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Identifying the key impact factors of carbon emission in China: Results from a largely expanded pool of potential impact factors

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ABSTRACT

Carbon emission reduction (CER) comes to be the principle in most countries particularly China, the largest carbon emitter. For finding an efficient solution, the priority is to find the key impact factors (KIFs) of carbon emission. Previous studies for identifying KIFs, which partially selected only a few potential impact factors (PIFs), are inconsistent in their findings. This study aims to explore the KIFs of carbon emission in China among 43 PIFs, which comprehensively covers 30 relevant studies. The KIFs in China are identified using the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model with correlation analysis, partial correlation analysis and stepwise regression. The findings of this study are as follows: (1) China's carbon emission has five KIFs: the real GDP per capita, urbanization rate, ratio of tertiary to secondary industry, ratio of renewable energy, and fixed assets investment; (2) the most significant carbon emission contributor is real GDP per capita and the most significant carbon emission inhibitor is urbanization rate. This study provides the reliable KIFs for governors' targeted decision-making on CER, and policy implications from the identified KIFs are highlighted.

1. Introduction

Carbon emission has been recognized as the main cause of climate change leading to various risks and economic loss (Shi et al., 2017). The total amount of carbon emission at the global level has increased approximately triple, i.e. from 9385.8 million tons in 1960 to 35,848.6 million tons in 2013, showing an annual increasing rate of 2.8% (World Bank, 2017). As reported by the United Nation Office for Disaster Risk Reduction, the average land surface temperature increased by 0.85 °C from 1880 to 2012, which has led to substantial species extinction and global food supply and demand imbalance (New York Times, 2015). Human-beings are suffering from the extreme weather, which has led to over 600,000 people died and 4.1 billion people wounded, as well as economic loss of over 1.9 trillion dollars in the past two decades (New York Times, 2015). A warning from Stern (2007) stated that there would be a loss of 5% annual global GDP to balance out the overall costs and risks from global warming if no action was taken to reduce carbon emission. Therefore, it is considered imperative to conduct the CER from a global perspective (Shuai et al., 2017a).

China, as the largest emitter in the world, has taken up more than a quarter of the global carbon emission (Ma et al., 2017a). Meanwhile, the industrialization in China, which is considered as the major contributor of carbon emission, will continue to play the role in the following decades (Chen et al., 2017). Such status quo has aroused global attention to the carbon emission of China, who is facing the great pressure and challenges for CER (Shen et al., 2018). To do that efficiently, there is a strong science consensus that it is significant to identify the KIFs of carbon emission, which may directly influence the constitution of the CER measures, policies and strategies (Fan et al., 2006).

The topic of studying KIFs on carbon emission has attracted much attention from researchers (Shuai et al., 2017b). The impact factors in previous studies can be classified into population, affluence and technology (Ma et al., 2017b). In those studies, a category of impact factors of carbon emission may have different proxies. For

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Nomenclature list

Abbreviation

CER	carbon emission reduction
GDP	gross domestic product
IPAT	Impact = Population × Affluence × Technology
KIF	key impact factor
PIF	potential impact factor
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology

example, "urbanization rate" was used as the proxy of population in Zheng et al. (2016), while Fu et al. (2015) adopted "total population" and Zoundi (2016) selected "population growth rate". One problem is that each of the three proxies can only partially stand for the population. The other problem is that researchers selected only several factors that could be tested with their available data as the PIFs. The incomprehensiveness of PIFs directly leads to the inaccurate identification of KIFs, i.e., previous studies ignored the factors that might become the KIFs when selecting PIFs. For addressing the two problems, this study aims to identify more reliable KIFs of carbon emission in China based on a largely expanded pool of PIFs for tailoring CER strategies.

This study is innovative owing to the following two aspects. First, previous studies selected limited amount of factors (usually less than seven), while this study systematically selected the 43 PIFs by reviewing the previous studies that explore the KIFs in different countries or regions, which enables the results with more reasonableness. Second, this study is also innovative in the research methodology, as this is the first study to eliminate the partial correlation between multiple PIFs, which makes the results more reliable. The contributions of this research are from the theoretical and practical aspects. Theoretically, this study provides a more integrated and accurate group of KIFs of carbon emission. The methodology can serve as a guidance for scientifically selecting KIFs. Besides, this comprehensive concept can be extended to other countries as well as to other pollutants such as sulfur, haze and waste water. Practically, the identified KIFs in this study are valuable reference for the governments to tailor policies for effective CER.

