



Energy-related CO₂ emissions in Hebei province: Driven factors and policy implications

Lei Wen^{1,2}, Yanjun Liu^{2*}

¹The Academy of Baoding Low-Carbon Development, Baoding 071003, China

²Department of Economics and Management, North China Electric Power University, Baoding 071003, China

ABSTRACT

The purpose of this study is to identify the driven factors affecting the changes in energy-related CO₂ emissions in Hebei Province of China from 1995 to 2013. This study confirmed that energy-related CO₂ emissions are correlated with the population, urbanization level, economic development degree, industry structure, foreign trade degree, technology level and energy proportion through an improved STIRPAT model. A reasonable and more reliable outcome of STIRPAT model can be obtained with the introducing of the Ridge Regression, which shows that population is the most important factor for CO₂ emissions in Hebei with the coefficient 2.4528. Rely on these discussions about affect abilities of each driven factors, we conclude several proposals to arrive targets for reductions in Hebei's energy-related CO₂ emissions. The method improved and relative policy advance improved pointing at empirical results also can be applied by other province to make study about driven factors of the growth of carbon emissions.

Keywords: CO₂ emissions, Driven factors, Hebei province, Ridge regression, STIRPAT model

1. Introduction

It has been proved that climate change, especially global warming, is mainly caused by the increasingly CO₂ emissions. The emissions of greenhouse gas, most notably CO₂ emissions, were treated as the priority of several international negotiations, as it would directly influence the environmental affairs and finally impairing the political or economic affairs. The increase of carbon emissions is a global issue that requires the collaboration of the international community. China intends to achieve the peaking of CO₂ emissions around 2030 and to make best efforts to peak early and intends to increase the share of non-fossil fuels in primary energy consumption to around 20% by 2030 [1]. Both sides intend to continue to work to increase ambition over time.

To complete the duty "hold the increase in global average temperature below 2°C above pre-industrial levels" [2], Chinese government attaches great importance to addressing climate change and treats the control of CO₂ emissions as a significant national strategy. As a result, by 2014, the carbon emissions per unit of GDP in China are 33.8% lower than the 2005 level. Furthermore, "the National Plan on Climate Change (2014-2020)" put a clearly description of the necessary sustained effort in China to achieve the nationally objectives on climate change. To reach the goal of low

carbon, the control of energy-related CO₂ emissions is important.

Hebei Province is located to the north of the yellow river and to the east of Taihang Mountains. Hebei includes 11 prefecture-level cities, 22 county-level cities, 109 counties and 6 counties, with the covering area of 187,693 square kilometers. The GDP of Hebei province grown form 285 billion Yuan to 2942.1 billion Yuan from 2005 to 2014. Since 1995, the GDP per capita in Hebei has increased at an average of 13.3 percent per annum, reaching 39984 Yuan at the year of 2014, which is actually a little lower than the average level of the whole China. In recent 10 years, the secondary industry share of GDP in Hebei was still higher than 50%, which would be a decreasing trend with the adjustment of industry structure. In 2014, the population was 73,840,000, and the percentage of urban population in total was 49.3% with a slow increasing trend.

It is hard for Chinese government to make a carbon reduction programme to satisfy every province's development in China. Thus, the study about Hebei's situation of energy-related carbon emissions and local driven factors of emissions provides a sample of provinces relying on heavy industrialization for a long time. As a typical industrialized region, the energy-related CO₂ emissions of Hebei from 185 million tonnes to 541 million tonnes with an average growth rate of 10.7% from 1995 to 2012. In recent year,



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* Corresponding author
Email: fastgu@163.com
Tel: +8618331126102

Chinese government frequently emphasizes the development strategy of coordinated development of Beijing-Tianjin-Hebei region. Compared with Tianjin and Beijing, Hebei Province shoulders a more arduous task of reducing CO₂ emissions as its lower proportion of the third industry and lower energy intensity (energy consumption /GDP).

Hebei province paid its main attention to heavy chemical industry since the 1950s, and gradually formed a high resource-dependent industrial system with a relatively complete technical level. In 2012, over 302.5 million tons of standard coal was consumed by Hebei province, which is appropriately two times higher than the non-industry based provinces, such as Fujian province. Accordingly, the control of energy-related CO₂ emissions is a serious issue in Hebei with the fact that an annual growth rate in CO₂ emissions up to 11.3% from 1995 to 2012. Recent years, as an important part of the Beijing-Tianjin-Hebei, more attention are paid to Hebei about building a Low-Carbon Industrial System. Thus, it is imperative for Hebei to implement kinds of enhanced actions on reducing its carbon emissions through and accelerate its green and low-carbon transformation.

