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Driving factors of electric carbon productivity change based on regional and sectoral dimensions in China

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ABSTRACT

In order to reduce carbon emissions and maintain economic development in the power industry of China, the improvement of electric carbon productivity (ECP) creates more efficiency. The carbon emission estimation in the power industry is significant to the ECP calculation in this study. Thus, to make the ECP calculation more reasonable and fair, this study estimates carbon emissions from the power industry by the consumption-based accounting principle considering power transfers among the provinces. In addition, this research analyzes seven driving factors of ECP change in China by exploring the time series decomposition (2003–2015) from the power consumption perspective. The Logarithmic Mean Divisia Index (LMDI) method takes the regional and departmental dimensions into consideration. By applying the data from 30 provinces (including province-level municipalities) and three industrial sectors between 2010 and 2015, the influencing factors of ECP in each province and each industrial sector are discussed. The results show that: 1) Regional and industrial sector ECP, per capita GDP are the driving factors of increasing ECP; conversely, environmental efficiency of power consumption, industrial structure effect from the perspective of power consumption, economic efficiency effect of power consumption, and the ratio of total population to electric CO_2 emissions play leading roles in the decline of ECP. 2) From 2003 to 2015, there are four distinct stages of the ECP changes. 3) The sub-regional decomposition indicates, during 2010–2015, the main power exporters have higher or medium level ECP, and the main power importers with rapid economic development manifest lower or medium level ECP. 4) Instead of solely focusing on GDP, the Chinese government should pay more attention to increasing the economic and environmental efficiency of power utilization. 5) The sub-sector decomposition shows, during 2010–2015, although the economic and environmental efficiency of power utilization are negative in the secondary industry, they are the greatest among the three industrial sectors, and the influence of the economic scale effect is stronger than that of technological impact on different industrial sectors. Finally, several conclusions are obtained which might be useful for the central and local governments to improve the national and regional ECPs.

1. Introduction

As a large developing country, China has been contributing the most carbon emissions around the world (BP. Statistical Review of World Energy, 2012). In 2015, carbon emissions from China accounted for about 22.9% of the total emissions of the world (BP. Statistical Review of World Energy, 2016). Such a grim situation draws great attention to the emission issue from the Chinese government, who aims to drop the CO_2 emissions per unit of GDP in China to 20% in 2020 compared with 2015 (China Electricity Council. 13th Five Year Planning of National Power Sector, 2016). The Chinese government intends to achieve the peak CO_2 emissions by around 2030 and to decrease the carbon intensity by 60–65% in 2030 (Shao et al., 2016).

The power industry in the world produced 13,625 million tonnes (Mt) CO_2 emissions in 2014, which accounted for about 42% of total CO_2 emissions from fuel burning. In same year, carbon dioxide emissions from the Chinese power industry were 4384 million tonnes (Mt), which accounted for about 48.2% and 13.5% of the CO_2 emissions from the nation and the world respectively (OECD/IEA, 2016). However, carbon capture technologies and carbon recycling technologies are still not broadly used because of

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technology and cost constraints (Charles, 2009). Carbon dioxide emissions from burning fossil fuels are inevitable. Therefore, enhancing carbon productivity are principal measures for coordinating economic progress and energy consumption.

Carbon productivity was defined as the GDP per unit carbon emission, which was coined by Kaya and Yokobori (1999). He et al. (2010) considered that the carbon productivity change was the major standard reflecting the global climate change. Increasing carbon productivity is the main approach to respond to climate change in the context of sustainable development (He and Su, 2011). Carbon productivity, as a highly integrated indicator, represents the combination of cutting down CO_2 emissions and keeping stable economic growth (Shao et al., 2014). It also helps to explain the national and regional low-carbon economy level (Zheng et al., 2012). The impact of environmental tax reform on productivity has been assessed by using carbon productivity (Ekins et al., 2012).) To allocate the responsibility of controlling emissions in different areas by applying ECP is very appropriate (Meng and Niu, 2012). Besides, based on the regional economic development level, regional ECP contributes directly to the national ECP. For explicating the influencing factors of ECP change in each area, different industrial sectors in each region are also considered in this study.

There are three common decomposition methods to research the environmental problems in literature: index decomposition analysis (IDA) (Ang, 2004), structural decomposition analysis (SDA), and production-theoretical decomposition analysis (PDA). Su and Ang (2012) compared the methodological development of IDA and SDA. An overall comparison of the three decomposition methods was discussed by Wang et al. (2017, 2018). They compared IDA with SDA from the methodological and application viewpoints with specific reference to economy-wide analysis and showed the overlap between the two methods was the greatest; while from a production system viewpoint, PDA helped to understand the driving forces of CO_2 emissions with a focus on technical efficiency and production technology. The IDA decomposition techniques consist of the Arithmetic Mean Divisia Index method (AMDI) and LMDI (Ang et al., 1998). There is a large residual in some cases about AMDI, conversely, LMDI does not produce residuals but allows data to be zero and negative values (Ang, 2005; Zhang and Zhu, 2012). Also, the LMDI method contents the perfect decomposition character at the sub-attribute and aggregation consistency (Ang and Wang, 2015). Thus, when managing the energy data that include multiple attributes, the IDA method is suggested. Therefore, this study applies LMDI to discussing the driving factors of ECP change.

