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Drivers of carbon emission intensity change in China

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ABSTRACT

Carbon emissions per unit of GDP (also called carbon emission intensity, CEI) can be utilized to measure regional carbon emission performance. In this study, structural decomposition analysis (SDA) and quantile regression are employed to investigate the factors that drive changes in CEI in China. Based on input-output SDA, CEI in China during 1992–2012 is decomposed from the perspectives of the total economy and economic sectors. The results specify that the industrial sector is the key sector for energy conservation and emission reduction. Energy efficiency contributes the most to CEI reduction, whereas input structure, final demand structure, and final product structure are factors that hinder reductions. Furthermore, energy mix, technical progress, industrialization index, and final consumption rate are introduced as proxy variables. To reveal the changes of influencing factors with CEI increasing, the effects of these proxy variables on CEI are explored by quantile regression with panel data of 30 provinces from 1999 to 2014. The results indicate that energy mix, industrialization index, and final consumption rate have positive effects on CEI. As CEI increases, the effect of energy mix increases gradually, whereas the effect of industrialization index tends to decrease, and the effect of final consumption rate increases initially and then decreases. Technical progress and urbanization are both effective in reducing CEI. With CEI increasing, the negative effect of technical progress presents a trend of decrease, then increase. Conversely, the negative effect of urbanization is through the process of increase, then decrease.

1. Introduction

The rapid economic development has led to overwhelming energy consumption and unprecedented rise in greenhouse gas (GHG) emissions due to human activities, so the environmental problem has become increasingly prominent which can hardly be neglected. While CO_2 emissions account for the most of GHG caused by anthropogenic activities (Fernando and Lin Hor, 2017), global carbon emissions are expected to increase by 30% above the 2010 level by 2030 (Liu et al., 2017), and China has exceeded the United States in carbon emissions and became the world's largest carbon emitter in 2007 (Dong et al., 2013a). China has made a lot of efforts to reduce carbon emissions and committed to reduce its CEI by 40%–45% by 2020 from the 2005 level (Dong et al., 2013b; Yang et al., 2016; Qi et al., 2017). Furthermore, the Chinese government aimed to peak CO_2 emissions no later than 2030 (Guo et al., 2017; Dong et al., 2017) and increase the proportion of non-fossil fuels in primary energy consumption to 20% by 2030 (Den Elzen et al., 2016). Moreover, China proposed to cut CEI by 60%–65% by 2030 compared to the 2005 level (Chen et al., 2017). In the 13th Five-Year Plan (2016–2020), China formulated the mitigation targets of reducing aggregate energy intensity and aggregate CEI by 15% and 18%, respectively (NDRC, 2016). Therefore, it has been an urgent problem to be solved in how to effectively mitigate CEI in China. Many scholars have studied the feasibility of the said goals. For example, Yi et al. (2016) and Xiao et al. (2016) perform the scenario analysis to suggest that China is very likely to achieve CEI reduction goal by 2020. Yuan et al. (2014) propose that a 17% clean energy target can meet the target of 40–45% reduction in CEI by 2020. Zhang et al. (2017) employ the dynamic Monte Carlo simulation and scenario analysis to indicate that China can meet the 2020 and 2030 CEI reduction targets under the existing policy, while it is uncertain whether China can reach its peak CO_2 emissions level by 2030. One important issue underlying these mitigation targets is whether China can promote collaborative carbon reduction and economic growth. This requires scrupulous and comprehensive study on the mechanism of China's regional carbon emissions.

Compared to aggregate carbon emissions and per capita carbon emissions, CO_2 emissions per unit GDP (i.e. CEI) is a better indicator which better reflects the energy and economic performance of a country, what's more, it is an important indicator of China's