To realize these objectives and overcome some existing problems, stochastic impact by regression on population, affluence, and technology (STIRPAT) models, which is one of the most popular ways used to examine the impact factors of CO₂ emissions, would be attempted to be improved in this paper. Although the carbon emissions have been focused by a lot of studies, the theory for impact factors of CO₂ emissions is relatively weak. The former works focused mainly on population, economic level and technology level, and seldom on energy structure, industrial structure, urbanization level, industrialized level and foreign trade degree. Besides, former studies often adopt the input-output method and the structure decomposition method, but seldom use the econometric analysis method. The novelty of this paper compared with other articles lies in its searching for other unusually factors influencing energy-related CO₂ emissions, such as foreign trade degree, energy structure, industrial level and service level, rather than the basic ones, which can eventually provide a useful outcome beneficial to the formulation of environmental policies. Besides, Ridge Regression can be used instead of ordinary least squares (OLS) regression to avoid instability as the existing of multicollinearity between independent variables. In addition, much more studies focus on the CO₂ emissions and its driven factors in macroscopic level, but this article takes Hebei province as a unit to provide suitable advances. Lastly, the empirical results illustrate the important level of each influencing factors, which can be useful for the Hebei's policy makers to put forward decisive actions about energy-saving and CO₂ emission cutting.

2. Literature Review

Recently, many researches are took about carbon emissions [3, 4], the methods used to decompose CO₂ emissions can be concluded as three ways: the LMDI method, the DEA & Malmquist index model and the STIRPAT model. In addition, some researchers also provide their new approach to solve environmental crises [5-7].

The DEA & Malmquist index model is developed from traditional DEA model, which was widely applied to static efficiency evaluation. Through the DEA & Malmquist index model, not only the efficiency of different decision-making units can be compared at the same time, but also the variation's efficiency of the same decision unit in different periods can be studied. Zhang N. used Malmquist index analysis, which is calculated based on DEA model, to investigate decompositions of the Chinese regional transportation industry's dynamic CO₂ emission from 2002 to 2010 [8]. This improved Malmquist Index was also adored to show the difference the changes in CO₂ emission performance of state-owned fossil fuel power plants between China and Korea [9].

The Divisia index (LMDI) is applied through the weighted sum of logarithmic growth rates, which are actually the components' shares in total value. LMDI holds an evident advantage about the "0" value problem and the "remaining" problem occurred during decomposition [10]. Song et al. decomposed carbon emissions from energy consumption of Shandong province with LMDI, MRCI and Shapley value models [11]. Hatzigeorgiou decomposed the changes of CO₂ emissions in Greece into four factors and confirmed the biggest contributor is the income effect [12]. Sheinbaum et al. studied the energy consumption and decomposed CO₂ emissions in Mexico's iron and steel industry [13]. Xu et al. decomposed the energy consumption and CO₂ emissions in China's cement industry base on the LMDI decomposition analysis [14].

As a linear model converted to a logarithmic form, the STIRPAT model, which is a improvement of IPAT Model, can examine much more impact factors to ensure the reliability of its conclusions can be rewritten.

In the 1970s, IPAT Model, known as $I = P \times A \times T$, was first built by Ehrlich and Holden [15] as a concise environmental pressures and control model to show the influence of human's action on their surrounding ecological environment. Since then, this model was wisely applied to study the impact of population (P), affluence (A) and technology (T).

Waggoner and Ausubel then introduced the fourth variable—C (energy consumed per GDP) to the IPAT Model [16], thus, a new model called ImPACT was set. IPAT and ImPACT were reasonable enough to indicate the effects of influencing factors on surrounded environment. But these models, as a kind of identity, have to be established with the assumption of driven factors' proportionality. In addition, since the IPAT equation is an identity, it is required that the units of both sides of the equation are unified, and the driving force is the same. And the change occurred among the driven factors of environment would remain the same proportion. So, IPAT and ImPACT are not perfect to respect human activities' influence to environment for the fact that the non-monotonicity and non-proportion between the driven factors caused by the human activities and the environmental influence. Dietz and Rosa proposed a new model named STIRPAT [17], which make it possible to analyze non-proportionate relationship between driven factors and environment.

In recent years, the STIRPAT model was constantly applied to make research on the environment pollution and carbon emissions. Shao et al.[18], O'Neill et al. [19], Wang et al. [20], Li et al. [21], made some studies on influencing factors of carbon

emissions to illustrate the importance of each factor and the change of CO₂ emissions. The impact of Urbanization on CO₂ emissions was specially considered using an improved STIRPAT model by Wang et al. [22], Lin et al. [23], Barido et al. [24] and Liddle [25]. Additional, the relationship between urbanization, energy consumption, and CO₂ emission in MENA countries was explored by Al-mulali et al. through STIRPAT model [26]. The STIRPAT framework was also used to describe the US county-level carbon dioxide emissions by Roberts [27]. Besides, Chikaraishi found that urbanization provide different influence when GDP change through STIRPAT model [28]. Yuan et al. concluded that the impact of affluence was more important than urban population on CO₂ emissions in China using STIRPAT model [29].

