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Original Research

Factor Decomposition Analysis of China's Energy-Related CO_2 Emissions Using Extended STIRPAT Model

Lei Wen[1, 2]*, Ye Cao[1], Jianfeng Weng[1]

[1]Department of Economics and Management, North China Electric Power University, Baoding, Hebei 071003, China
[2]The Academy of Baoding Low-Carbon Development, Baoding, Hebei 071003, China

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Abstract

For the purpose of diminishing the growing impact of energy use on the environment and providing policy focus in China, this study decomposes impact factors of energy-related CO_2 emissions into nine parts using various economic methods, typically using the extended stochastic impacts by regression on population, affluence, and technology (STIRPAT) model to incorporate necessary factors and ridge regression to eliminate multicollinearity. Results indicate the positive and conversely inhibitory impact factors, which we sort by influencing degrees as: total population, industrialization level, service level, energy consumption structure, urbanization level, GDP per capita, capital asserts investment, foreign trade degree, and technology level. Factors excluding technology level and energy consumption structure are main positive determinants of accelerated CO_2 emissions. Above all, total population has the greatest interpretative ability. Given these regression results, policy proposals concerning key impact factor regulations are provided to maintain carbon emission abatement and sustainability.

Keywords: CO_2 emissions, energy preservation, impact factors, Ridge regression, STIRPAT model

Introduction

Excessive growth of energy use has made the greatest impact on the environment of any human living environment, especially the greenhouse effect. Global warming has come to the forefront of policy debates on international and national levels, thus seriously affecting people's living environment and energy sustainability. Global warming is being driven by greenhouse gases (GHG) growth, most notably CO_2 emissions that account for 56% of the greenhouse effect among six kinds of GHG. Anthropogenic activities – more specifically fossil fuels combustion and consequent carbon emissions – are responsible for significant warming of the global climate.

The 2009 Copenhagen Agreement has urged the Chinese government to commit to a significant cut in carbon intensity of at least 40% by 2020 from 2005 levels. Since the Copenhagen Agreement, the persistent combustion of fossil fuels responsible for greenhouse gas growth has made China a focal point of international attention. During the past 20 years, China's economic development has shown an over-reliance on energy consumption with annual growth rate of energy consumption approaching 6.3% since 1991. Accordingly, CO_2 emissions have increased sharply and pose a significant problem as far as energy conservation and emission reduction are restrictive in China.

*e-mail: 441477582@qq.com

Literature Review

Research on the impact factors of CO_2 emissions in general have been in the vanguard of attention and have led to a large body of empirical mainstays that are helpful in CO_2 abatement for each country. Shi regards increasing energy consumption as the main cause of growing CO_2 emissions, without considering the impact of population and technology [1], and that population, economy, and technology are key factors for determining CO_2 emissions, with further claims that their impact on CO_2 emissions is heterogeneous across different countries [2, 3]. When it comes to detailed factor impact on CO_2 emissions like population structure, urbanization level, economic level, industrial structure, energy intensity, and so on, large theoretical explorations and empirical investigations reveal key impact factors and degree, respectively [4, 5].

Besides, in previous research of CO_2 emissions on regional areas, Shao et al. estimates energy-related industrial CO_2 emissions (ICE) in Shanghai from 1994 to 2009, and they summarize ICE characteristics. Their findings show that ICE's largest source is from coal-type consumption. By employing the ICE-STIRPAT model, the relationship between ICE and per capita output presents an inverted N-shaped curve with two turning points resulting from the Environmental Kuznets effects – namely scale, composition, and technique, and most sub-sectors remain in the second stage of the curve [6]. Based on the two-level logarithmic mean divisia index (LMDI) method and Tapio index, Wang and Yang constructed an expanded decomposition model for decoupling elasticity and effort index of industrial carbon emissions. Their findings show that rapid economic growth was the main factor responsible for industrial decoupling blocking. The energy structure and energy intensity made significant contributions to industrial decoupling progress [7].

