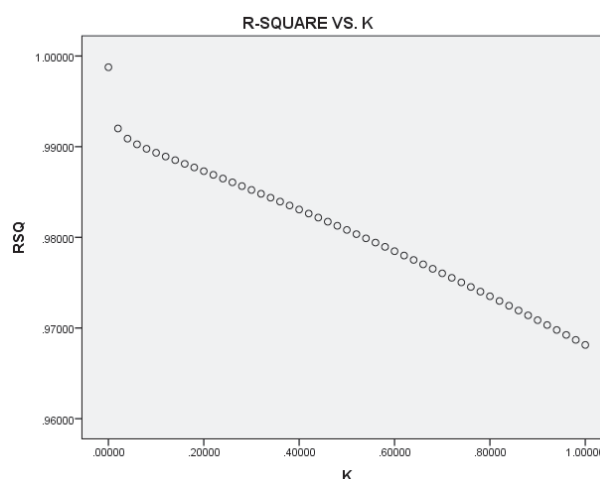


Fig. 16. Changes of RSQ under different K (Hebei).

density, age structure, industrial structure, education level, per capita disposable income, GDP and energy intensity.

The improvement of urbanization level in Beijing has a distinctive positive influence on CO₂ emissions. Its elastic coefficient is 1.5258, indicating that every 1% improvement in urbanization level will give rise to a 1.5258% increase in CO₂ emissions. However, to be noted, the process of urbanization in Beijing has become slow. The annual growth rate of urbanization level in Beijing was 0.71% from 1996 to 2014. Thus, though urbanization level has great impact on CO₂ emissions, the improvement of urbanization in Beijing is little and it will not bring a huge increase in CO₂ emissions.

Family size is another significant contributing factor to the growth of CO₂ emissions. The coefficient of family size indicates that the influence of family size on CO₂ emissions is negative, and that every 1%

decrease in family size will bring about a 0.6761% increase in CO₂ emissions. Energy consumption in daily life has much to do with the number of people in a family. Total energy consumption of a family is almost unchanged. The fewer persons in a family, the more families in a city, and therefore the larger total energy consumption in a city. CO₂ emissions as a byproduct of energy consumption will increase. According to Fig. 7, the family size in Beijing has been decreasing these years. Consequently, CO₂ emissions will grow with the decrease of family size.

Population density has an important effect on CO₂ emissions as well. Its elastic coefficient is 0.3524, which means that every 1% growth in population density will give rise to a 0.3524% increase in CO₂ emissions. The large population in Beijing is bound to increase the energy consumption of economic activities. Moreover, energy consumption in residents' daily life

also increases. Growth of population density in Beijing will increase CO₂ emissions and could not be ignored. The coefficient of elasticity of other influencing factors is small, indicating that their impact on carbon dioxide emissions is not significant. It is worth noting that age structure and industrial structure generally have a positive impact on CO₂ emissions. But they have played negative roles in the growth of CO₂ emissions in Beijing.

Due to technological improvement and industrial structure adjustment, increasing population aging 15-64 is absorbed by the tertiary industry instead of the expansion of the second industry. Therefore, CO₂ emissions have decreased with the development of the service industry. Moreover, industrial output value-added owing to technological progress is much higher than that owing to extensive growth. Thus, even if the scale of the second industry is reduced, the gross industrial output value also increases. CO₂ emissions decrease with the increasing secondary industry share of GDP.

Besides, in general, education level has a negative influence on CO₂ emissions. But the coefficient of it is 0.0970, contrary to common sense. Due to the high modernization level and rapid technology improvement, it is unlikely for Beijing to reduce energy consumption through technical progress. The space of it is limited. Consequently, more emerging industries grow fast with the development of higher education, which increases CO₂ emissions instead of reducing CO₂ emissions on the basis of original industry scale through advanced technology.

Analysis of Ridge Regression Results in Tianjin

The signs of the coefficients in Eq. (10) indicate that most impact factors have a positive effect on CO₂ emissions except for family size and energy intensity. Ignoring the influence direction, influence degree could be represented by the absolute value of elastic coefficient in decreasing order as: family size, population density, industrial structure, per capita disposable income, GDP, energy intensity, education level, age structure, and urbanization level.

The decrease of family size is the first contributor to the CO₂ emissions growth in Tianjin. Coefficient of family size indicates that the influence of family size on CO₂ emissions is negative, and every 1% decrease in family size will bring about a 0.7630% increase in CO₂ emissions. The reason behind this phenomenon is the same as in Beijing. Under the decreasing trend of family size in Tianjin, the influence of it on CO₂ emissions should be paid attention.