3. Materials and Methods

3.1. Measurement of Energy-Related CO₂ Emissions

Carbon emissions (unit: million tons) in Hebei province is measured through the specific formula released by 2006 IPCC guidelines:

$$CE = \sum_s E_s \times NCV \times CEC_s \times COF \times \frac{44}{12} \quad (1)$$

where CE stands for the total amount of carbon emissions from energy consumption; E is the consumed amount of primary energy; NCV denotes Net Calorific Value; CEC refers to carbon emission coefficient; s refers to the type of primary energy; COF is carbon oxidation factor of primary energy in the combustion process, and all the carbon oxidation of these energy is assumed normally 100%. The number 44/12 stands for the ratio of CO₂ and C. It can be learned that the CO₂ emissions of various primary energies are determined together by NCV, CEC and COF.

3.2. STIRPAT Model

The STIRPAT model was first defined as follows:

$$I_t = aP_t^b A_t^c T_t^d e_t \quad (2)$$

where I means environment impact, a is the constant term, b, c, d is the exponential term of the population (P), affluence (A) and technology (T), e refers to the error term. The subscript t represents the year. As a kind of exponential model, STIRPAT model provide more possibilities to examine the impacts of each variable on the surrounded environment.

To solve some non-proportional impacts on the environment and analyze more quantitative questions, the natural logarithm was applied to STIRPAT. Thus, the new form is as follows:

$$\ln I_t = \ln a + b \ln(P_t) + c \ln(A_t) + d \ln(T_t) + \ln e_t \quad (3)$$

The STIRPAT model could turn to be IPAT model when a = b = c = d = e = 1. The influence of human activities on the environment and relative environmental change with the normally fixed driven factors is usually IPAT is usually applied

to make research about the. Whereas, the STIRPAT model provides room for complex diagnostic analysis of other unknown influencing factors and estimate the coefficient of every factor as a parameter [30].

To analyze the best needed policies and solutions about the control of carbon emissions in Hebei, the traditional STIRPAT model will be improved to ensure all of the essential driven factors are considered.

First, population and technology must be included, because the increase of population will eventually cause a corresponding increase of social activities, whereas, the development of technology will presented a negative correlation to CO₂ emissions [31], whereas the EKC might not suit every province in China. Second, the environmental Kuznets curve (EKC) should be considered when it terms at affluence due to the existence of "inverted U" curve relationship between per capita GDP and air pollution [32-34].

Thus, a square term of affluence will be added to prove the EKC relationship between air pollution (CO₂ emissions) and economic growth (GDP per capita). This index is also widely considered in other research areas, such as water irrigation [35-38]. As a glorious manufacturing base of China, Hebei's secondary industry share of GDP is a little higher than Chinese average level. Industries belong to the secondary industry always have extensive energy consumption and emissions. So, the relationship between this industry structure and CO₂ emissions deserve being added.

In addition, the urbanization is an important factor of CO₂ emissions. Living with various modern electrical equipment, such as cooling units, vehicles, factories and industrial enterprise, urban inhabitants tend to consume more energy. Designed with modern buildings and convenient road system, cities are usually short of sufficient vegetation. More energy is needed in urban area to maintain daily fundamental operation, and non-fossil energy can release few CO₂ emissions compared with traditional fossil energy. Thus, energy structure (non-fossil energy to total energy consumption) should be considered in our extended STIRPAT model.

Finally, foreign trade degree is also a typical indicator to explain the variation of CO₂ emissions for the reason that foreign trade is one of the most useful methods to extend local economy. Foreign trade can reduce production costs, improve production efficiency and expand employment. The change in percentage of gross import and export value to GDP can be somehow impact carbon emissions.

According all the information, the final formula in this paper is expressed as below.

$$\ln C = \ln a + \beta_1 \ln A^2 + \beta_2 \ln P + \beta_3 \ln T + \beta_4 \ln U + \beta_5 \ln S + \beta_6 \ln I + \beta_7 \ln F \quad (4)$$

where C represents the aggregate CO₂ emissions, A² refers to the squared term of GDP per capita, P and T, respectively, denote population (year-end) and technological level, U is the urbanization level, S refers to energy structure, I means industrial level, F represents foreign trade degree. The variables are particularly described in Table 1.