In addition, studies on various methods to examine the determinants of energy-related CO_2 emissions are emerging endlessly. Methods like the LMDI and STIRPAT models are widely used to identify impact factors of CO_2 emissions. The representative models include Laspeyres method [8], total factor energy efficiency index [9], grey forecasting model [10], TIMES model [11], data envelopment analysis [12], multiple linear regression, binary choice model, and ordinal choice regression [13], and so on. Above all, STIRPAT models with an increasingly dominant status examining the impact factors has been proven more reliable than LMDI models [14, 15]. Meanwhile, there is a necessity to consider the rebound effect during the process of improving energy efficiency to lowering emissions and relative policy implications [16-20].

Despite abundant literature, few papers have researched carbon emission factors from the perspective of all of China. In view of the above-mentioned studies, this paper is organized to examine the CO_2 emission impact factors using the STIRPAT model, discuss the empirical process, obtain key impact factors, and provide suggestions.

Methodology

Data

All data covering the period of 1991-2011 were obtained from the *Chinese Statistical Yearbook*. Besides, consumption of total primary energy, coal, fossil oil, natural gas, and nonfossil energy are all converted into standard coal measures (units: 10^3 tons). Population scale is represented by the total population of China at year's end (unit: 10^3 persons). Urbanization level, industrial level, service level, foreign trade degree, and energy consumption structure are respectively defined as a percentage of non-agricultural population, the ratio between value-added of secondary industry and GDP, the ratio between value-added of tertiary industry and GDP, the percentage of gross import and export value to GDP, and the percentage of fossil oil consumption to total energy consumption.

Measuring Energy-Related CO_2 Emissions

This paper is designed to account for the calculation method of energy-related CO_2 emissions released by the IPCC in 2006.

$$I = \sum_{i=1}^{4} E_i \times K_i \times \frac{44}{12} \tag{1}$$

...where I denotes total CO_2 emissions, K_i is carbon emission coefficient of the ith kind of primary energy, E_i refers to the ith kind of primary energy consumption, and 44/12 is the ratio of molecular weights of CO_2 and C. Coefficients for coal, fossil oil, natural gas, and nonfossil energy are 0.7476, 0.5825, 0.4435, and 0, respectively (ton C/ton standard coal).

Extended STIRPAT Model

IPAT specifies population (P), affluence (A), per capita consumption or production (C), and technology (T) as key driving forces for environmental change, namely $I=P\times A\times T$ [21]. However, IPAT examines only a limited number of variables, thus limiting the research to energy, economy, population factors, and their ratio relationship. Thus there is a necessity to establish stochastic models to analyze the non-proportional effect of human factors and overcome these shortcomings. Some scholars, particularly Dietz and Rosa, have addressed this issue by proposing the basic STIRPAT model, which can model non-proportionate impacts of variables on the environment [22]:

$$CE_i = aP_i^b A_i^c T_i^d e_i \tag{2}$$

...where CE indicates that environmental impact, population (P), affluence (A), and technology (T) are taken as the decisive factors of CE, t denotes the year, e_t denotes the error term, a is the constant, and b, c, and d are the coefficients of P, A, and T, respectively. This paper adopts the following equation taking time-series data in logarithm terms:

$$\ln CE_i = \ln a + b\ln P_i + c\ln A_i + d\ln T_i + \ln e_i \quad (3)$$

...where b, c, and d can be seen as the percentage change in environmental impact caused by a 1% change in an impact factor when other factors remain unchanged, just as elastic coefficient in economics. It should be pointed out that the meaning of technology (T) has changed when the IPAT is extended as STIRPAT. Technology (T) in IPAT is deterministic, while technology (T) in the STIRPAT model is implicitly assumed depending on affluence, population, and other drivers, which should be included in the error term rather than separately estimated [23].

Considering the specific situation in China and learning from past research experience, we carried out corresponding decomposition and improvements on the relevant variables. Compared with the basic STIRPAT model, the extended one with its supplementary variables – including urbanization level, industrial structure, energy structure, and foreign trade degree – allows for much more impact factors of CO_2 emissions to be examined [24]. Specifically, it rejects the unit elasticity assumption and adds randomness for convenience of empirical analysis. Moreover, the extended STIRPAT model can also be used to examine the impact factors on environmental pressure of multiple driving factors such as urbanization, industrial structure, and energy structure by decomposing the population and technology terms.

