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Identifying key impact factors on carbon emission: Evidences from panel and time-series data of 125 countries from 1990 to 2011

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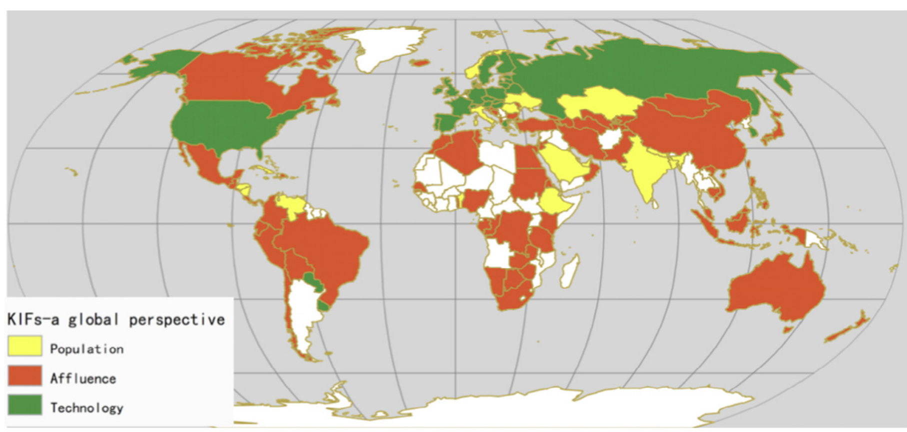
HIGHLIGHTS

- KIFs of carbon emission in 125 countries are identified.
- The panel and time-series data are both utilized.
- Influence degree of factors on carbon emission varies at different income levels.
- The identified KIFs offer reliable references to promote global carbon emission reduction.

GRAPHICAL ABSTRACT



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ABSTRACT

Global warming caused by carbon emission has been recognized as a threat to public health and welfare. Carbon emission reduction is therefore a necessary task for each country to address the severe challenges arising from global warming. This research combines the STIRPAT model with the use of the panel and time-series data to analyze the impacts of population, affluence and technology on the carbon emission of 125 countries at different income levels over the period of 1990–2011. The results show that the key impact factor (KIF) at global level is affluence, followed by technology and population in the order of their impacts on carbon emission. For countries at high-income (HI) level, technology has the greatest impact on carbon emission, while affluence has the least. Affluence, prior to technology and population, is identified as the KIF of carbon emission for countries at upper-middle-income (UMI) and lower-middle-income (LMI) levels. When it comes to the low-income (LI) level, affluence serves as the factor greatest affecting on carbon emission, and technology has the least impact. In particular, two generic patterns are identified based on the empirical results: higher income leads to greater impact of the technology and lower impact of the affluence on carbon emission. The KIFs of different income level countries identified in this study provide policy-makers and practitioners with valuable references for adopting effective policies and strategies to stimulate the global carbon emission reduction.

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1. Introduction

Human activities since the Industrial Revolution, particularly the accumulated carbon dioxide emissions from the intensive fossil fuels consumption, have resulted in significant increase of the atmospheric concentration of greenhouse gases, which exacerbated climate change primarily characterized by global warming [1]. Global warming has significant impacts on global natural ecosystems, causing temperature increase and sea level rise as well as more frequent extreme climate events, all of which pose a huge challenge to the survival and development of the human race [2]. Intergovernmental Panel on Climate Change (IPCC) [3] reported the year 2100 could witness a global temperature increase of 1.1–6.4 °C and a sea level rise of 16.5–53.8 cm. Moreover, annual report by the IPCC [4] identified that 1983–2012 was likely the warmest 30-year period during the last 1400 years, and the land surface temperature increased by 0.85 °C during 1880–2012, which could lead to substantial species extinction and global food supply and demand imbalance. More seriously, according to the report by the United Nation Office for Disaster Risk Reduction, over 600,000 people died and 4.1 billion people wounded from extreme weather over the last two decades, inflicting economic loss of over 1.9 trillion dollars [5].

It is commonly appreciated that the major increase in Greenhouse Gas (GHG) is largely attributed to carbon dioxide (CO_2) as the principal gas leading to global warming. According to the Fifth Report of the IPCC [4], the total amount of global carbon emission has increased from 9434.4 million tons in 1961 to 34649.4 million tons in 2011, which may double or even triple by the middle of this century if it fails to be effectively controlled. Stern [6] further warned that, if no action was taken to reduce carbon emission, the overall costs and risks of global warming would be equivalent to a loss of 5% annual global GDP. It is therefore considered urgent to conduct the carbon emission reduction at the global level. To do that efficiently, it is significant to identify the KIFs affecting carbon emission in different countries at global level, which may directly influence the constitution of the carbon emission reduction measures, policies and strategies [7]. The research by Wang et al. [8] and Li et al. [9] echoed this view and proposed that investigating the KIFs of carbon emissions is the key to making polices and conducting scenario analysis for carbon emission reduction efficiently.