2. Literature review

2.1. Methods for identifying the KIFs of carbon emission

There are various methods for identifying the KIFs, such as interpretive structural modeling (Samantra et al., 2016), social network analysis (Webster et al., 2016) and structural equation model (Xiong et al., 2014). However, these methods were critiqued relatively subjective, since the data used in these methods are from questionnaire surveys rather than the second-hand data (Shen et al., 2016). The samples of carbon emission are actual second-hand data, which indicates these methods are inappropriate for identifying KIFs on carbon emission in this study.

The current methods for exploring the KIFs of carbon emission can be classified into two categories, namely Kaya identity and STIRPAT (Wu et al., 2016). Wu et al. (2016) employed the Kaya identity with Monte Carlo simulation to examine the KIFs of carbon emission in China. Sumabat et al. (2016) applied the re-write Kaya identity to analyze factors that influence carbon emissions due to fossil energy consumption in China to explore key factors for policies promoting CER. Nian et al. (2014) combined the Kaya identity and the decomposition technique to identify KIFs of carbon emission from nuclear power generation. Similarly, Shahiduzzaman and Layton (2015) decomposed the Kaya identity into population, GDP per capita, energy intensity and carbon intensity to examine the KIFs in the United States. Conventionally, using the Kaya identity, carbon emission is decomposed into limited factors as the decomposed factors needed to be explained logically and possess the real meaning. However, STIRPAT, derived from IPAT model, describes environmental impact (I) as a function of population (P), affluence (A) and technology (T) with stochastic status, and each function can be represented into different factors. As STIRPAT model can be expanded to incorporate unlimited additional factors, this method became a well-known technique that was widely adopted to identify the KIFs of carbon emissions. For example, Wang et al. (2017) selected eight PIFs of carbon emission using STIRPAT model for examining the KIFs in Xinjiang, China. Employing STIRPAT model with panel data analysis, the research by Poumanyvong and Kaneko (2010) identified the critical KIFs of carbon emission in 99 countries from eight nominated factors. This method is thus adopted to explore KIFs of carbon emission based on the PIFs in this study.

2.2. PIFs of carbon emission

Studies that examined the KIFs of the carbon emission select different PIFs. The PIFs are reviewed and listed in Table 1.

It can be easily shown from Table 1 that different researchers select different PIFs in their studies to identify KIFs. For example. Wang et al. (2012) selected factors including urbanization rate, GDP per capita, the share of the industry output value over the total GDP, and the share of the tertiary industry output value over the total GDP as the PIFs to explore the KIFs of carbon emission in Beijing, China. Li et al. (2015) examined the KIFs of carbon emission in Tianjin city on the basis of factors such as foreign direct investment, total permanent population, and energy use per GDP; Wang et al. (2017) used factors including total population, total fixed assets investment, percentage of gross import and export value to GDP and percentage of coal consumption to total energy consumption for studying Xinjiang, China; Zoundi (2016) adopted renewable energy consumption per capita population growth and GDP per capita as the PIFs to examine the KIFs in 25 African countries; and the PIFs adopted in de Alegría et al. (2016) are renewable energy consumption share as a proportion of total Primary Consumption, total population and energy intensity; and Ohlan (2015) analyzed the KIFs of carbon emission in India using the factors including energy consumption per capita, GDP per capita, population density and the total exports and imports.

The inconsistence of using potential factors for one category not only happens for different regions, but also happens between the researches on identifying the KIFs in the same region. For identifying KIFs in China, Zhou and Liu (2016) used factors such as the share of the working-age population (16–64 years old), average household size, and GDP per capita as the PIFs; Xu and Lin (2017) used the total energy use divided by GDP, industry's coal consumption by its total energy consumption and urbanization rate as the PIFs; Xu et al. (2016) used GDP per unit energy consumption, total population and the ratio of industry sector value added in GDP as the PIFs; and Guan et al. (2017) adopted farmers annual net income per capita, population density, urban employment and the ratio of tertiary industry sector value added in GDP as the PIFs. The inconsistence of selecting PIFs definitely leads to the differences of the identified KIFs between their studies, which could partially guide the CER. Therefore, it is important to enlarge the pool of PIFs