Extended STIRPAT model can be expressed as:

$$\ln I = a_0 + a_1\ln P_s + a_2\ln P_c + a_3\ln A + a_4\ln T + a_5\ln G + a_6\ln F + a_7\ln W + a_8\ln GDZC + a_9\ln O \quad (4)$$

...where I represents CO_2 emissions, P_s is total population, P_c refers to urbanization level (population urbanization rate), A represents affluence (GDP per capita), T is technology level (carbon emission intensity, i.e. CO_2 emissions per unit GDP in ton/10^4 Yuan), G is industrialization level (percentage of the increased value of secondary industry to GDP), F represents service level (percentage of the increased value of tertiary industry to GDP), W is foreign trade degree (percentage of gross import and export value to GDP), $GDZC$ is capital assets investment, and O refers to energy consumption structure (percentage of fossil oil consumption to total energy consumption).

Specifically, population level is replaced by the variable of total population and urbanization level to describe the energy demand and CO_2 emissions. Affluence level is represented by GDP per capita to further explore the relationship between environmental pollution and variations of per capita GDP at different income levels. York et al. decomposed technical factors into industrial structure and energy intensity, and used empirical methods to confirm that the influence of these two factors are significant in CO_2 emissions [25, 26]. In this regard, we employ carbon emission intensity to replace energy intensity and explain namely CO_2 emissions per unit GDP. The less the energy intensity, the higher the efficiency of economic activities and the less the CO_2 emissions. As there is no clear consensus on valid technology indicator, the variable of carbon emission intensity directly calculated by energy intensity is in accordance with complicated conditions in China and provides a more intuitive observation, while it should be noticed that we choose the default of constant-price GDP to overcome the impact of inflation and analyze the relationship between variables.

Multicollinearity Test

Under conditions of multicollinearity, two or more predictor variables in a multiple regression model are highly correlated, meaning that one can be linearly predicted from others with a non-trivial degree of accuracy. Serious multicollinearity may lead to the failure of regression model thus providing invalid results. Generally, multicollinearity of variables is tested by OLS regression and VIF value. A VIF greater than 10 indicates severe multicollinearity [27]. Mixed estimation and ridge regression are used to mitigate the effects of multicollinearity due to least-squares estimation.

Ridge Regression

Based on the ridge regression research of Wang and Wu et al. in 2013, we can make the following description. Multiple linear regression equation is as follows:

$$Y = X\beta + \varepsilon Y = X\beta + \varepsilon \quad (5)$$

...where X is an $n\times p$ matrix of independent variables, β is a $p\times 1$ vector of unknowns, and ε notes the errors following the hypothesis of zero-mean and equal variance. The parameter estimate of multiple linear regression and ridge regression are respectively given as Eq. (6) and Eq. (7):

$$\widehat{\beta} = (X^{'}X)^{-1}X^{'}Y \quad (6)$$

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

$$\widehat{\beta}^{*} = [I + k(X^{'}X)^{-1}]^{-1}\widehat{\beta} \quad (8)$$

The $X'X$ matrix fails validity if serious multicollinearity exists among independent variables. Thus, ridge regression including a small-positive quantity k is provided to eliminate multicollinearity and keep general stability. In this regard, variance of estimated parameter is less than that in Eq. (6). Ridge regression can be converted back to OLS regression under a special case of k=0 given as Eq. (8) [25]. The bias is shown as Eq. (9), just defined as the ratio of ridge regression estimation $\widehat{\beta}^{*}$ to OLS estimation $\widehat{\beta}$.

$$Bias = \left| I + k(X^{'}X)^{-1}]^{-1} \right| \quad (9)$$

Table 1. Correlation test results.

	ln$W$	lnP_s	lnP_c	ln$A$	ln$O$	ln$G$	ln$F$	ln$GDZC$	ln$T$
ln$W$	1								
lnP_s	0.468*	1							
lnP_c	0.509*	0.987**	1						
ln$A$	0.528*	0.984**	0.977**	1					
ln$O$	-0.434*	-0.902**	-0.887**	-0.916**	1				
ln$G$	0.166	0.502*	0.412	0.554**	-0.420	1			
ln$F$	0.432	0.928**	0.953**	0.879**	-0.826**	0.189	1		
ln$GDZC$	0.537*	0.970**	0.974**	0.995**	-0.904**	0.549**	0.874**	1	
ln$T$	-0.480*	-0.977**	-0.943**	-0.981**	0.935**	-0.579**	-0.854**	-0.960**	1

*Correlation is significant at 0.05 level. **Correlation is significant at 0.01 level.
W, P_s, P_c, A, O, G, F, $GDZC$, and T – explanation in text

Table 2. OLS regression results.