Therefore, this paper aims to identify the KIFs of carbon emission in different countries, and proposed the applicable policy implications for the governments to effectively conduct the global carbon emission reduction. The innovation and contribution of this paper compared with other references mainly lies in the following two aspects. On one hand, this research innovatively applies both the time-series and panel data analysis to identify the KIFs in different countries to ensure the empirical results more reliable. On the other hand, this is the first study providing detailed country-by-country analyses aiming to identify the KIFs of carbon emission in 125 individual countries. These KIFs findings provide national governments with a scientific basis for effective and targeted policy-making, which is a contribution particularly for global carbon reduction.

The reminder of this paper is organized as follows. Section 2 reviews the literatures applying the IPAT method to identify the KIFs. Section 3 introduces the IPAT and STIRPAT models, time-series and panel data. Section 4 presents the steps for identifying the KIFs with STIRPAT model. Section 5 displays the empirical analysis conducted to identify the KIFs. Section 6 demonstrates the discussion on the results from the empirical analysis. Section 7 draws a conclusion and raised policy implications of this study.

2. Literature review

Currently, various methods have been developed for identifying the KIFs. Based on the comprehensive literature review, methods frequently adopted are summarized as shown in Table 1.

Table 1 lists four methods to identify KIFs. The results from the first three methods, namely ISM, SNA and SEM, were found relatively subjective, since the samples for data analysis are basically from questionnaire survey rather than the actual statistics data [10]. However, the results from IPAT are objective as the samples of IPAT are based on the actual statistics data. Therefore, this research adopts the IPAT method to identify the KIFs of carbon emission.

The IPAT method is universally applied to identify the KIFs of carbon emission in numerous previous studies at industrial, regional and national level. For example, at the industrial level, Xu and Lin [11] investigated the KIFs of carbon emission in China's iron and steel industry by applying IPAT model with panel data analysis. Similarly, Xu and Lin [12] explored the KIFs of carbon emission in China's transport sector using IPAT model with dynamic non-parametric additive regression. Zhang and Liu [13] used the random form of IPAT model, i.e. STIRPAT, to study the KIFs of carbon emission in the Information and Communication Technology (ICT) industry in China.

At regional level, for example, Tan et al. [14] selected Chongqing, a city in China as an example to analyze the KIFs of carbon emission by using STIRPAT. Wang et al. [15] analyzed the KIFs of carbon emission in Beijing, the capital China, and concluded that carbon emission is dominantly driven by population and inhibited by technology. Li et al. [16] adopted the STIRPAT model with partial least squares regression to identify the KIFs of carbon emission in Tianjin, China and pointed out that technology is the key influence factor. Wang et al. [17] also employed the STIRPAT model with scenario analysis to find out the main driving factors of carbon emission in Shanghai, China. Using the STIRPAT model with ridge regression, Wang et al. [18] revealed the population factor is the KIF of carbon emission in Guangdong province, China. The research of Deng and Dong [19] stressed affluence is the KIF of carbon emission from coal consumption in Shandong province by employing the STIRPAT model with vector autoregression. Yue et al. [20] combined the IPAT model with scenario analysis to optimize carbon emission reduction in Jiangsu province, China and concluded that economic growth is the KIF of carbon emission.

When it comes to national level, the research by Zhou and Liu [21] studied the KIFs of carbon emission in China by using the STIRPAT model with balanced provincial panel data. Burnett et al. [22] integrated the IPAT model with Kaya identity to analyze the relationship of the carbon Kuznets curve in US, and suggested that economic growth is the KIF of carbon emission. By applying the IPAT model with input-output analysis, Cansino et al. [23] tested the main drivers of changes in carbon emission in Spain.

Table 1
Frequently adopted methods for identifying the KIFs.

Method	Related references
Interpretive structural modeling (ISM)	Shen et al. [10], Samantra et al. [62], Sahney [63], Yadav and Barve [64]
Social network analysis (SNA)	Fritsch and Kauffeld-Monz [65], Loughead et al. [66], Webster et al. [67]
Structural equation model (SEM)	Chou and Yutami [68], Xiong et al. [69], Xiong et al. [70]
Impact, population, affluence and technology (IPAT)	Wang et al. [8], Wang et al. [18], Yue et al. [20]