Table 1. Explain of Variables Used in This Paper

Symbol	Variable	Definition	Unit of measurement
C	CO ₂ emissions	Hebei's total carbon emissions from energy consumption	10,000 tons
A	Affluence level	GDP per capita	Yuan in constant 2000 price
P	Population	population size	10,000 units
T	Technological level	CO ₂ emission per unit of GDP	ton/104 Yuan
U	Urbanization level	The ratio of urban population in total over total population	%
S	Energy structure	The proportion of non-fossil energy to total energy consumption	%
I	Industrial level	The secondary industry share of GDP	%
F	Foreign trade degree	The proportion of gross import and export value over GDP	%

3.3. Ridge Regression

The classical model of basic multiple linear regression can be written [39, 40] as:

$$Y = X\beta + \epsilon \tag{5}$$

Where X and Y are respectively a (n × p) array of independent variables and (n × 1) matrix of dependent variables, β is a (p × 1) vector referring to regression coefficients and ε implies random errors, as Eq. (6).

$$\epsilon = [\epsilon_{+1}, \epsilon_2, \dots, \epsilon_n]^T \tag{6}$$

As one of the most universal method, the ordinary least square (OLS) regression is frequently used for parameter estimate [41]. The estimation of β is given as Eq. (7):

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

There are two unbiasedness property should be guaranteed for OLS estimator:

$$E(\hat{\beta}) = \beta, \text{Var}(\hat{\beta}) = \sigma^2(X'X)^{-1} = \sigma^2 \sum_{i=1}^p \frac{1}{\lambda_i} \tag{8}$$

The correlation relationships between different independent variables make Eq. (8) unsatisfied, and the lead to instable coefficient of OLS estimator.

The Ridge regression was first demonstrated by Hoerl [42]. The algorithm was improved through the introduce of factor k onto the diagonal of standard system matrix X'X. Consequently, the deficiency of OLS estimation can be overcome by biased ridge regression parameter estimation as below:

$$\hat{\beta}(k) = (X'X + kI)^{-1}X'y, \quad k > 0 \tag{9}$$

Hoerl also testified the MSE of ridge regression estimates is smaller than MSE of the OLS estimates due to the existence of a series of k. When k = 0, the estimator of Ridge regression would be the same as the OLS estimator (β).

4. Results and Discussion

4.1. Data Source

The analysis data used in this article are collected from Hebei's Statistical Yearbook the China Energy Statistical Yearbook for the period 1995-2013 including Gross Regional Product, population, urban population, GDP caused in the secondary industry ,import and export value, the consumption of coal, fossil oil, natural gas and non-fossil energy. Beside population and GDP per capita, the other variables are figured out through fixed formula. The urbanization level, technological level, energy structure, industrial level and foreign trade degree are, respectively, given as percentage of urban population, the ratio of carbon emissions per standard coal, the secondary industry share over GDP, proportion of non-fossil energy to total energy consumption, and the count of import and export value on GDP.

The Hebei's energy-related CO₂ emissions are listed in Fig.1 estimated through Eq. (1). The CO₂ emissions had a relative rapid rise from 234.44 million tons in the year of 2002, whereas turned to be gentle after 2011 reaching 550.24 million tons in 2013. The average annual growth rate is over 10% during the periods (1995-2013). However, the average rise rate in the latest three years is 5.5%. The change trend of energy consumption is roughly similar to CO₂ emissions. Increasing in a relatively moderate trend, energy consumptions' average growth rate in the periods of 1995-2000 and 2010-2013 are respectively 5.8% and 5.7%. However, the average growth rate from 2000 to 2013 is more than 14.5%.

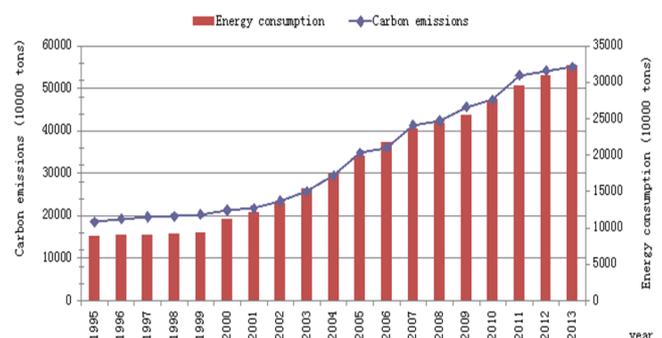


Fig. 1. The energy-related CO₂ emissions and energy consumption in Hebei Province, China.

4.2. Multicollinearity Test

A basic assumption of multiple linear regression analysis is that no multicollinearity exist among the independent variables and rank (X) = p + 1. If there is a complete linear relationship between the independent variables, their correlation coefficient would be 1.