OLS result	Unstandardized coefficient	t-Statistic	Sig.	VIF
Constant	-9.906	-61.860	0.000	-
ln$W$	3.434E-6	0.131	0.898	2.070
lnP_c	1.057	81.771	0.000	954.043
lnP_s	-0.010	-3.031	0.011	1434.699
ln$A$	1.003	831.519	0.000	2620.229
ln$G$	0.002	0.949	0.363	12.772
ln$F$	0.009	4.497	0.001	117.055
ln$GDZC$	0.000	-1.246	0.238	583.063
ln$T$	1.003	1010.780	0.000	669.135
ln$O$	-0.008	-1.019	0.330	16.663
R^2	1.000[a]	-	-	-
F-statistic	4.421E7	-	-	-
Sig.	0.000	-	-	-

W, P_s, P_c, A, O, G, F, $GDZC$, and T – explanation in text.
Sig – significance level, with more significance level lower than 0.05.
VIF – variable inflation factor.
[a] – R value is obtained from the predicted independent variables value.

Empirical Investigation and the Estimation Results

Measurement Results of Energy-Related CO_2 Emission

Fig. 1 shows annual variation of energy-related CO_2 emissions in China. In terms of CO_2 emissions measurement in Eq. (1), Fig. 1 reports an annual growth rate of 6.2% with an annual growth from 208,143,033 tons in 1991 to 6,853,620,988 tons in 2011. From 2001, growth rate accelerated significantly, reaching 8.6%.

Multicollinearity Test

Table 1 shows Multicollinearity test results, showing serious multicollinearity among variables. Table 2 indicates OLS regression results in multicollinearity test. Results show serious multicollinearity due to most VIF values much higher than 10. Hence, as an unreliable method OLS fails to carry out CO_2 emissions analysis. Hence there is a necessity to eliminate multicollinearity.

Ridge Regression Estimation

Based on ridge regression estimation Eq. (4), Fig. 2, and Fig. 3 respectively illustrate ridge trace and the relationship between R^2 and k. Due to the stable value of R^2 in k=0.20, this paper selects k=0.20 to perform ridge regression.

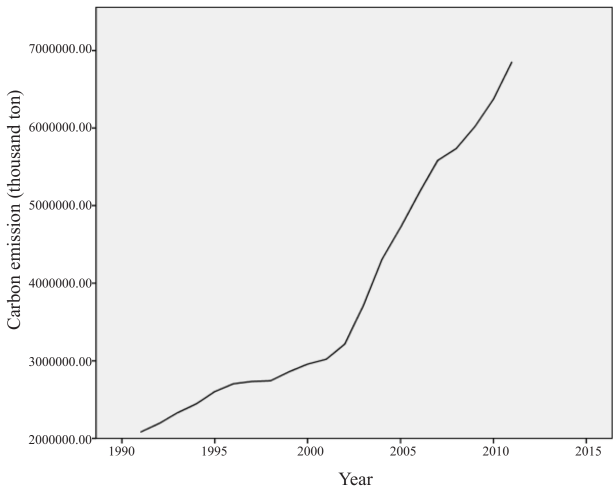

Fig. 1. Annual variation of energy-related CO_2 emissions in China.

