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Spatial correlation of factors affecting CO_2 emission at provincial level in China: A geographically weighted regression approach

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A B S T R A C T

Carbon dioxide (CO_2) emissions have become a rising concern in China. Few studies have considered spatial correlation and agglomeration effect of CO_2 emissions for adjacent regions and provinces. This paper employs Geographical Weighted Regression (GWR) model to examine the impact of urbanization, industrial structure and energy intensity on CO_2 emissions and reveals the spatial correlation in different provinces in 2005, 2008, 2011 and 2015. The results indicate that there is an obvious spatial effect on CO_2 emissions of each province based on the GWR results. Urbanization is the most significant factor in the increase of CO_2 emissions for all provinces in each year. For the neighboring provinces, a coordinated low-carbon urban construction plan should be carried out based on the urbanization development level. Energy intensity has a positive effect on CO_2 emissions, but the effect on the emission reduction is relatively weak and unstable. It should strengthen exchanges and cooperation between provinces and regions by jointly exploring and promoting technologies to improve the efficiency of resource use and reduce CO_2 emissions. The influence of industrial structure on CO_2 emissions is positive, indicating that the industrial structure adjustment plays an important role in carbon emission reduction.

1. Introduction

The rise in greenhouse gas (GHG) emissions, especially carbon dioxide (CO_2) emissions has become a severe problem because it hinders the development of both society and the global economy. As the world's largest emitter of GHG, China accounted for 28% of global total CO_2 emissions in 2013, which was mainly caused by the rapid urbanization and industrialization. In addition, the goods from China embodied much more virtual CO_2 based on consumption perspective, which becomes an important source of virtual GHG emissions (Liu et al., 2017). Under international pressure for CO_2 emissions reduction, the Chinese government announced that the carbon intensity would be cut by 40–45% in 2020 compared to 2005 (Geng, 2011). "The Outline of National Economic and Social Development Plan in The Twelfth Five-year (2011–2015)" explicitly noted that the energy consumption must be reduced by 16% and that the CO_2 emissions per unit GDP must be lowered by 17% during the period of this plan. In 2014, China made a commitment that it would achieve its peak CO_2 emissions around 2030 and reduce its carbon intensity by 60–65% in 2030 compared to 2005 (Wang et al., 2016a). This will be a great challenge for China, especially over the next five years. Reducing CO_2 emissions is not only the target for general emission reduction, but also beneficial for solving China's current environmental problems. As an atmospheric resource, CO_2 emissions can be transmitted to the neighboring areas under the influence of natural factors. There are similar characteristics of CO_2 emission in adjacent regions and provinces. The government should adopt measures to control the inherent spatial effects of carbon emissions (Han et al., 2018). Given the similarity, it is essential to examine the spatial correlation of factors affecting provincial CO_2 emission.

At present, a number of previous studies have analyzed the factors affecting CO_2 emissions at national and regional level. Urbanization have complex impacts on the environment through changes in human activity patterns. The impacts include direct causal effect, mediated causal effect and moderated causal effect (Chikaraishi et al., 2015). Most of them considered that urbanization increased energy consumption and carbon emissions. With the

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accelerating process of urbanization, a large number of private and public facilities needed to meet the rapid growth of urban population and urban economic development (Yang et al., 2015). Energy demand and carbon emissions will increase accordingly (Wang et al., 2017). Rising income also leaded citizen to use more household appliances and private cars (Xu and Lin, 2015). Using the STIRPAT model, Poumanyvong and Kaneko (2010) investigated the impact of urbanization on energy use and CO_2 emissions in three different income groups. The results showed that the impact of urbanization on energy use was greater in the high and middle income groups than that in the low income group, whereas the impact on emissions was the greatest of middle income group. Zhang and Lin (2012) pointed that the impact of urbanization on CO_2 emissions in central region was greater than that in the eastern region. Wang and Zhao (2015) indicated that the urbanization in under developed region was higher than that of the highly developed and developing region. Sheng and Guo (2016) found that whether in the long-term or short-term, rapid urbanization always increased carbon dioxide emissions. Based on the Ecological modernization theory, urbanization is one important indicator of social transformation and modernization. Further modernization can minimize the influence of urbanization on the environment (Poumanyvong and Kaneko, 2010). The development of urbanization will reduce energy consumption and carbon emissions, especially in high income countries (Ewing and Rong, 2008). Shahbaz et al. (2016) analyzed the impact of on CO_2 emissions in Malaysia and found that the relationship between urbanization and CO_2 emissions is U shaped. Technical level was another important impact factor on CO_2 emissions. Energy intensity is used to represent the technical level. It is generally known that reducing energy intensity has a positive effect on carbon emission reduction (Wang and Zhao, 2015). Through technological advances to develop wind, solar, biomass energy and other renewable energy can decrease energy intensity (Wang et al., 2017). Improving technical level was an important approach to decrease energy consumption and CO_2 emissions, but it produced a small reduction in CO_2 emissions (Li et al., 2012). Using the environmental learning curve (ELC) model, Yu et al. (2016) selected energy intensity as the independent variables to evaluate the emissions reduction potentials for 43 economic sectors. Guo et al. (2016) indicated that energy intensity has the strongest potential to mitigate carbon intensity. Wang and Lu (2014) found that there exists rebound effect, which means that the improvement of energy efficiency does not necessarily reduce energy consumption and can even increase energy consumption (Wang et al., 2016b). Industrial structure has a positive impact on the increase of carbon emissions (Cheng et al., 2017). Changing the industrial structure were an imperative measure for carbon emission reduction (Xu et al., 2017a). Promoting the optimization of industrial structure can lead to a decrease in CO_2 emissions effectively (Zhang and Zhao, 2014). Based a multisectoral decomposition analysis, Li et al. (2017) indicated that industrial structure has a relatively large impact on carbon emissions.