In general, there are correlations of different degree between independent variables, and the correlation coefficients between the independent variables can be varied from 1 to 0. This phenomenon is called approximate multicollinearity. Eq. (10) is multiple linear regression equation.

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p + \epsilon \tag{10}$$

When multicollinearity exists, there is rank (X) < p + 1 for matrix X and absolute value the covariance matrix |X`X|=0. Thus, (X`X)⁻¹ does not exist. The solution of Eq. (11) is not unique.

$$x' X\hat{\beta} = X' y \tag{11}$$

When there is approximate multicollinearity, diagonal elements would be too large although rank (X) = p + 1. That is to say, the accuracy of estimate $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ is low because the diagonal elements' value in Eq. (12) would be too large [43].

$$D(\hat{\beta}) = \sigma^2 (X' X)^{-1} \tag{12}$$

Regression analysis will be affected by approximate multi-

collinearity on the following aspects:

1) The variance of estimator is too large, thus the impact degree of independent variables on the explained variables cannot be judged correctly.

2) The variance of the regression coefficient is increasing, causing an increasing uncertainty of the estimated value of the regression coefficient. Therefore, it would be more possible to accept a false assumption and make the risk of making mistakes.

3) The analysis result might show the large value of multiple factors, but the test of individual regression coefficients may not be significant. It is difficult to distinguish each independent variable's influence in dependent variable.

As the most traditional method, OLS regression was completed in this paper to examine whether there was multicollinearity among independent variable through the correlations showed in Table 2. Most of the Pearson correlation coefficient presented in Table 2 is significant illustrating a serious multicollinearity exists between these independent variables. According to the results of OLS regression in Table 3, adjusted R² is almost equal to 1 and the F-statistic value is very large with an extremely significance. These all prove a high regression prominence. However, the t-statistic is unacceptable with most of coefficients' significance reaching 0.05 level. Five of independent variables' VIF are higher than 10 excluding energy structure and foreign trade degree. The VIF above 10 is a reliable indicator of multicollinearity and the higher VIF means a more serious multicollinearity [44]. Thus, the regression results obtained by OLS are meaningless and unreliable to be accepted to analyze Hebei's carbon emissions.

Table 2. Results of Correlation Test

	lnA ²	lnP	lnU	lnT	lnS	lnI	lnF
lnA ²	-						
lnP	0.990**	-					
lnU	0.962**	0.962**	-				
lnT	-0.987**	-0.992*	-0.965**	-			
lnS	-0.622*	-0.578*	-0.699**	0.595**	-		
lnI	0.919**	0.874**	0.899**	-0.898**	-0.584*	-	
lnF	0.865**	-0.821**	0.794**	-0.795**	-0.610**	0.836**	-

*Correlation is significant at the 0.05 level.

**Correlation is significant at the 0.01 level.

Table 3. Results of OLS Regression

OLS result	Unstandardized coefficient	t-Statistic	t-Statistic Sig.	VIF
Constant	-8.099	-3.387	0.007	-
lnA ²	0.510	66.978	0.000	214.257
lnP	0.818	3.152	0.010	195.995
lnU	0.020	1.811	0.100	24.788
lnT	1.037	39.256	0.000	153.465
lnS	0.003	0.313	0.761	3.021
lnI	0.051	0.847	0.417	15.133
lnF	-0.008	-1.091	0.301	9.627
Adjusted R ²	1.000	-	-	-
F-statistic	44291.482	-	-	-
F-statistic Sig.	0.000	-	-	-

4.3. Ridge Regression Estimation

The Ridge Regression method is particularly useful to overcome the multicollinearity existed between independent variables. In this study, the Ridge Regression method is applied to establish an extended STIRPAT model for population, energy consumption structure, economic level, industrial structure, emissions intensity, foreign trade degree and CO₂ emissions in order to avoid the limitations of OLS. The estimated coefficients of STIRPAT model can provide the driven factors' influence on CO₂ emissions.

Based on Eq. (9), the consequence of ridge regression are obtained through a ridge trace in Fig. 2 and the relationship between R² and k is demonstrated in Fig. 3. To clearly show the change of regression coefficients and find the least k value, only fifty-one points are drew in Fig. 1 because the coefficients all maintain the stable trend with little change when k increase from 0.5 to 1. The curves in Fig. 2 become smooth after the point of k = 0.02, where the regression coefficients of each variable first become stable. The value of R² changes from a sharp downward trend to a slower steady decrease when k = 0.02. As the k value is decided through the observation of Fig. 2 and Fig. 3, four different k values (k = 0.01, 0.02, 0.03 and 0.04) were respectively tried to search the best outcome, which is reliable to reduce uncertainties. According to the comparison of these four results, k = 0.02 is a reasonable choice in this study to obtain relative coefficient of driven factors.