Population density is another important factor for CO₂ emissions. Its elastic coefficient illustrates a 0.7061% increase in CO₂ emissions owing to every 1% growth in population density. Population agglomeration will inevitably lead to the increase of energy

consumption in social life, resulting in the increase of CO₂ emissions. With the rapid development of Tianjin in recent years, more immigrants will flood into the city, which brings about CO₂ emissions growth.

Industrial structure is the third contributor to CO₂ emissions, with an elastic coefficient of 0.4399. This means that a 1% increase of the secondary industry share of GDP will cause 0.4399% growth of CO₂ emissions. The proportion of the secondary industry in GDP stays around 50 percent, which indicates that the secondary industry is the dominant industry in Tianjin. However, technology improvement in Tianjin is not as fast as that in Beijing, resulting in huge CO₂ emissions with the expansion of the secondary industry.

CO₂ emissions are less responsive to other factors. However, the influence directions of education level and energy intensity shown by Eq. (10) are not as expected.

The reason behind the phenomenon that educational progress causes growth of CO₂ emissions in Tianjin is the same as in Beijing. As for energy intensity, lower energy intensity should bring about a CO₂ emissions decrease. However, if energy consumption growth rate is lower than economic development rate, energy intensity decreases. On this condition, although energy intensity decreases, total energy consumption and economic scale are expanding, leading to an increase in CO₂ emissions. As shown in Fig. 8, annual growth rate of GDP in Tianjin has achieved 15.80% during 1996-2014. The growth rate of energy consumption is slower than the expansion of the economy. Thus, even if energy intensity is expressed as a downward trend, total CO₂ emissions increase.

Analysis of Ridge Regression Results in Hebei Province

Eq. (11) provides ridge regression estimation results of Hebei Province. Impact factors – including urbanization level, population density, per capita disposable income, age structure, GDP and industrial structure – have a positive influence on CO₂ emissions. Education level, family size and energy intensity have a negative impact on CO₂ emissions. The importance degree of all impact factors could be expressed by the absolute values of elastic coefficients in decreasing order without considering the influence direction, namely population density, family size, industrial structure, age structure, GDP, energy intensity, per capita disposable income, urbanization level and education level.

Population density is the most important factor for CO₂ emissions in Hebei. Obviously, the coefficient value of population density indicates that a 1.5661% growth in CO₂ emissions is from every 1% growth in population density. However, CO₂ emissions in Hebei do not seem to increase because of the steady trend of population density.

Family size is the second contributing factor to CO₂ emissions. From the coefficient value of family size, it suggests that a 1% decrease in family size would cause

a 1.4592% increase in CO₂ emissions. Family size of Hebei has dropped during 1996-2014, and there is still a declining trend in the future. Thus, increasing CO₂ emissions will be largely affected by the decreasing family size since then.

Industrial structure is another significant impact factor for CO₂ emissions with a coefficient value of 1.4554. This indicates that a 1% increase of the secondary industry share of GDP will cause 1.4554% growth of CO₂ emissions. The secondary industry is a major field of energy consumption. In recent years, the development of it in Hebei province mainly relies on extensive growth accompanied by huge energy consumption, rather than the advances in industrial technology. Therefore, CO₂ emissions increase greatly. Secondary industry accounts for approximately 50% of GDP in Hebei. The progressive decrease of energy consumption in secondary industry seems to be a key promotion to the decrease of CO₂ emissions.

Age structure is an impact factor could not be ignored. The coefficient of it indicates that every 1% growth in the ratio of population between the ages of 15 and 64 over total population will cause a 1.0954% increase in CO₂ emissions. Economic development in Hebei depends mainly on industrial development, but tertiary industry is undeveloped. Thus, more people aging 15-64 are involved in industrial production, which makes CO₂ emissions increase.

Other impact factors have no significant effect on CO₂ emissions. But it is worth noting that the influence direction of energy intensity is not in general cognition. The cause of this phenomenon in Hebei could be explained the same way as in Tianjin. Due to advanced technology, energy consumption per unit of GDP declines. However, total economic scale is still expanding, eventually leading to an increase in CO₂ emissions.

Conclusions and Policy Suggestions

In this study, the extended STIRPAT model is established as a foundation to explore the impact factors and their influence degrees to CO₂ emissions in Beijing, Tianjin and Hebei. Focusing on the influence of demographic impact factors to CO₂ emissions is the novelty of this paper. In addition to the generally considered factors, such as GDP, industrial structure and energy intensity, demographic factors include urbanization level, population density, per capita disposable income, age structure, education level, and family size.