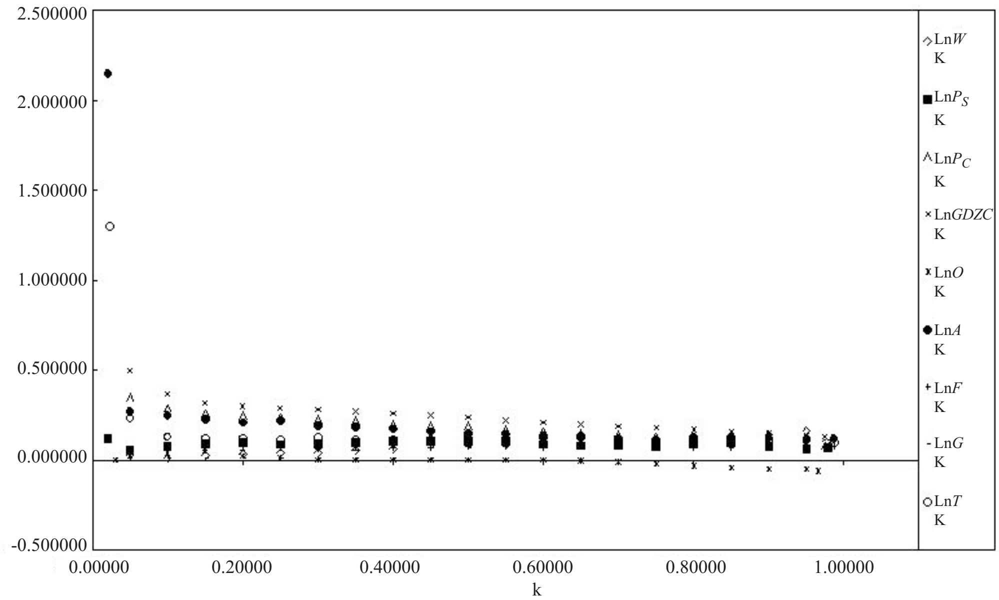

Fig. 2. Ridge trace.

Ridge regression with k=0.28 provides valid and reliable results, including significant ridge coefficients of all variables at 0.05 level, excellent fitting effect with R^2=0.9456, and prominent F statistic value at 21.2571 at 0.01 level. Eventually, the fitted ridge regression equation is as follows:

$$\ln I = 2.0827 + 0.8693 \ln P_s + 0.3781 \ln P_c +$$

$$0.0865 \ln A - 0.00991 \ln T + 0.5908 \ln G +$$

$$0.3897 \ln F + 0.0306$$

$$\ln W + 0.0844 \ln GDZC - 0.3877 \ln O$$

Results Analysis

Based on ridge regression result, the importance of all impact factors can be expressed by the absolute values of elastic coefficients in decreasing order, namely total population, industrial level, service level, energy consumption structure, urbanization level, GDP per capita, capital asserts investment, foreign trade degree, and technology level.

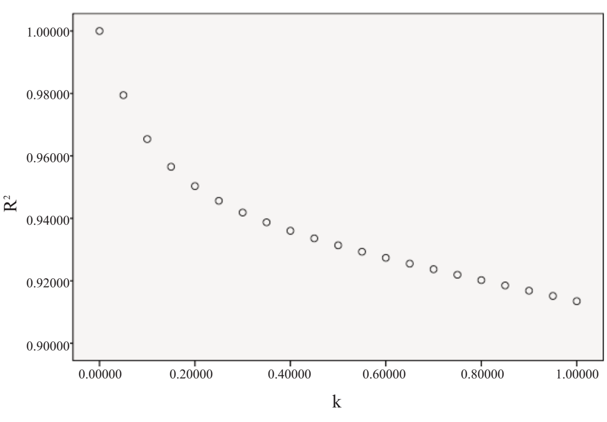

Fig. 3. Relationship variation between R^2 and k.

Population, providing a distinctively positive impact on CO_2 emissions in China, is represented by total population and urbanization level, thus being expressed as population urbanization rate. Obviously, the former shows a 0.8693% growth in CO_2 emissions from every 1% growth in total population, compared to every 1% growth in population urbanization rate, giving rise to 0.4782% growth. The impact of population scale and structure on carbon emissions is prominent. With urbanization and the process of industrialization increasingly speeding up in China, rapid urbanization brings more urban residents, thus greater consumption of high-carbon products for enjoyment. The increasing urban area stimulates urban infrastructure construction, housing heating, and refrigeration systems, thus increasing energy consumption and CO_2 emissions.