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international commitment in reducing emissions. There are some disputes about applying CEI to represent decarbonization efforts in an economy. For instance, Cansino et al. (2015) indicate that the 2020 intensity reduction target in China can be easily achieved without additional active migration policies by using a combined input–output method and the World Input–Output Database. We acknowledge the fact that total carbon emission reduction target can better present the efforts of carbon mitigation in an economy. However, as we have mentioned above, economic development and emissions reduction are both of great importance in China against the background of the new normal and sustainable development. The abatement target of CEI means reducing CO_2 emissions without damaging economic growth. Moreover, given the implement of international carbon tax, a country with lower CEI has larger product competitiveness. At present, the existing studies on CEI mainly adopt econometric analysis and decomposition analysis methods. Econometric methods have been widely used in CEI research. Dong et al. (2016) adopt a combination of static spatial econometrics and dynamic panel co-integration methods to study the effects of urbanization and energy mix on CEI in China, and find that urbanization and energy mix have positive impacts on CEI. Li et al. (2017) employ Moran's I index and dynamic evolution model to study China's CEI in construction sector from the space and time dimensions, respectively. Similarly, using the spatial panel econometric model, Cheng et al. (2014) analyze the influencing factors and spatiotemporal dynamics of CEI in China, and the results specify that energy intensity, energy mix, industrial structure and urbanization are the main driving forces of CEI. Wang et al. (2016b) employ OLS regression to investigate what influences CEI at national and regional levels. Zhu et al. (2014) utilize cross-sectional data econometric analysis to analyze the influencing factors of CEI change differences among 89 countries during 1980–2008. Threshold regression model is applied to study the determinants of CEI as well (Pan et al., 2016; Li and Lin, 2016). However, it should be noted that the econometric approaches documented in the literature are based on the hypothesis of conditional-mean function. Thus, it is difficult to obtain the information of the tail distribution (non-central position) of dependent variable. Moreover, it is assumed that the effect of individual independent variable on CEI is homogeneous and does not differ throughout the conditional distribution of CEI, which is not consistent with the reality. When it comes to decomposition analysis, the most widely used method is the index decomposition analysis (IDA). IDA was first employed to investigate the effect of change in product structure on industrial energy demand on the background of oil crisis in the 1970s. Since then, IDA has been increasingly applied to deal with energy-related environmental issues (Ang and Zhang, 2000; Ang et al., 2016). The Laspeyres index (Sun and Malaska, 1998; Ebohon and Ikeme, 2006) and the Divisia index methods are popular in CEI research. For instance, Shrestha and Timilsina (1996) utilize Arithmetic Mean Divisia Index (AMDI) decomposition method to decompose CEI in 12 Asian countries during 1980–1999, and find that energy intensity is the main determining factor of CEI. The Adaptive Weighting Divisia Index (AWDI) decomposition method proposed by Liu et al. (1992) is increasingly adopted in CEI studies (Greening et al., 1998, 1999, 2001; Greening, 2004; Schipper et al., 2001; Fan et al., 2007). These studies all suggest that energy intensity is the dominant factor resulting in the reduction of CEI. In addition, Logarithmic Mean Divisia Index(LMDI)method, an important branch of IDA method, has been widely employed in the literature about CEI in recent years (Chen, 2011; Tan et al., 2011; Gonzalez and Martinez, 2012; Liu et al., 2015; Cruz and Dias, 2016; Zhang et al., 2016; Wang et al., 2016a; Xu et al., 2017a). Ang and Wang (2015) conclude LMDI-I is excepted to be a preferred Divisia decomposition method in multidimensional and multilevel analysis compared to LMDI-II and AMDI. We can conclude two characteristics from these studies using LMDI method: first, the driving factors decomposed from CEI mainly include the energy intensity effect, energy mix effect, industrial structure effect, and emission coefficient effect; second, the analysis is further conducted to explore the contributions of these driving factors to the change in CEI from the perspectives of total economy and economic sectors.

Since IDA method has lower requirement of data and can easily conduct spatial and temporal comparison analysis, it has been more widely applied to examine CEI in comparison to other decomposition methods. However, IDA only considers direct energy-related carbon emissions dismissing the fact that energy is utilized repeatedly in practice, thus, carbon emissions can come from direct and indirect energy consumption. Therefore, the application of IDA analysis will lead to the loss of considerable information, while input-output structural decomposition analysis (I-O SDA) method can effectively solve this problem. Input-output model method is an economic quantitative analysis method, which is first introduced by Leontief (1970). Recently, input-output method has been widely applied in resource environment field. As an important application of input-output method, SDA is first proposed by Syrquin (1976) at European econometric conference. Its core idea is to decompose the change of dependent variable in economic system into the variation of various independent variables and calculate the contribution of each independent variable to the change of dependent variable. Since I-O SDA is presented, it has been gradually applied in research on energy consumption and economic structure (Rose and Casler, 1996), as well as energy and emissions (Su and Ang, 2012a,b). Many scholars adopt I-O SDA method to study the driving forces of carbon emissions. For example, Common and Salma (1992) analyze carbon emissions in Australia using I-O SDA method, and decompose total carbon emissions into three factors: the final demand effect, energy structure effect and technology effect. Casler and Rose (1998) improve I-O SDA method and analyze the source of American carbon emissions, finding that the substitution effect of energy is the primary reason for carbon emissions reduction. Recently, an increasing number of studies investigate China's carbon emissions issue through I-O SDA, e.g., the study on the effects of technology, economic structure, urbanization, and life style on China's carbon emissions (Peters et al., 2007), and the decomposition analysis about carbon emissions in Xinjiang and Jiangsu provinces (Wang and Wang, 2015; Xu et al., 2017b). As described above, most studies adopt SDA method to decompose total carbon emissions, while literature about CEI decomposition is relatively rare. Study on CEI is more useful and meaningful in supporting policy making in China, as CEI reflects the relationship between carbon emissions and economy. Compared to IDA, I-O SDA can be employed to explore direct and indirect effects, especially the indirect effect of demand change in one sector on other sectors (Hoekstra and van den Bergh, 2003). IDA and SDA differ in methodological foundation, and they all decompose an aggregate/intensity indicator into effects associated with several predefined factors (Wang et al., 2017a). An advantage of SDA over IDA is that SDA can analyze demand-said effects and the impact of trade (Wang et al., 2017b). Most IDA studies suggest energy intensity is the main reason for the reduction in CEI/carbon emissions, such as AMDI (Shrestha and Timilsina, 1996), AWDI (Fan et al., 2007), LMDI (Zhang et al., 2016), while in SDA studies the main factor may be energy intensity (Xu et al., 2017b), per capita GDP (Wang and Wang, 2015), input mix (Zhang, 2009) or the substitution effect of energy (Casler and Rose, 1998). Wang et al. (2017a) provide an up-to-date review of IDA and SDA studies with respect to energy and emissions analysis, and compare the application of two techniques. In addition, a study by Wang et al. (2018) presents a comprehensive comparison among IDA, SDA and PDA. About the sub-aggregate SDA studies, Wang et al. (2017b) and Wang et al. (2017c) employ multiplicative decomposition to investigate the changes in CEI at national and sectoral levels, respectively. In SDA studies, multiplicative decomposition form is rarely used because of the complexity in result interpretation at the sectoral level (Su and Ang, 2015). Moreover, conventional multiplicative SDA can only compute results at the aggregate level (Wang et al., 2017c). Since multiplicative SDA at the sub-aggregate level is not well developed, we perform additive