Based on the discussion of different influence degrees to CO₂ emissions of each impact factor in Beijing, Tianjin and Hebei, targeted policy implications to reduce CO₂ emissions in three areas are provided respectively.

In terms of Beijing, because of the "one-child policy" in China and the high divorce rate in recent

years, family size has decreased. Encouraging fertility and propagating social values of marriage stability and family togetherness could be advisable. Besides, from the perspective of population development, the population of Beijing, especially in the city center, should be evacuated. Government could improve the existing household registration system, reasonably distribute population, and actively guide the flow of migrant workers to surrounding cities. Meanwhile, in order to avoid excessive population growth, population quality and structure need to be optimized in order to control the population size under the scale of environmental carrying capacity.

Besides, government should also evacuate non-core functions of Beijing to achieve industrial restructuring while maintaining moderate economic growth. Specifically, retain the core functions of Beijing as the political, cultural, and international communication and technological innovation center, and eliminate high pollution and high energy consumption industries represented by the non-ferrous metal industry, textile printing and dyeing industry, machinery industry, printing industry and paper industry. Simultaneously, guide Beijing exiting parts manufacturing, the petrochemical industry and other manufacturing industries. Moreover, government should vigorously support new energy and high-tech industry, and encourage tourism, cultural industry, lifestyle service and other emerging services as well.

For Tianjin, such actions could also be considered to expand family size and limit population inflow as in Beijing. Besides, Tianjin's economic growth is mainly driven by the secondary industry at present. It is suggested that local government should adjust the industrial structure to the direction of low energy consumption and low CO₂ emissions. Moreover, Tianjin should strengthen its cooperation with Beijing and maximize its advantages in science and technology, resulting in the appearance of more high-value and high-efficiency industrial clusters. At the same time, continuously improve the proportion of the tertiary industry in the regional economy, including the information industry, Big Data, e-commerce, eco-tourism, etc. Additionally, during China's 13th Five-Year Plan period, based on Tianjin's resource advantages, higher priority should be given to further improve the renewable energy industry system, which focuses on wind power and the solar photovoltaic industry, and further intensify the combination of production, learning and research in order to build a renewable energy industry gathering area.

As far as Hebei is concerned, family size should be expanded through the measures provided above. However, to be noted, the development of Hebei is relatively backward, so adjustment and optimization of energy structure in family daily life should be paid attention while expanding the scale of family. Thus, government needs to increase the use of natural gas, wind energy, biomass energy and other clean energy.

Meanwhile, a low-carbon lifestyle and low energy consumption concept are praised. This point not only increases support for a variety of energy saving and emissions reduction products, but also improves the encouragement of the use of energy-saving appliances and new energy vehicles.

Moreover, adjacent to Beijing and Tianjin, Hebei should give full play to the advantages of strengthening collaborative innovation with Beijing and Tianjin, and accelerate the pace of transition to a low-carbon economy. In particular, high energy consumption and polluting industries such as iron and steel, electric power, building material and chemical, ought to be strictly restricted, and low-carbon environmental protection technology should be applied to upgrade traditional industries. Furthermore, according to local conditions, the development of low-carbon environmental protection and competitive industries, such as green ecological agriculture, tourism and other special industries, should be promoted.

Conflict of Interest

The authors declare no conflict of interest.