GDP per capita, generating a positive impact on CO_2 emissions of China, explain CO_2 emissions rise by 0.0865% for every rise of one point in GDP per capita. Hence, economic sustained growth will directly affect CO_2 emissions variation. Currently, in consideration of China's national conditions, sustainable economic development presents an urgent need for energy consumption, subsequently huge CO_2 emissions growth. A relatively rapid increase in CO_2 emissions is surely evoked by the rapid economic development in China. During the process of rapid industrialization, the government paid much attention to economic growth and excessively pursued the single goal of high-speed GDP growth, and lacked awareness of energy saving and emission reduction work in the past. Thus, economic growth is at the cost of a considerable amount of energy consumption and high, intensive carbon emissions.

Technology progress characterized by carbon emission intensity shows a limited role in CO_2 emissions in China. Although China has gained a certain achievement in the aspect of technology progress regarding the reduction of carbon emission intensity as a symbol, the limited role in China is boil down to several reasons:

1) the technology effect is lagging,
2) some technologies have nothing to do with improving environmental quality,
3) the coal-dominated energy consumption structure has not been greatly improved,
4) three types of carbon emissions – namely carbon emission intensity, per capita carbon emissions, and total carbon emissions – display different peaks,
5) the lack of emission-cutting policies and the lag of implementing energy conservation policy.

Concretely, the elastic coefficient is -0.0099, implying that every 1% increase in carbon emission intensity will cause a 0.0099% decrease in CO_2 emissions. Technological level improvement is contributed to energy efficiency enhancement and energy consumption reduction per unit of GDP. However, in views of invisibility of technological progress effect, there is great potential for technological progress to reduce carbon emissions.

Industrialization and service levels perform a relatively large positive impact on CO_2 emissions, while industrialization level is larger than service level; every 1% increase in industrialization level will cause a 0.5908% increase in CO_2 emissions compared to a 0.3897% increase from every 1% increase in service. As for China, combined with the importance of industrialization level and service level, the increase of industrialization and service level can contribute to energy consumption, thereby promoting the growth of CO_2 emissions. It gradually becomes a top priority to reduce dependence on energy and adjust energy structure in the industrial and service sectors.

As main economic growth points of China, foreign trade degree and capital assets investment also perform a small but positive influence on CO_2 emissions in China, with elastic coefficients, respectively, of 0.0306 and 0.0844. It is imbalance between import trade and export trade. Actually, exported goods from China are mostly primary products, whose development requires a lot of energy, thus directly promoting the growth of CO_2 emissions.

Energy consumption structure contributes a rather prominent and negative impact on CO_2 emissions in China, with elastic coefficient at 0.3877, meaning that every 1% increase in the proportion of fossil oil consumption results in a 0.3877% decrease in CO_2 emissions. CO_2 emission coefficients vary greatly according to energy source, with coal ranking first, followed by fossil fuels, natural gas, and nonfossil fuels. Recently, energy consumption of fossil fuels, natural gas, and nonfossil sources has increased in China, while that of coal has been reduced. Besides, energy consumption structure is optimized gradually and plays an inhibitory effect on CO_2 emissions.

Conclusions and Policy Implications

This paper attempts to provide new evidence in diminishing the growing impact of energy use on the environment and encouraging sustainable energy preservation with the extended STIRPAT model incorporating ridge regression in China from 1991 to 2011. We provide the following proposals.

In consideration of the greatest interpretative ability of the population, China should exert a continuous effort to control total population, promote stable population urbanization, and reinforce population structure optimization. Meanwhile, it is crucial to increase publicity and education to improve the public's low-carbon awareness.

As for positive influencing factors, it is vital to optimize industrial structure, eliminate backward production capacity, develop low energy consumption vigorously, make an appropriate reduction in secondary industrial proportion, and greatly develop the tertiary industry and reduce energy consumption of export products. Moreover, reduction of GDP growth rate and capital assets investment has proven to be favorable. Gradually, it is hoped that we can reduce the dependence of economic growth on resources and damage to the environment.

In views of technology level and energy consumption structure, China should reinforce industrial structure upgrading, energy structure adjustment, energy efficiency improvement, investment in science and technology, and technical level advancement. Besides, high-tech industrial development and limitation of high energy consumption industries are beneficial to energy savings and emissions reduction.

The conclusion drawn by this study is important for the government to adopt relative strategies and enrich the low-carbon-economic system in China. However, the research is still preliminary and worthy of further study, such as method improvement and in-depth analysis of variable relationships.

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