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Investigating the drivers of energy-related CO_2 emissions in China's industrial sector: From regional and provincial perspectives

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ABSTRACT

This paper utilizes the Logarithmic Mean Divisia Index (LMDI) to quantify the contributions of various factors on industrial CO_2 emissions (ICE) at both the regional and provincial levels, and then analyzes the decoupling index and its components. The main results include: (1) Industrial activity was the leading promoting factor in ICE, while energy intensity was the decisive factor for controlling ICE in most provinces. (2) Energy structure change only had a marginal impact on ICE and varied considerably across provinces. (3) The effects of various factors are distinctly diverse in different provinces; generally, the inhibiting effects only partly offset the promoting effects. (4) Most provinces exhibited weak decoupling effect, energy intensity decline was the crucial factor in their decoupling progress, while energy structure switch only played a negligible role in decoupling progress, even exerted an opposite effect in emission mitigation in some provinces, and therefore dragged down their decoupling progress.

1. Introduction

According to the *BP. Statistical Review of World Energy* (2016), in 2015, China's CO_2 emissions up to 9.15 billion tonnes, occupied 27.3% of global emissions. Being the largest CO_2 emissions contributor in the world, China has promised that in 2020, CO_2 emission intensity decreased by 40%–50% compared with 2005 level (Bi et al., 2011; Zhou et al., 2016). Constrained by the twin goals of steady economic growth and carbon emission reduction, formulating scientific and targeting emission reduction strategies become an important consideration for Chinese central and local governments. Under this circumstance, it is fairly essential to understand the evolutions and reveal the salient drivers of ICE in China's different regions and provinces.

Industrial sector holds a crucial position in China's economy, indeed plays an important role in promoting economic growth. Additionally, industrial sector is usually highly energy intensive, and therefore consumed tremendous fossil energy as well as emitted a mass of carbon dioxide. Approximately 70% of China's total carbon dioxide emissions from fossil energy are induced from industrial activities (Li et al., 2016; Xu et al., 2017). It means that energy-saving and CO_2 emission-reduction in industrial sector is crucial for achieving the target of low carbon economy in China. Thus, China faces great challenges regarding the reduction of CO_2 emissions from industrial sector. Under the circumstances, the main purpose of this study is to (1) understand the ICE characteristic in different areas, this paper contrastively analyzes the change evolutions of ICE from regional and provincial perspectives. (2) Indentifying the main factors affecting ICE and quantizing the contributions of various factors on ICE. (3) Analyzing the decoupling relationship between CO_2 emissions and output growth in China's industrial sector.

The remainder of this paper is organized as: Section 2 reviews the relevant literatures. Section 3 introduces the LMDI method and decoupling index. Section 4 compares and discusses the empirical results from the perspective of regions. Section 5 compares and discusses the empirical results from the perspective of provinces. Section 6 analyzes the decoupling progress and its components for industrial sector. Section 7 provides the conclusions and corresponding policies.

2. Literature review

The sharp increase in global carbon emissions has drawn great attention of all countries on sustainable economic development. Scholars have paid close attention to the relationship between environmental pressure and economic development (Gray et al., 2006; Sorrell et al., 2012; Govindaraju and Tang, 2013), and proposed the

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concept of low-carbon economies development (Upton, 2015) and green economies development (Haszeldine, 2009). In recent years, decoupling is usually used to analyze the relationship between economic growth and environmental changes. The decoupling concept was first adapted to environmental studies in 2000 by Zhang (2000). OECD (2002) developed the decoupling concept into an indicator. Juknys (2003) defined three decoupling: primary, secondary, and doubled decoupling. Tapio (2005) also defined three decoupling statuses: decoupling, coupling, and negative decoupling, and further broken down them to eight degree. This definition is very detailed but confusing. Based on Tapio's decoupling index framework, Vehmas et al. (2007) redefined the decoupling index. In their study, the degrees of the linking process include six levels.

Decoupling analysis can explain the relationship of economic growth and CO_2 emissions, but could not explain the driving forces of CO_2 emissions changes. Decomposition analysis is one of the most broadly used approaches for investigating the drivers of CO_2 emissions. SDA (structural decomposition analysis) decomposes CO_2 emissions change by using input-output tables (Mi et al., 2016), and has been employed by Peters et al. (2007), Guan et al. (2008), Su and Ang (2012), Mi et al. (2017a), etc. However, the data requirement of SDA is relatively high, because the input-output tables are not compiled every year (Mi et al., 2015; Borghi, 2017; Brizga et al., 2017). Besides, SDA method cannot be performed multiplicatively, which limits its application in decomposition analysis (Hoekstra and Van den Bergh, 2003). Zhou and Ang (2008) utilized a decomposition approach based on the DEA model (Song et al., 2012, 2016) and production theory, to disintegrate CO_2 emission changes in OECD countries and other regions, and first named this approach the PDA (production-theoretical decomposition analysis). This approach also was utilized by Kim and Kim (2012); Lin and Du (2014); Li et al. (2017); Du et al. (2017); Wang et al. (2018), etc. PDA method has low data requirement and can reveal technology-related factors. However, only the multiplicative decomposition form can be used in the PDA method.