References

1. AGENCY I.E. Energy technology perspectives 2012: pathways to a clean energy system. International Energy Agency. **2012**.
2. SHABANI ZAHRA DEHGHAN., SHAHNAZI ROUHOLLAH. Energy consumption, carbon dioxide emissions, information and communications technology, and gross domestic product in Iranian economic sectors: A panel causality analysis. *ENERGY*, **169**, 1064, **2019**.
3. WANG C.J., WANG F., ZHANG H.G., YE Y.Y., WU Q.T., SU Y.X. Carbon emissions decomposition and environmental mitigation policy recommendations for sustainable development in Shandong province. *Sustainability*, **6** (11), 8164, **2014**.
4. CETIN M., SEVIK H., SAAT A. Indoor Air Quality: the Samples of Safranbolu Bulak Mencilis Cave. *Fresenius Environmental Bulletin*. **26** (10), 5965, **2017**.
5. SEVIK H., AHMAIDA E.A., CETIN M. Chapter 31: Change of the Air Quality in the Urban Open and Green Spaces: Kastamonu Sample. *Ecology, Planning and Design*. Eds: Irina Koleva, Ulku Duman Yuksel, Lahcen Benaabidate, St. Kliment Ohridski University Press, ISBN: 978-954-07-4270-0, 409, **2017**.
6. CETIN M., SEVIK H. Change of air quality in Kastamonu city in terms of particulate matter and CO₂ amount. *Oxidation Communications*. **39**, 3394, **2016**.
7. CETIN M. A Change in the Amount of CO₂ at the Center of the Examination Halls: Case Study of Turkey. *Studies on Ethno-Medicine*, **10** (2), 146, **2016**.
8. TURKYILMAZ AYDIN., SEVIK HAKAN., ISINKARALAR KAAH. MEHMET CETIN. Use of tree rings as a bioindicator to observe atmospheric heavy metal deposition. *Environmental Science and Pollution Research*. **26** (5), 5122, **2019**.
9. TURKYILMAZ A., SEVIK H., CETIN M., AHMAIDA SALEH E.A. Changes in Heavy Metal Accumulation Depending on Traffic Density in Some Landscape Plants. *Pol. J. Environ. Stud.* **27** (5), 2277, **2018**.
10. TURKYILMAZ A., SEVIK H., CETIN M. The use of perennial needles as biomonitors for recently accumulated heavy metals. *Landscape and Ecological Engineering*. **14** (1), 115, **2018**.
11. SEVIK H., OZEL HB., CETIN M., OZEL H.U., ERDEM T. Determination of changes in heavy metal accumulation depending on plant species, plant organism, and traffic density in some landscape plants. *Air Quality Atmosphere and Health*. **12** (2), 189, **2019**.
12. TURKYILMAZ A., SEVIK H., ISINKARALAR K., CETIN M. Using Acer platanoides annual rings to monitor the amount of heavy metals accumulated in air. *Environmental monitoring and assessment*. **190** (10), **2018**.
13. CETIN M. Chapter 27: Landscape Engineering, Protecting Soil, and Runoff Storm Water, In *Tech-Open Science-Open Minds. Book: Advances in Landscape Architecture-Environmental Sciences*, ISBN 978-953-51-1167-2, 697, **2013**.
14. CETIN M., ZEREN I., SEVIK H., CAKIR C., AKPINAR H. A study on the determination of the natural park's sustainable tourism potential. *Environmental Monitoring and Assessment*. **190** (3), 167, **2018**.
15. CETIN M., ADIGUZEL F., KAYA O., SAHAP A. Mapping of bioclimatic comfort for potential planning using GIS in Aydin. *Environment, Development and Sustainability*, **20** (1), 361, **2018**.
16. WANG Q., CHIU Y.H., CHIU C.R. Driving factors behind carbon dioxide emissions in china: a modified production-theoretical decomposition analysis. *Energy Economics*, **51**, 252, **2015**.
17. XU S.C., HE Z.X., LONG R.Y., CHEN H. Factors that influence carbon emissions due to energy consumption based on different stages and sectors in china. *Journal of Cleaner Production*, **115**, 139, **2016**.
18. YANG G., SUN T., WANG J., LI X. Modeling the nexus between carbon dioxide emissions and economic growth. *Energy Policy*, **86**, 104, **2015**.
19. KAIS S., MOUNIR B. M. Nuclear energy, renewable energy, CO₂ emissions, and economic growth for nine developed countries: Evidence from panel Granger causality tests. *Progress in Nuclear Energy*, **88**, 364, **2016**.
20. WANG C., ZHANG X., WANG F., LEI J., ZHANG, L. Decomposition of energy-related carbon emissions in Xinjiang and relative mitigation policy recommendations. *Frontiers of Earth Science*, **9** (1), 65, **2015**.
21. WANG P., WU W.S., ZHU B.Z., WEI Y.M. Examining the impact factors of energy-related CO₂ emissions using the STIRPAT model in Guangdong Province, China. *Applied Energy*, **106**, 65, **2013**.
22. ZHANG C.G., LIN Y. Panel estimation for urbanization, energy consumption and CO₂ emissions: A regional analysis in China. *Energy Policy*, **49**, 488, **2012**.
23. LI J.X., CHEN Y.N., LI Z., LIU Z.H. Quantitative analysis of the impact factors of conventional energy carbon emissions in Kazakhstan based on LMDI decomposition and STIRPAT model. *Journal of Geographical Sciences*. **28** (7), 1001, **2018**.
24. WANG C., CHEN J., ZOU J. Decomposition of energy-related CO₂ emission in China: 1957-2000. *Energy*, **30**, 73, **2005**.
25. RAMANATHAN R. A multi-factor efficiency perspective to the relationships among world GDP, energy consumption

