Energy Economics 67 (2017) 268–277

Contents lists available at ScienceDirect

Energy Economics

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

A regional analysis of carbon intensities of electricity generation in China

Nan Liu [a], Zujun Ma [a], Jidong Kang [b,*]

[a] *School of Economics & Management, Southwest Jiaotong University, Chengdu 610100, PR China*
[b] *Department of Industrial Systems Engineering and Management, National University of Singapore, Singapore*

ARTICLE INFO

Article history:
Received 19 February 2017
Received in revised form 15 July 2017
Accepted 11 August 2017
Available online 23 August 2017

JEL classification:
C21
C22
Q54
Q56
Q58
R58

Keywords:
China
Regions
Carbon intensity of electricity
Temporal-IDA
Regional attribution analysis
Spatial-IDA

ABSTRACT

Index decomposition analysis (IDA) has been widely applied to study CO_2 emissions from electricity generation. However, most have focused on emissions at the country level, less attention has been given to emissions at the regional level. To fill the gap, this study firstly utilized a Logarithmic Mean Divisia Index (LMDI) method to analyze the driving forces of aggregate carbon intensity (ACI) of electricity generation in China from 2000 to 2014. A regional attribution analysis was introduced to look into the contributions from 30 provinces to the driving forces. Then, a multi-regional spatial-IDA was further adopted to assess the emission performance of electricity generation in 30 provinces. The results of temporal-IDA and regional attribution analysis show that the ACI in China dropped notably by 14.5% from 2000 to 2014. Thermal efficiency improvement was a major driver for the decrease, due largely to the significant improvement in thermal generation efficiency in the eastern coastal regions. Clean power penetration reduced ACI remarkably as well, of which the western regions were the main contributors. The spatial-IDA results indicate that the emission performance of electricity generation in different regions varied significantly. While the western regions performed better in clean power penetration, the eastern regions performed better in thermal generation efficiency. Based on the findings, several regional policy strategies were recommended to further lower down ACI of electricity in China.

1. Introduction

As the world's largest carbon dioxide (CO_2) emitter[1] (IEA, 2016), China shoulders enormous responsibility in reducing CO_2 emissions. On the 30th of June 2015, China submitted an Intended Nationally Determined Contribution (INDC), which includes an intention to lower its CO_2 emissions per unit of gross domestic product (GDP) by 60–65% from the 2005 level, and to raise its share of non-fossil fuels in primary energy consumption to around 20% in 2030 (INDC, 2015). The electricity sector alone accounts for 40% of China's total energy-related CO_2 emissions, more than any other sector (Hu et al., 2012; Yang and Lin, 2016). This can be due to China's heavy dependence on coal in electricity generation. In 2014, thermal power generation accounted for 75% of China's total electricity supply, and 97% of the fossil fuels consumed in thermal power plants were coal,[2] resulting in massive quantities of CO_2 emissions. Therefore, reducing emissions from electricity generation should be treated as the first priority in China's low carbon transition.

Generally, the CO_2 emissions from electricity generation can be reduced by several different ways. The emissions can be reduced by directly lowering the electricity demand. The mitigation target can be also achieved by improving generation efficiency, or switching fossil fuels mix from coal to gas in thermal power plants. Another approach to decrease electricity-related CO_2 emissions is to introduce clean power generation, i.e., hydro, nuclear, wind, solar, biomass, geothermal, and ocean power. However, controlling electricity demand directly may negatively impact a country's economic growth and people's living standards. As a result, more attention has been placed on how to reduce CO_2 emissions of electricity generation from the other several approaches, which can be all together captured by an indicator named as the "aggregate carbon intensity" (ACI) of electricity (Ang and Su, 2016; Ang and Goh, 2016). The indicator is defined as the ratio of total CO_2 emissions from fossil fuels in electricity generation to the total electricity generated, and normally expressed in kilograms of CO_2 emissions per kilowatt-hours ($kgCO_2$/kWh). It actually measures a country or region's capacity in decoupling CO_2 emissions from electricity generation. Because ACI is a normalization of CO_2 emissions from electricity generation, it can be easily compared between countries and regions. Obviously, an exploration of driving forces for ACI variations could be of interest not only for understanding the historical evolution of ACI but also in identifying the

---

* Corresponding author.
E-mail address: david-kjd@live.cn (J. Kang).