In addition, some results indicated that industrial activity was the major factor for the increase of industrial CO_2 emissions, while energy intensity was the major contributor to the decrease of CO_2 emissions (Ouyang and Lin, 2015), based on the decomposition analysis of the LMDI method. The LMDI method and scenario analysis were applied by Yang and Lin (2016) to analyse the influencing factors of carbon emissions. The corresponding potential reductions in Chinese power industry and some meaningful conclusions about emission-reduction and energy-saving in the power industry were obtained. Xie et al. (2016) used LMDI to study the driving forces of CO_2 emissions from the petroleum refining and coking industry in China, and the mitigation pathway of CO_2 emissions in this sector during 1995–2031 was discussed. The influencing factors of CO_2 emissions from the Chinese chemical industry were explained by using the LMDI method (Lin and Long, 2016). Lin and Zhang (2016) used LMDI to analyse the increments of CO_2 emissions from the Chinese cement industry from 1991 to 2010. Md and Allan (2017) made a quantitative evaluation of emission-reduction targets' challenge by using the LMDI and concluded that to achieve the emission reduction targets in the United States will be challenging. The LMDI method was also applied by Lin and Izhar (2017) to discuss the reduction potential and CO_2 emissions in Pakistan.

However, the LMDI is rarely used to analyse the carbon productivity change in the power industry. In recent years, Meng and Niu (2012) presented a three-dimensional absolute and relative decomposition model to discuss the carbon productivity change. The decomposition outcomes revealed that: 1) technological innovation played a far more important role than industrial structure adjustment; 2) industry and export trade exhibited great influence; 3) assigning the responsibility for CO_2 emission control to local governments, optimizing the structure of exports, and eliminating backward industrial capacity were highly essential to further increasing Chinese carbon productivity. Lu et al. (2015) applied a LMDI decomposition model based on the model proposed by Meng and Niu (2012) to analyse the carbon productivity change in China. Between 1990 and 2012, the LMDI method was wielded by Hu and Liu (2016) to research carbon productivity of the construction industry in Australia. From the views of the production and consumption of the power industry in China, Chen et al. (2018) analyzed the ECP change. They discussed the impact of power transfers among the provinces, imports and exports, and transmission losses, but they did not consider the influence of industrial sector. Nevertheless, to our knowledge there is no corresponding study that focuses on the ECP of different regions and industrial sectors. Thus, seven influencing factors are identified by investigating the time series (2003–2015) decomposition from but with the additional regional and sectoral dimensions being taken into consideration.

The carbon emission estimation in the power industry is crucial to the ECP calculation. There are two common principles about accounting carbon emissions: the production-based accounting principle and the consumption-based accounting principle. The so-called production-side responsibility principle means that the province's carbon emissions are equal to the direct carbon emissions from thermal power generation in the province. However, the production-based accounting principle has caused many issues and unfairness because it ignores the “carbon leakage” in the power dispatching among the provinces (Su and Ang, 2014). Moreover, the consumption-based accounting principle assesses carbon emissions according to the principle that “the ones who consume should take responsibility” (Zsófia, 2013). However, this principle needs complex data, which may cause more uncertainty. Liu et al. (2015) applied a multi-regional input-output model to estimate carbon emissions in different regions according to one production-based and two consumption-based accounting principles. Zhang (2015) compared the provincial responsibility for carbon emissions and provincial carbon multipliers in China using seven responsibility-allocating principles. Fan et al. (2016) explored the characteristics of production-based and consumption-based CO_2 emissions for 14 major economies. Besides, there are huge differences in the endowment of power resources among the provinces in China, which inevitably leads to a large number of power dispatches among the provinces. Large-scale power dispatches definitely affect the distribution of electric carbon emissions (Zhou et al., 2014). In order to make the calculated ECP more reasonable and fair, this research assesses carbon emissions from the power industry by the consumption-based accounting principle.

This article contributes to the following three aspects: 1) to better analyse the change of ECP, seven influencing factors are identified based on the additional region and industrial sector dimensions by using the LMDI method; 2) exploring the time series decomposition (2003–2015) of the ECP change by using the latest data from 30 provinces (including province-level municipalities) and three industrial sectors during 2010–2015, and discussing the influencing factors of ECP in each province and each industrial