Journal of Cleaner Production 195 (2018) 133–144

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

An empirical spatiotemporal decomposition analysis of carbon intensity in China's industrial sector

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ARTICLE INFO

Article history:
Received 22 November 2017
Accepted 22 May 2018
Available online 23 May 2018

Keywords:
Carbon intensity
China's industrial sector
Provincial disparity
Spatiotemporal decomposition analysis
Spatial autocorrelation

ABSTRACTS

In order to develop efficient industrial CO_2 emissions' strategies for China, it is important to compare the performance of carbon intensity and its major driving factors among different provinces. However, such studies are relatively limited so far. The present study describes the features of industrial aggregate carbon intensity (IACI) as well as its driving factors for China's thirty provinces based on the spatio-temporal logarithmic mean Divisia index (ST-LMDI) method. This method allows comparing all provinces against a common benchmark. The empirical results show that Beijing, Tianjin, Shanghai, Guangdong and Heilongjiang rank as the top five provinces while Hebei, Shanxi, Inner Mongolia, Ningxia and Xinjiang perform the worst. From 1999 to 2015, the IACI of most industrial sectors tends to decrease except in Ningxia and Xinjiang, with energy intensity playing a decisive role in all provinces, and both energy structure and emission coefficients yielding mixed effects across provinces and over time. Additionally, this study employs spatial autocorrelation to divide China's thirty provinces into four categories, combining the economic development level and geographical location into a common framework. Then the ST-LMDI method is used to explore how the four regions perform in IACI when the influences of neighbors are taken into account. The results show that the regions with high level of economic development perform better and the regions with the same level of economic development but which are surrounded by less-developed regions have lower IACI. Based on the results, differentiated policies in energy intensity, energy structure and emission coefficient for the local and central governments are recommended.

1. Introduction

Since the reform and opening up of China in 1978, China experienced strong economic growth accompanied by a large increase in energy consumption and CO_2 emissions. As a pillar of China's economic development, the industrial sector played an important role in this expansion even though the share of IVA (industrial value added) in GDP decreased slightly from 39.77% in 1999 to 34.32% in 2015 (current price) (NBSC, 2016b). From 1999 to 2015, industrial energy consumption increased from 907.97 to 2,922 Mtce (Million tons coal equivalent) and accounted for 67.99% of the national energy consumption in 2015 (NBSC, 2000-2016a). The corresponding industrial CO_2 emissions from fossil fuel consumption rose from 2119 Mt in 1999 to 6253 Mt in 2015, contributing to approximately 69.16% of national total emissions. In order to respond to the climate change caused by greenhouse gas (GHG) emissions, the Ministry of Industry and Information Technology of China published the *China Industrial Green Development Plan 2016–2020*, aiming to reduce the industrial energy intensity (energy consumption per unit of IVA) and carbon intensity (CO_2 emissions per unit of IVA) by 18% and 22% in 2020 compared with the 2015 level. Because large variations in the growth patterns of CO_2 emissions and economic development at provincial level exist, the authors of this study believe it is important to identify the factors driving the IACI at both provincial and regional levels to find effective measures for carbon intensity mitigation.

The main objectives of this paper are as follows. First, the present study uses a spatiotemporal logarithmic mean Divisia index (ST-LMDI) (Ang et al., 2016), which integrates spatial and temporal

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https://doi.org/10.1016/j.jclepro.2018.05.185

analyses in a single analytical framework, to disentangle the IACI of China's thirty provinces into energy intensity, energy structure and emission coefficient effects. Because the changes in provincial IACI and their underlying driving forces are calculated on the basis of a common benchmark, this study allows for a more accurate comparison of those drivers across provinces over time. Second, spatial autocorrelation is used to aggregate the thirty provinces into four regions and explore their IACI as well, in order to better depict the interaction among adjacent provinces. Finally, some targeted policy implications for local government and central government are provided.

The rest of this paper is organized as follows. Section 2 reviews the existing literature. Section 3 introduces the decomposition analysis and data sources. Section 4 discusses the comparisons among provincial/regional IACI and the related factors. Section 5 concludes the study and provides policy recommendations.

2. Literature review

As a prerequisite for reducing CO_2 emissions, it is important to determine the factors influencing the changes in CO_2 emissions. In this regard, econometric techniques and decomposition analysis have become popular in recent years. Concerning the former, Xu and Lin (2016a) and Dong et al. (2016) explored the spatial characteristics of industrial emissions and the impacts of socio-economic factors conducting spatial autocorrelation and regression analysis. Also, using panel data, Wang et al. (2016a, b, c) and Xu and Lin (2016b) employed the STIRPAT model to examine, respectively, the driving forces of national and industry's carbon intensity and CO_2 emissions at the regional level. Commonly used decomposition analysis consists of structure decomposition analysis (SDA) and index decomposition analysis (IDA). SDA is often used combining with input-output analysis, such as Wang et al. (2017a), Su and Ang (2017) and Su et al. (2017). Within IDA (index decomposition analysis) the Laspeyres and Divisia index approaches are the two most often used decomposition methods (Ang and Zhang, 2000). The Laspeyres index approach has the advantage of easily handling the presence of zero values in time series, but nevertheless the decomposition formula becomes very complicated if there are many factors (Ang and Zhang, 2000). Another family of IDA methods, the Divisia index analysis includes the arithmetic mean Divisia index (AMDI) and the LMDI methods. The AMDI has the residual problem and cannot solve the zero-value data problem (Ang, 2004). The LMDI method possesses the advantages of path independency, the ability to handle zero values and consistency in aggregation (Ang, 2004), and has therefore been widely used, such as Brazil (Freitas and Kaneko, 2011), China (Xu et al., 2014a; Zhang and Da, 2015; Xu et al., 2014b), EU (González et al., 2014a, 2014b), and Ireland (Mahony, 2013).