[1] In 2014, China contributed to 28% of the global CO_2 emissions, ranking the largest CO_2 emissions emitter in the world (IEA, 2016).

[2] The data came from the authors' own estimation.

http://dx.doi.org/10.1016/j.eneco.2017.08.018
0140-9883/

appropriate strategies for mitigation of CO_2 emissions from electricity generation.

Index Decomposition Analysis (IDA) is an effective tool to analyze driving forces of CO_2 emissions and CO_2 emission intensity. Recent surveys for IDA studies of CO_2 emissions were given by Xu and Ang (2013) and Wang et al. (2017), which indicate that the method has been extensively applied at the global, national, sectoral, and regional level. Specifically for CO_2 emissions from electricity generation, the number of IDA studies is large as well. A summary of IDA studies of CO_2 emissions from electricity sector is offered in Table 1. As can be seen, most IDA studies focused on the CO_2 emissions from electricity generation at the country level, but less attention was paid to the emissions at the regional level. Given large diversities existing among various regions in terms of the regional circumstances and policy contexts, the emission driving forces and performance in different regions can be significantly different. Taking China as an example, the northern and northeastern regions mainly reply on coal for electricity generation, while in the southwest, the location of massive hydroelectric projects, there is a larger share of hydroelectric power. The wind resources are abundant in the northern, northeastern, and northwestern regions. The nuclear power projects were primarily launched in the eastern coastal regions, while the solar power plants are mainly concentrated in the western regions (NDRC, 2013). Plus, most advanced technologies for electricity generations are concentrated in the eastern coastal regions which are more economically developed. However, the technologies in the western regions are relatively backward, leading to lower efficiency of electricity generation. Under this circumstance, it is necessary to analyze CO_2 emissions from regional electricity generation by using the decomposition analysis. The results may not only help to understand regional disparities in emission mitigation performance, but also be used to evaluate effectiveness of regional policies and measures for emissions reduction in the electricity sector. Even though Zhou et al. (2014) and Yan et al. (2016) have studied CO_2 emissions from regional electricity generation by using the decomposition analysis, some gaps can be found in their studies. First, their studies focused on absolute CO_2 emissions rather than ACI. Second, their studies only employed the temporal-IDA, but never incorporated the spatial-IDA further compare the emission performance in various region. Finally, their studies only considered thermal power generation with ignorance of clean power generation. Given an increasing attention being paid to clean energy recently, its impacts on CO_2 emissions should not be ignored.

To fill the research gaps, this study firstly utilized a Logarithmic Mean Divisia Index (LMDI) method to disentangle ACI of electricity generation in China from 2000 to 2014 into four factors, including the thermal efficiency effect, the clean power penetration effect, the fossil fuel mix effect, and the regional shift effect. The clean power considered includes hydro, nuclear, wind, solar, biomass, geothermal, and ocean power. A regional attribution analysis was introduced to look into the contributions of 30 provinces to each driving factor. Then, a recently proposed multi-regional spatial-IDA was employed to assess the emission performance of electricity generation of 30 provinces in 2000 and 2014. Based on the obtained results, the underlying regional policies and measures for CO_2 emissions mitigation in China's electricity sector were analyzed and discussed.