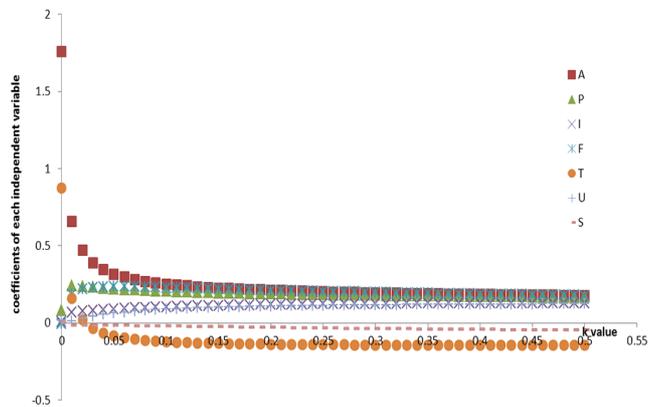


Fig. 2. The curves of ridge trace.

The results represented in Table 4 illustrates a perfect adjusted R² (0.9893) and a significant F statistic value. Besides, the significant of each independent factor is lower than the level of 0.05. The VIF of each variables is much smaller than 10. Based on these analyses, it can be confirmed the fitted STIRPAT equation is reasonable without negative influence of multicollinearity. The regression equation is written as:

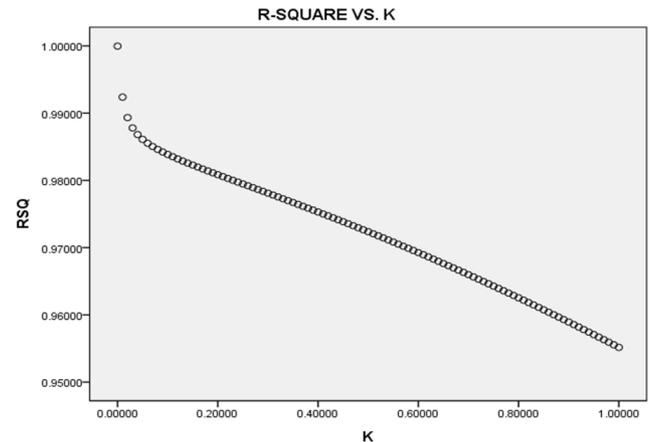


Fig. 3. Relationship between k and R².

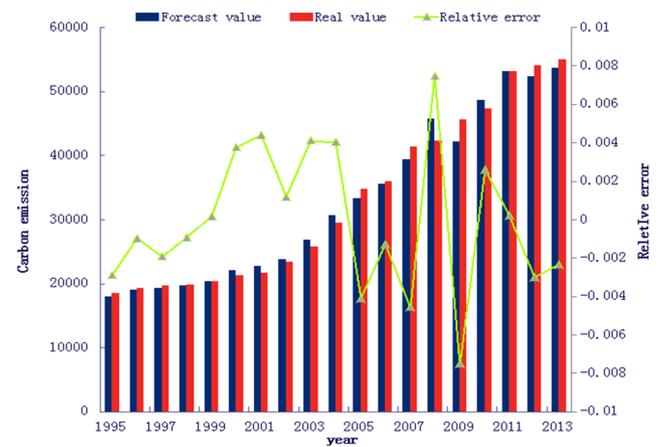


Fig. 4. The comparison of predicted carbon emissions and real value.

Table 4. Results of the Ridge Regression

The ridge result	Unstandardized coefficient	t-Statistic	t-Statistic Sig.	VIF
Constant	-17.225	-2.672	0.0234	-
lnA2	0.1361	6.108	0.0001	0.932
lnP	2.4528	3.311	0.0078	0.412
lnU	0.0369	2.305	0.0392	0.619
lnT	0.0246	2.196	0.0483	0.353
lnS	-0.0523	-2.723	0.0211	0.176
lnI	0.6654	2.971	0.0136	0.759
lnF	0.2902	3.674	0.0043	0.145
Adjusted R ²	0.9893	-	-	-
F-statistic	132.5387	-	-	-
F-statistic Sig.	0.00000002	-	-	-

$$\ln C = -17.225 + 0.1361\ln A^2 + 2.4528\ln P + 0.0246\ln T + 0.0369\ln U - 0.0523\ln S + 0.6654\ln I + 0.2902\ln F$$

The fitting effect of Ridge Regression can be proved to be great through the comparison between the predicted value calculated by Eq. (11) and real CO₂ emissions (from 1995 to 2013) in the Fig. 4. Additionally, the value of relative error is fluctuated between -0.75% and 0.74%.