A great number of empirical results also analyzed the factors affecting CO_2 emissions in individual province. Taking Guangdong province as an example, Wang et al. (2013) examined the key influencing factors of energy-related CO_2 emissions, concluding that population, urbanization level, GDP per capita, industrialization level and service level had positive impacts on CO_2 emissions. While the technology level, energy consumption structure and foreign trade degree were identified as having a negative influence. The same study also includes Beijing (Wang et al., 2012), Tianjin (Shao et al., 2014), Liaoning (Geng et al., 2013), Shanghai (Zhao et al., 2010) and Anhui (Wang et al., 2016c). Emission reduction policies were put forward according to the characteristics of different provinces. In recent years, with the development of spatial econometrics, Liu et al. (2017) investigated the effect of urbanization on energy consumption in different regions of China from the perspective of spatial econometrics. The results showed that the spatial spillover effect on adjacent areas was positive. Requia et al. (2017) conducted a spatial analysis of traffic emissions across 5570 municipal districts in Brazil. They found a significant association between emissions inventories and the variables used to evaluate spatial clusters. To investigate the impacts of different spatial-modal strategies on reducing commuting emissions, Chow (2016) estimated the range of emissions under 42 spatial-modal scenarios. To understand the spatial and temporal emissions pattern within transportation, Luo et al. (2017) analyzed the taxi's energy consumption and emissions and their spatial-temporal distribution in Shanghai. It was helpful for the policy makers to better understand the travel patterns and related environmental implications in Shanghai metropolis by investigating the spatial and temporal emissions distribution of taxis.

Among previous studies, LMDI (Logarithmic Mean Divisia Index) is a commonly used decomposition method for analyzing the influencing factors of carbon emission. It is easy to use, and the results are easy to explain with sound theoretical foundation and no residuals (Ang, 2005). The decomposition factors are limited by the LMDI method. The STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model is used to analyze the impact of population, affluence and technology on carbon emission, which comes from the IPAT model and allows other impact factors to be added to analyze their influence on environmental pressure (Wang et al., 2013). It is widely used to solve realistic environmental issues combining societal, economic, and technological factors (Fu et al., 2015). The Panel Granger causality is also used to examine the factors that influence the CO_2 emission. Based on the panel data, the model is more efficient in recognizing and measuring effects than other models (Al-mulali, 2012). It does not reflect the differences between provinces. Due to the difference in geographical position, the relationship between variables and the structure of the model will be changed accordingly. CO_2 emissions, as an atmospheric resource, are obviously changeable with different geographical position. Due to the significant differences in resource structure and infrastructure, the effects of carbon emissions are distinctly varied in different provinces (Tian et al., 2016). Spatial analysis is a technique that takes into account various geographic phenomena, providing data that can be communicated to potentially affected people, as well as government agencies considering policies to reduce exposure and adverse effects (Cai et al., 2016). Considering the spatial effect of CO_2 emissions, the GWR model is more appropriate to estimate parameters than the OLS (Ordinary Least Square) model in the study of CO_2 emissions (Sheng et al., 2017). The geographically weighted regression (GWR) model allows the estimated parameters to vary across regions, making it possible to assess potential spatial differences. Xu and Lin (2017) investigated the differential effects of various factors on CO_2 emissions in the agricultural sector by a GWR model and found that the impacts were homogeneous across countries. Chen et al. (2018) found that the GWR model can effectively examine the spatial effect on the industrial agglomeration and diffusion of different regions. Xu et al. (2017b) investigated the driving forces of CO_2 emissions in the manufacturing industry using a GWR model. Videras (2014) explored the geographical variability of CO_2 emissions using a GWR model and found strong evidence of spatial heterogeneity in the estimated elasticities of emissions. These existing studies has proved that the GWR model is considered more appropriate to estimate parameters in CO_2 emissions studies than other models (Sheng et al., 2017). Spatial analysis can provide reliable reference for regional policy making.

Although existing researchers already have dealt with the impact factors of CO_2 emissions and its spatial heterogeneity. There is still blank space in the research. First, existing researches rely on standard regression methods such as OLS, LMDI and STIRPAT model