The attribution analysis was firstly proposed by Choi and Ang (2012) to further additively allocate the percentage change of driving indexes into various attributes. The method can be regarded as a perfect extension of the traditional decomposition method. Since its proposal, the attribution analysis has been applied to study energy consumption and related CO_2 emissions in numerous cases as an extension of both the Index Decomposition Analysis (IDA) (González and Martınez, 2012; Fernández González et al., 2013, 2015; Choi and Oh, 2014; Fernández González, 2015; Liu et al., 2015; Wang et al., 2016) and the Structure Decomposition Analysis (SDA) (Su and Ang, 2014, 2015, 2016; Kim et al., 2015). Recently, the attribution analysis has been also used in spatial-SDA to construct the sectoral emissions performance index (EmPI) (Su and Ang, 2016). However, these studies concentrated on the sectoral attribution analysis which aims to attribute the driving effects to different sectors, but never focused on the regional attribution analysis aiming to explore regional contributions to the driving effects. As a matter of fact, the results of regional attribution analysis are of great significance as well as they may aid in policy making by indicating which regions are more receptive to policy strategies and programs intended to decrease CO_2 emissions. Moreover, since the carbon intensity changes are often studied by the multiplicative decomposition, the regional attribution analysis can be the only way to derive the regional contributions to carbon intensity changes thanks to its nice property to transform the geometric mean index into the arithmetic mean index. Recent studies applying multiplicative IDA to study carbon intensity changes include Liu et al. (2015) and Wang et al. (2016). Besides practices in IDA, analyzing carbon intensity changes has also become popular by using multiplicative SDA. Su and Ang (2015) show different I—O models for studying carbon intensity changes using multiplicative SDA. Su and Ang (2017) further proposed the aggregated embodied intensity (AEI) indicator to analyze the carbon intensity from demand perspective by using multiplicative SDA. Even though some researchers such as Xu et al. (2017) attempted to directly use the additive decomposition to explore the regional contributions to carbon intensity change, it is generally not recommended as the additive decomposition results of carbon intensity are with little substance (Ang, 2015).

In terms of the spatial decomposition, it can be used to decompose cross-country/region variations in energy and emissions. Literature reviews of spatial decomposition studies on energy and emissions have been given in Ang and Xu (2015), Ang and Goh (2016), and Ang et al. (2016) for spatial-IDA and Su and Ang (2016) for spatial-SDA. Recently, Ang and Xu (2015) proposed a multi-regional spatial-IDA approach to assess multi-region energy performance in one specific year. The approach has been further extended to spatial-SDA approach in Su and

Table 1
Summary of IDA studies of CO_2 emissions from electricity sector.

Study	Time period	Countries	Aggregate indicator	IDA method	Temporal or spatial IDA
Shrestha and Timilsina (1996)	1980–1990	12 Asian countries	ACI	AMDI	Temporal
Nag and Parikh (2005)	1974–1998	India	ACI	AMDI	Temporal
Steenhof (2007)	1980–2020	China	ACI	Laspeyres	Temporal
Malla (2009)	1990–2030	7 countries	CO_2 emissions	LMDI	Temporal
Shrestha et al. (2009)	1980–2004	15 countries	CO_2 emissions	LMDI	Temporal
Steenhof and Weber (2011)	1990–2008	Canada	GHG emissions	Laspeyres	Temporal
Zhang et al. (2013)	1991–2009	China	CO_2 emissions	LMDI	Temporal
Zhou et al. (2014)	2004–2010	30 provinces in China	CO_2 emissions	LMDI	Temporal
Yan et al. (2016)	2000–2020	30 provinces in China	CO_2 emissions	LMDI	Temporal
Yang and Lin (2016)	1985–2011	China	CO_2 emissions	LMDI	Temporal
Karmellos et al. (2016)	2000–2012	EU countries	CO_2 emissions	LMDI	Temporal
Ang and Su (2016)	1990–2013	124 countries	ACI	LMDI	Temporal
Ang and Goh (2016)	1990–2013	10 ASEAN countries	ACI	LMDI	Temporal and spatial
Ang et al. (2016)	1990–2010	10 countries	ACI	LMDI	Temporal and spatial