4.4. Analysis of Results of Ridge Regression

It is clear through the Ridge Regression result that the energy-related CO₂ emissions is directly correlated with the economic development, population, technological level, urbanization level, energy structure, industrial level and foreign trade degree.

The results of this study suggest that the increase of population, GDP per capita, urbanization level, technological level as well as the ratio of gross import and export value over GDP contribute to explaining the positive variations in energy-related CO₂ emissions, whereas, the improvement of energy structure (proportion of non-fossil energy to total energy consumption) lead to an adverse impact on CO₂ emissions. In terms of these positive driven factors, population has the most explanatory ability in this paper. The affecting abilities of industry level, foreign trade degree, the squared term of GDP per capita and urbanization level are decrease in turn. The change of technological level plays the least important role in restraining carbon emissions. The specific effect of each driven variables on CO₂ emission in Hebei province will be analyzed separately.

1) The change of population will cause the most variation of total CO₂ emissions in Hebei province. The elastic coefficient of population scale is 2.45, representing a 2.45% increase in CO₂ emissions from every 1% growth of population. Human is the foundation of all human related activities. The average population growth rate in Hebei in the period from 1995 to 2014 is 0.735%, which is higher than Chinese average level. At a certain stage of development, more resources can be consumed with the increase of population, ultimately leading to more CO₂ emissions.

2) Industrialization level performs the second-largest positive impact on CO₂ emission. The elastic coefficient of industrialization level, 0.6654, means every 1% increase in the secondary industry share of GDP will cause a 0.6654% increase in CO₂ emission. The second industry is a pillar industry in Hebei, including the information industry, metallurgy, medicine, building materials, chemicals, machinery, textiles and food. Since the items belong to the second industry all bear high energy consumption and carbon emissions, reducing the proportion of secondary industry in terms of reducing carbon emissions is essential.

3) The foreign trade degree has the third prominent, positive influence on carbon emissions in Hebei, causing a 0.2902% increase in CO₂ emissions of 1% increase in foreign trade degree. Foreign trade is an important part of national economic development, playing an important role in expanding opening up, boosting economic growth, promoting structural adjustment, increasing employment. In the period of 12th Five-Year Plan (2011–2015), Hebei's foreign trade growth rate is 3.5 percentages higher than its GDP growth rate, even 2 percentage higher than Chinese average foreign trade growth rate. The growth rate of foreign trade developed is now

higher than the growth rate in coastal provinces. Since 1990, the value of exports is larger than the import value in Hebei province. However, exported goods in Hebei are mainly traditional labor-intensive products (including textiles and clothing, furniture and parts, luggage, footwear, plastic products, toys), heavy industrial products (such as mechanical and electrical products), metal products, machinery equipment. So, development of foreign trade requires plenty of energy, which would unavoidably cause the growth of carbon emissions.

4) The squared term of GDP per capita has a relative smaller positive impact on CO₂ emissions with an elastic coefficient at 0.136, representing that carbon emissions would rise 0.136% when the square term of GDP per capita increase 1%. This is approve of no EKC existed in Hebei's CO₂ emissions' change in the recent 19 years. Urbanization and economic development are closely linked, the development of social economy can objective boost urbanization. Therefore, the economic development would lead to more energy consumption and carbon emissions due to the expansion of industries and trading.

5) Energy structure, namely the proportion of petroleum to total energy consumption, also contributes a prominent but negative influence on Hebei's carbon emissions. Its elastic coefficient is only 0.0523, indicating that every 1% growth in energy structure leads to a 0.0523% decrease in CO₂ emissions. This negative influence can be explained by the low proportion of petroleum compare to the coal. Burning 1unit coal (equivalent to 1 ton petroleum) can emit 1.04 ton carbons, and burning 1ton petroleum can emit 0.8 ton carbons. That is to say, the carbon emissions from petroleum would be less than from coal under the situation of providing the same thermal power. Throughout the world, a lot of developed countries consumed more petroleum rather than coal, such as the United States, Germany and Japan. So, with the growth of petroleum' proportion in the total consumed energy, the CO₂ emissions would decrease in some extent.

6) Urbanization level is also an important factor in the change of CO₂ emissions. Its coefficient is 0.1915, illustrating that every 1% increase in the proportion of urban population in total will give rise to a 0.0369% increase in CO₂ emissions. Promoted by industrial and economic development, the accumulated productivity in this region releases and generates distribution effect on urban population, and eventually it produces more aggregation, namely an increase in the urbanization level. In addition, the urbanization is a sign of modernization, associated with more employment opportunities, abundant resources for social services, convenient transportation, cultural facilities and modern building. Thus, enlargement of urbanization would cause an increase of CO₂ emissions.