IDA (index decomposition analysis) can be performed both multiplicatively and additively, and has relatively low data requirements (Ang and Zhang, 2000). Ang (2004) summarized and compared various IDA methods' merits and demerits, and reaching a conclusion that the LMDI was the preferential method. Many studies have adopted LMDI method to quantitatively identify the different factors. Such as González et al. (2014), Cansino et al. (2015); Song et al. (2015); Robaina-Alves et al. (2016); Jiang et al. (2017); Cantore et al. (2017); Wang and Feng (2018), etc. In addition, studies focusing on the specific sectors include Timilsina and Shrestha (2009); Zhang et al. (2011); Jung et al. (2012); Chen et al. (2013); Lin and Ouyang (2014); Branger and Quirion (2015); Lu et al. (2016); Lin and Tan (2017) (see Table 1), etc.

Currently, there are many researchers combined the decoupling index and decomposition method in their studies. For example, Diakoulaki and Mandaraka (2007) used the refined Laspeyres model to investigate the impacts of five factors in CO_2 emissions changes of EU manufacturing sector, and then evaluated the progress made in 14 EU countries in decoupling emissions from industrial development. De Freitas and Kaneko (2011) adopted LMDI to uncover the determinants of emissions in Brazil, and examined the decoupling relationship between its growth rate of economic activity and CO_2 emissions. Andreoni and Galmarini (2012) used IDA method to analyze the decoupling progress in Italian. Li et al. (2015) established the decoupling elasticity decomposition quantitative model to investigate the decoupling relationship and its driving factors between economic growth and carbon emissions in China. Wang and Yang (2015) used LMDI and Tapio index to study the ICE in Beijing–Tianjin–Hebei economic band case. Lu et al. (2015) used the complete decomposition technique and decoupling method to explore and quantitatively analyze the salient factors influencing industrial carbon emissions in Jiangsu, China. Wang et al. (2017) directly decomposed the CO_2 emission-GDP indicator changes into three decoupling indicator effects based LMDI method. Zhao et al. (2017) also studied the decoupling of economic growth from CO_2emissions in economic sectors through the decoupling index and LMDI method.

With regard to China's industrial sector, Liu et al. (2007) used LMDI to analyze the driving factors of ICE from 36 industrial sectors in China. Wang et al. (2016) utilized this method to disintegrate the CO_2 emission changes of China's industry from a national perspective. Xu et al. (2016) analyzed carbon emissions based on different sectors (industry sector is contained) in China. Zhou et al. (2017) applied this method to study the industrial carbon emissions in eight regions of China. Note that the industry in their study includes agriculture, industry, construction, transport, storage, postal services, business, and other tertiary sectors. Zhao et al. (2010) used this method to explore the influencing factors of industrial carbon emissions in Shanghai. Liu et al. (2012) investigated China's greenhouse gas emission from regional and sectoral perspectives. It should be pointed out that these two perspectives cover 30 provinces and five groups sectors (i.e., agriculture, manufacturing, construction, commercial industry and transportation). Zhou et al. (2016) disintegrated carbon emission changes of industries in China's 29 provinces.

Summarizing the previous literature, we can conclude that most of the scholars focused on national perspective, individual provinces, several groups sectors or two-digit sectors. The specific investigation on ICE in Chinese provinces remains limited. However, as presented in Fig. 1, the industrial development and energy consumption sources among Chinese provinces are diverse (Feng et al., 2017a), which may led the drivers of ICE are also discrepant across provinces. Thus, it is essential to reveal the drivers of CO_2 emissions from the provincial perspective. Moreover, in the literature, little attention has been devoted to the decoupling progress in China's industrial sector, especially at the provincial level. Considering these benefits, this study attempts to fill such gap. Firstly, this paper estimates both the direct and indirect industrial energy-related CO_2 emissions over the period of 2000–2014. Next, this paper contrastively analyzes the characteristics of ICE among regions and provinces, and applied LMDI to quantify the contributions of various factors on ICE at both the regional and provincial levels. Then, this paper analyzes the decoupling progress and its components for industrial sector. Finally, policies for inhibiting ICE are provided.

3. Methodology and data

3.1. LMDI model

The Kaya identity is usually used for the driving factors investigation of CO_2 emissions. The related factors usually include population, per capita income, emission coefficient, and energy intensity (Kaya, 1989). In this study, the industrial CO_2 emission changes (C) are decomposed into four factors: carbon dioxide emission coefficient change, energy consumption structure, energy intensity, and industrial activity. Accordingly, we obtain:

$$C = \sum_{i,j} C^{ij} = \sum_{i,j} \frac{C^{ij}}{E^{ij}} \times \frac{E^{ij}}{E^{i}} \times \frac{E^{i}}{Y^{i}} \times Y^{i} = \sum_{i,j} Coe^{ij} \times Es^{ij} \times Ei^{i} \times Y^{i} \quad (1)$$

where subscript i and j denote the i^{th} province and j^{th} fuel type, respectively; C represents the CO_2 emissions; E represents the energy consumption, and Y represents the industrial output. In

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