



Review

Impacts of energy-related CO₂ emissions: Evidence from under developed, developing and highly developed regions in China

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ABSTRACT

A large accumulation of carbon dioxide and other greenhouse gases have caused great concern around the world. A great deal of general literature focus on the impact factors of CO₂ emissions at the national, regional and city levels. However, there is little specific guidance on regional difference in CO₂ emissions. In this paper, 30 provincial-level administrative units of China are divided into three different levels of economic development regions according to the GDP per capita from 1997 to 2012. A STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model is used to examine the impact factors on energy-related CO₂ emissions, including population, economic level, technology level, urbanization level, industrialization level and foreign trade degree. The results indicate that the effect of energy intensity is the greatest in highly developed region. Nevertheless, the impact of urbanization, industry structure and foreign trade degree in under developed region is higher than the other two regions. Population and GDP per capita have greater effect on carbon emissions in developing region than the others. Finally, differentiated measures for CO₂ reductions should be adopted according to local conditions of different regions.

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1. Introduction

There is a global consensus that climate change is a severe problem that affects the survival and development of all human beings. China, as the largest developing nation in the world, faces a severe challenge that climate change is being accelerated by an

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increase in atmospheric greenhouse gases with the rapid development of China's economy. That has tremendously affected people's living environment and the development of the society. Under international pressure for CO₂ emissions reduction, Chinese government announced that the carbon intensity will cut by 40–45% in 2020 compared with 2005 (Geng, 2011). Furthermore, "the Outline of National Economic and Social Development Plan in The Twelfth Five-year (2011–2015)" explicitly pointed out that energy consumption must be reduced by 16% and CO₂ emissions per unit GDP must be lowered by 17% during the period of its validity. Actually, China's average annual real GDP growth is 10.30% from 2002 to 2012, which is much higher than that of the world economy in the same period, while energy consumption increased from 1.93 billion to 4.82 billion ton of standard coal, with an average annual growth rate of 9.70%. Therefore, rapid economic growth may be one of the most important reasons of increased carbon emissions.

There has been an increasing interest in the impact factors of energy-related CO₂ emissions at the national, regional and city level. All seem to agree that GDP per capita, population and urbanization are the most impact factors. From the national perspective, Poumanyong and Kaneko (2010) investigated the impact of urbanization on energy use and CO₂ emissions with consideration of three different income groups by regression on population, affluence and technology (STIRPAT) model. The results showed that the impact of urbanization on energy use is greater in high and middle income groups than in low income group, while the impact on emissions was greater in the middle income group than in other income groups. Martínez-Zarzoso et al. (2012) attributed the impact of urbanization on CO₂ emissions to developing countries and found that there was an inverted-U shaped relationship between urbanization and CO₂ emissions. Moreover, the urbanization level had a significant difference among the three groups.

From the regional perspective, Zhang and Lin, 2012 pointed that population, GDP per capita, urbanization and technology level had positive impacts on CO₂ emissions. Moreover, the impact of urbanization on CO₂ emissions in central region was greater than that in the eastern region. However, technology level was effective but limited in reducing emissions due to increasing demands from economic development and population growth in the transport sector. (Zhang and Nian, 2013). In addition, Li et al. (2012) researched the same issue by adopting different criteria to the classification, which employ the STIRPAT model to discover the effects on energy-related CO₂ emissions of five emission regions based on the CO₂ emissions per capita. The authors found that urbanization and GDP per capita had greater impacts on CO₂ emissions than other factors.

In terms of analysis at the city level, many literatures on these issues have obtained valuable results from different perspective by using different methods. Among them, Wang et al. (2012) adopted STIRPAT model to study the influence on CO₂ emissions of Beijing. They argued that economic level, urbanization level, and industry proportion positively influenced CO₂ emissions, while tertiary industry proportion, energy intensity and R&D output negatively did. Taking Guangdong as a case, Wang et al. (2013) illustrated that factors such as population, urbanization level, GDP per capita, industrialization level and service level, could cause an increase in CO₂ emissions. However, technology level, energy consumption structure and foreign trade degree could lead to a decrease in CO₂ emissions. Using the log-mean divisia index (LMDI) method, Zhao et al. (2010) investigated the influencing factors of industrial carbon emissions (ICE) in Shanghai, and revealed the industrial output was the main driving force of ICE.

In general, there is little guidance on regional difference in CO₂ emissions, especially China's regional differences. Furthermore,

the existing research on regional level is mainly based on the classification of geographical location. However, due to the different regional characteristics, it may not be appropriate to study the impacts on carbon emissions according to the geographical location. For example, Hainan Province and Shandong Province are located in eastern region of China, but the economic level of Shandong Province is two times more than that of Hainan Province, and the carbon emissions are over by 22 times. According to early studies, economic level is the most important factor affecting China's regional carbon emissions. (Zhu and Peng, 2012; Zhang and Lin, 2012) Moreover, unbalanced regional economic development is the main characteristic of Chinese economic development. Therefore, it is necessary to study the impacts of carbon emission factors and enact targeted environmental policy in different economic level regions. This paper divides China's 30 provinces into three regions of different economic level according to GDP per capita by cluster analysis method. In order to examine regional differences of CO₂ emissions, STIRPAT model should be used to study the impact of carbon emissions factors.

The remainder of this paper is organized as follows. Section 2 describes the methodology of STIRPAT model incorporating PLS (partial least square) regression. Section 3 presents the data sources. Results and discussions are given in Section 4, and the conclusions and policy implications are summarized in Section 5.

2. Methodology

2.1. Estimation of CO₂ emissions

The energy-related CO₂ emissions can be estimated by multiplying consumption of individual fuels with their carbon emission coefficients and a conversion coefficient as follows.

$$I = \sum_i^9 E_i \times K_i \times \frac{44}{12} \quad (1)$$

where I represents CO₂ emissions (in 10⁴ tons), E_i refers to the i th kind of primary energy consumption, K_i is carbon emission coefficient of the i th kind of primary energy, and the factor 44/12 is the ratio of molecular weights of CO₂ and C.

In this paper, nine types of energy are calculated, namely coal, coke, crude oil, fuel oil, gasoline oil, kerosene oil, diesel oil, natural gas and electricity. The carbon emission coefficient is 0.7476, 0.1128, 0.5854, 0.5532, 0.3416, 0.5913, 0.6176, 0.4479 and 2.2132, respectively (National Development and Reform Commission Energy Research Institute, 2003).

2.2. The STIRPAT (stochastic impacts by regression on population, affluence, and technology) model

Much attention has been paid to the IPAT model to specify the driving forces that influence economic activity on the environment (Chertow, 2000; Feng et al., 2009; Kwon, 2005). The IPAT model was firstly proposed by Ehrlich and Holdren (1971), and its general form is:

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

where I represents the environment impact (usually proxied by CO₂ emissions or energy consumption), P stands for population size; A means affluence (usually proxied by per capita affluence), and T denotes technological level (usually proxied by energy intensity). The quantitative models are widely used in the analysis of the impact of human factors on the environment. However, the major limitation of IPAT is that, it does not permit hypothesis testing since the known values of some terms determine the value

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