7) The change of technology level, namely the CO₂ emission per unit of GDP, generates the smallest variation on the scale of Hebei's carbon emissions. It has a similar regression coefficient of 0.0246 with urbanization level, indicating 1% growth in technology level causes 0.0246% increase in CO₂ emission. In fact, the decrease of CO₂ emission per unit of GDP is associated with the improvement of energy efficiency, the reduction of fixed carbon emissions in the production process and promotion of low-carbon way of life and consumption throughout society. These improvements are all positive to the control of CO₂ emissions. Currently,

a lot of relative solutions involving increase technology level have been conducted, including lower coal-fired power plants' coal consumption of electricity generation process, low-carbonized urbanization (such as Power Valley in Baoding) and highly-efficient transportation. The CO₂ emissions can be reduced based on continual technological innovation.

5. Conclusions

Population, urbanization level, economic development level, industry structure, foreign trade level, energy structure and technological level were analyzed with the extended STIRPAT model to explore their impact on Hebei's energy-related CO₂ emissions. The estimation results imply that population, economic development level, industry structure and foreign trade level should be focus more attention to reach the goal of controlling energy-related CO₂ emissions. Based on our study results, following proposals are put forward.

Population scale is the most important support to take low-carbon development in Hebei during the period from 1995 to 2013. Currently, Hebei province remains the rapid development, positively affected by the coordinated development of Beijing-Tianjin-Hebei region, as well as the twenty-fourth Winter Olympics planned to be hosted in Hebei. The local government should continual pay attention to control the growth of population. In addition, the urbanization should also be considered to make a balance of local prosperity and energy-related CO₂ emissions' reduction. Government should make limitation for large-scale industrialization and urbanization, and encourage moderate concentration of population by unified planning. More activities and education should be spread to guide residents live in the Low-Carbon Way and advocate green, low-carbon, healthy and civilized way of life and consumption patterns.

GDP per capita, foreign trade degree and industrialization level play a positive role in the variation of Hebei's carbon emissions. It is clear that the economy in Hebei province would remain a rapid development trend. To mitigate such a positive impact, government should try to establish Low-Carbon industrial system, adjust the product types and function of foreign trade. The control of carbon emissions generally associated with innovation and better quality of life, which conversely strengthen economic growth. In terms of optimizing industry structure, service and creative industries, such as logistics industry, high-tech electronic industry, should be encouraged. The government should make scientific and rational development of the second industry, promote the transformation and upgrading of the original scientific research institutions, regard the information industry, metallurgy, medicine, building materials, chemical, machinery, textiles and food as ten center of Hebei Province's second industry. Besides, Hebei would actively settle the transfer of industries and technology from Beijing, accelerate the transformation of scientific and technological achievements, foster strategic emerging industries export base, and promote electronic information, equipment manufacturing, new energy, new materials, bio industry, modern agriculture and high-end service industry exports, to create a leading area of foreign trade development. All of these improvements contribute to lower

the increase of CO₂ emissions, ensuring a balanced development of trade, industry and environment.

Energy structure has a negative impact on energy-related CO₂ emissions. It is useful to reduce emissions through increase the proportion of petroleum. Local government should make relative policies to control coal consumption, improve the share of concentrated and highly-efficient electricity generation from coal, and increase the consumed proportion of petroleum. The negative impact of energy structure partly indicates the necessary of reducing the use of coal. Local government should focus develop new energy and renewable technologies, organize the implementation of nuclear power, wind power and solar photovoltaic technology, accelerate the development of coastal wind power base in Qinhuangdao, Tangshan and Cangzhou (cities of Hebei province).

Technical level holds the least impact on energy-related CO₂ emissions in this paper. That is to say, control CO₂ emission per unit of GDP is not so remarkable to decrease total emissions. However, the CO₂ emission per unit of GDP would continually decrease with the technical innovation and improvement in cities building, industry enlargement and power providing, eventually promoting low-carbon development. Thus, local government should enhance carbon intensity control through encouraging energy conservation and efficiency improvement of key sectors including power, iron and steel, nonferrous metal, building materials and chemical industries, establishing a recycling-based industrial system to ensure recycling restructure in industrial parks, applying new tech to establish green communities with low-carbon supporting facilities.

The results and analysis presented in this paper can provide guidance for local government to design more reasonable and comprehensive policies. This to some extent is a positive promotion on Hebei province's low-carbon development on the premise of flourishing economic development. The conclusion and research method also can be referenced by scholars to analyze the driven factors of other regions. Finally, the factors include foreign trade degree, population, urbanization level, economic development, technological level, industry structure and energy structure can be pay more attentions in Hebei province's future control of CO₂ emissions.

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