- and carbon dioxide emissions. *Technological Forecasting & Social Change*, **73** (5), 483, **2006**.
26. STRETESKY P.B., LYNCH M.J. A cross-national study of the association between per capita carbon dioxide emissions and exports to the united states. *Social Science Research*, **38** (1), 239, **2009**.
 27. HUBACEK K., FENG K., CHEN B. Changing lifestyles towards a low carbon economy: an IPAT analysis for china. *Energies*, **5** (1), 22, **2012**.
 28. YORK R., ROSA E.A., DIETZ T. STIRPAT, IPAT and impact: analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, **46** (3), 351, **2003**.
 29. SHI A. The impact of population pressure on global carbon dioxide emissions, 1975-1996: evidence from pooled cross-country data. *Ecological Economics*, **44** (1), 29, **2003**.
 30. LI J.X., CHEN Y.N., LI Z., LIU Z.H. Quantitative analysis of the impact factors of conventional energy carbon emissions in Kazakhstan based on LMDI decomposition and STIRPAT model. *Journal of geographical sciences*, **28** (7), 1001, **2018**.
 31. JIEKUN S., QING S., DONG Z., YOUYOU L., LONG L. Study on influencing factors of carbon emissions from energy consumption of Shandong province of china from 1995 to 2012. *The Scientific World Journal*, **1**, **2014**.
 32. ZHANG J.Y., ZHANG Y., YANG Z.F., LI S.S. An Estimation and Factor Decomposition Analysis of Energy-related Carbon Emissions in Beijing. *Procedia Environmental Sciences*, **13**, 1602, **2012**.
 33. YANG YU., YU RU DENNG., FEI FAN CHEN. Impact of population aging and industrial structure on CO₂ emissions and emissions trend prediction in China. *Atmospheric Pollution Research*, **9** (3), 446, **2018**.
 34. AGENCY I.E. IPCC guidelines for national greenhouse gas inventories. *Energy*, **2**, **2006**.
 35. WANG C.J., WEN B., WANG F., JIN L.X., YE Y.Y. Factors Driving Energy-Related Carbon Emissions in Xinjiang: Applying the Extended STIRPAT Model. *Pol. J. Environ. Stud.* **26** (4) 1747, **2017**.
 36. ARBULU I., LOZANO J., REY-MAQUIEIRA J. Waste Generation Flows and Tourism Growth: A STIRPAT Model for Mallorca. *Journal of industrial ecology*, **21** (2), 272, **2017**.
 37. LIN S.F., WANG S.Y., MARINOVA D., ZHAO D.T., HONG J. Impacts of urbanization and real economic development on CO₂ emissions in non-high income countries: Empirical research based on the extended STIRPAT model. *Journal of cleaner production*, **166**, 952, **2017**.
 38. WANG Z., YIN F., ZHANG Y., ZHANG X. An empirical research on the influencing factors of regional CO₂ emissions: evidence from Beijing city, China. *Applied Energy*, **100**, 277, **2012**.
 39. HANKE MICHAEL., MAERZ ROSWITHA., TISCHENDORF CAREN. Least-squares collocation for higher-index linear differential-algebraic equations: estimating the instability threshold mathematics of computation. **88** (318), 1647, **2019**.
 40. NAIK JYOTIRMAYEE., DASH PRADIPTA KISHORE., DHAR SNEHAMOY. A multi-objective wind speed and wind power prediction interval forecasting using variational modes decomposition based Multi-kernel robust ridge regression. *RENEWABLE ENERGY*, **136**, 701, **2019**.
 41. KURAN OZGE., OZKALE M REVAN. Model selection via conditional conceptual predictive statistic under ridge regression in linear mixed models. *Journal of statistical computation and simulation*, **89** (1), 155, **2019**.
 42. HOFF PETER., YU CHAOYU Exact adaptive confidence intervals for linear regression coefficients. *Electronic journal of statistics*, **13** (1), 94, **2019**.
 43. TAMURA RYUTA., KOBAYASHI KEN., TAKANO YUICHI Mixed integer quadratic optimization formulations for eliminating multicollinearity based on variance inflation factor. *Journal of global optimization*, **73** (2), 431, **2019**.
 44. CUI H.R., WU R.R., ZHAO T. Decomposition and Forecasting of CO₂ Emissions in China's Power Sector Based on STIRPAT Model with Selected PLS Model and a Novel Hybrid PLS-Grey-Markov Model. *Energies*, **11** (11), **2018**.
 45. XIE CHUNPING., HAWKES ADAM D. Estimation of inter-fuel substitution possibilities in China's transport industry using ridge regression, *Energy*, **88**, 260, **2015**.
 46. LIN B.Q., ANKRAH ISAAC., MANU SYLVESTER ADASI Brazilian energy efficiency and energy substitution: A road to cleaner national energy system, *Journal of cleaner production*, **162**, 1275, **2017**.