As a large country, China exhibits major heterogeneities in the geographical location of resource endowments, industrial structures and the level of economic development between provinces and regions (Zhou et al., 2017). Hence, in order to promote balanced economic growth China should not only focus on the development of the country as a whole but also pay attention to the local features. IDA has been employed in many recent studies conducted from regional and provincial perspectives in order to formulate sound provincial or regional emission reduction policies. Chen and Yang (2015) decomposed the CO_2 emissions of each province into different factors in eight sub-periods from 1995 to 2011. Xu et al. (2017) and Xu et al. (2016) explored regional contributions to national carbon intensity by decomposing the factors which influence the national carbon intensity. Wang and Feng (2017a) examined the spatial distribution of CO_2 emissions using a gravity model and identified the determinants of CO_2 emissions across provinces to explore possible pathways for China's low-carbon development. Zhang and Li et al. (2016) extended the LMDI method and investigated the factors (i.e., energy density and energy intensity) influencing the provincial carbon intensity in China. Gao et al. (2016) compared the driving forces of CO_2 emissions in China's east and south coastal regions and identified their provincial features. Li et al. (2016) focused on both carbon emissions per capital and carbon intensity of China's nine typical regions, and then compared their influencing factors. Ding and Li (2017) examined the driving forces and reduction potential of CO_2 emissions in China's different sectors and thirty provinces in the context of rapid urbanization. Jiang et al. (2017) evaluated the contributions of impact factors of 30 provinces to the national carbon emissions combining the two-layer LMDI method with Q-type hierarchical clustering. Yang et al. (2017) analyzed the dynamic CO_2 emissions and the underlying influencing factors at time series. Afterwards the GIS-based approach was employed to verify the previous obtained results from a spatial perspective. Ye et al. (2017) calculated both direct carbon emissions from final energy consumption and the indirect carbon emissions from electricity at the provincial level.

Given that the industrial sector is a highly emission-intensive industry in China, it has been subject to intensive scrutiny. For instance, Liu et al. (2007) studied the evolution of CO_2 emissions and its influencing factors in each of China's 36 industrial sub-sectors. Wang et al. (2012) regarded the energy-intensive sectors as a whole and analyzed its changes in CO_2 emissions comprehensively. Xu et al. (2014a, b, c) examined the changes in GHG emissions of China's major economic sectors and pointed out that industrial sector played an extremely important role in China. These five studies used the LMDI method and consistently observed that economic activity was the major contributor to the increase in industrial CO_2 (GHG) emissions, whereas the reduction in energy intensity greatly inhibited the expansion of CO_2 (GHG) emissions. Over the past few decades, the energy intensity of China's industrial sector has been continuously decreasing (Xu et al., 2014c), which indicates that energy efficiency has been improving and inevitably led to lower carbon emissions. Yan and Fang (2015), Wang et al. (2016a) and Zhang et al. (2017) integrated the LMDI method and scenario analysis to examine the industrial CO_2 emissions and carbon intensity from historical and future perspectives. Combining the LMDI method and attribution analysis, Liu et al. (2015) and Wang et al. (2017a, b) respectively identified the factors influencing carbon intensity of China's industrial sector and energy-intensive industries, as well as the contribution of each sub-sector to the aggregate carbon intensity. Moreover, some typical sub-sectors that play important roles in China's industrial sector have also been studied separately by using the LMDI method, such as the cement industry (Wang et al., 2013), the textile industry (Lin and Moubarak, 2013), the mining sector (Shao et al., 2016) and the chemical industry (Lin and Long, 2014). These studies were all based on time-series data, whereas other studies had a regional focus. Ren et al. (2012) analyzed the regional differences of industrial CO_2 emissions as well as the relevant influencing factors also using the LMDI method. Zhou et al. (2017) first investigated the decoupling between industrial carbon emissions and economic growth of China's eight major regions and then explored the factors influencing carbon emissions using the LMDI method, finding that there were large differences between these regions. Wang and Feng (2017b) combined the LMDI method and production-theoretical decomposition analysis (PDA) to explore the key factors driving the CO_2 emissions of industrial sector at the national, regional and provincial levels. Wang et al. (2018) also used the IDA and PDA to study the factors influencing industrial carbon intensity, and identified the contributions of different provinces to each driving