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Exploring sources of China's CO_2 emission: Decomposition analysis under different technology changes

Toshiyuki Sueyoshi[a,b], Aijun Li[c,*], Xiaohong Liu[c]

[a] New Mexico Institute of Mining and Technology, Department of Management, 801 Leroy Place, Socorro, NM 87801, USA
[b] Tokyo Institute of Technology, Tokyo Tech World Research Hub Initiative, School of Environment and Society, 3-3-6 Shibaura, Minato-ku, Tokyo 108-0023, Japan
[c] The Center for Economic Research, Shandong School of Development, Shandong University, Jinan 250100, China

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A B S T R A C T

This study proposes a decomposition approach based upon data envelopment analysis that identifies various sources of CO_2 emission. In addition to the previously identified seven sources, we propose three new ones. As an empirical application, this study applies the proposed approach to examine ten sources of CO_2 emission across Chinese provinces from 2008 to 2015. In the empirical study, we overcome methodological difficulties related to (a) what methodological merits of technology change indexes are and how to measure them in a separated manner and (b) how to separate effects of various sources and how to identify the annual shift of those sources of CO_2 emission changes. This study finds three empirical implications. First, three sources may increase the amount of CO_2 emission. They include an economic activity, a technology change on a desirable output and a potential energy intensity change. Second, two sources are important in reducing the amount of CO_2 emission. They are an operational efficiency change on a desirable output and a change in energy saving technology. Finally, conflicting results exist in some sources in the manner that they increase CO_2 emission in some provinces but decrease it in the other provinces.

1. Introduction

China has experienced rapid economic growth and consequently it has drastically increased the Carbon Dioxide (CO_2) emission. According to National Bureau of Statistics of China (2018), China's Gross Domestic Product (GDP) reached 82,712.17 billion RMB (i.e. China's currency unit) in 2017, which was 1.67 times higher than 2010 and 4.54 times of the amount in 2000. The average annual economic growth rates were 10.34% from 2000 to 2009 and 7.95% from 2010 to 2017. Along with the rapid economic growth, China has increased the amount of CO_2 emission. For example, British Petroleum (BP, 2018) has reported that China's CO_2 emission has increased from 3352.7 million tons in 2000 to 9123.0 million tons in 2016. The share of China's CO_2 emission has also increased in the world total. For example, the share increased from 13.97% in 2000 to 27.29% in 2016. Under such a situation, it has attracted great policy attention on how to reduce the emission amount.

Along with the increase, China faces a growing international pressure to reduce the amount of CO_2 emission. The Chinese government has pledged to control the amount. According to State Council (2015), the target was to reduce the CO_2 emission by 2030. Under the policy direction, a top priority for the Chinese government is to set the target on CO_2 emission. In following the direction, this study is concerned with identifying potential sources which influence China's CO_2 emission changes at a provincial level.

In discussing the Chinese policy on climate changes, this study needs to consider provincial imbalance. Historically, China has been a transitional and developing economy. At present, provinces are important administrative divisions in China and those governments make profound effects on provincial economies. As a consequence, there have been significant differences across provinces. Until now, many studies have confirmed the existence of provincial disparities in energy and environmental performance, such as Li, Zhang, Zhou and Yao (2017), Sueyoshi, Yuan, Li and Wang (2017b), Sun, Liu and Li (2018), Wang and Zhou (2018), Sun, Liu and Li (2018), Wang, Chiu and Chiu (2015) and Li, Zhang, Huang and Yao (2018).

In addition, previous studies revealed that technology changes played an important role in determining energy or carbon related targets (e.g. Tan & Lin, 2018; Yao, Zhou, Zhang & Li, 2015). How-

* Corresponding author.
E-mail addresses: toshiyuki.sueyoshi@nmt.edu (T. Sueyoshi), liaijun@sdu.edu.cn (A. Li), 2292923312@qq.com (X. Liu).

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ever, they have not yet discussed the effect of biased technology changes (e.g. an energy based technology change and a desirable output based technology change). Furthermore, the existing technology changes were not useful in detecting the existence of cross-over or retreat among efficiency frontiers.

Methodology: Acknowledging the contribution of previous research efforts on Chinese studies on energy and environment, this study discusses two methodological concerns. One of them is that this study adds three new technology indexes and discusses their implications on different technology changes. To attain the objective, this study considers how new indexes are incorporated into Production-theoretical Decomposition Analysis (PDA) and Index Decomposition Analysis (IDA). Both PDA and IDA are measured by Data Envelopment Analysis (DEA) in this study. The other is that we investigate what methodological merits of new technology changes are and how to measure them in a separate way. We also examine separated effects of various sources and identify main sources of CO_2 emission changes in a time horizon.

Implications: Our empirical study separates potential sources that influence CO_2 emission changes across Chinese provinces after considering different technology changes. For the purpose, this study examines ten potential sources by applying the proposed approach. Those contain three technology change indexes, two existing ones, three efficiency change indexes, an energy consumption structure index and an economic activity effect index. Based on these separated indexes, this study discusses sources of CO_2 emission changes, along with a special focus on provincial differences in China.

The abbreviations, used hereafter, are summarized as follow: *AE*: Activity Effect, *CBTC*: Combined Based Technology Change, DMU: Decision Making Unit, DTS: Damages To Scale, *EA* (or *AE*): Economic Activity (i.e. GDP), *EBTC*: Energy Based Technology Change, *EMF*: Emission Factor of Energy, *EMX*: Energy Mix change, *ESTC*: Energy Saving Technology Change, EU: European Union, *EUEF*: Energy Use Efficiency, *GBTC*: GDP Based Technology Change, *GEF*: GDP based operational Efficiency, *GTC*: GDP Technology Change, IDA: Index Decomposition Analysis, *IE*: Intensity Effect, *OE*: Operational Efficiency, *PEI*: Potential Energy Intensity change, RTS: Returns to Scale, SDA: Structural Decomposition Analysis, *SUBE*: Substitution Effect, *STRE*: Structure Effect, *TE*: Technology change Effect and *TOT*: Total change.

It is important to note that *OE* is conventionally termed as “technical efficiency”. This study uses G in *GBTC*, *GEF* and *GTC* to express GDP that corresponds to a desirable output (g) in the proposed DEA formulations. The above specifications drop C from *EMX* and *PEI* even if it stands for a change. This study uses “italic” to express decision variables. Concepts do not use the italic.

The remainder of this study is organized as follows: Section 2 provides a literature review. Section 3 proposes mathematical models and describes a data set used for the empirical study. Section 4 discusses empirical results and summarizes policy implications for China. The last (5) section provides concluding comments along with future extensions.

2. Literature review

This study proposes a combined approach between PDA and IDA to investigate potential sources on CO_2 emission changes. As a method, we use DEA to measure decomposed components of the combined approach. This section summarizes DEA-related studies and then describes previous research efforts on decomposition analysis.

2.1. Previous efforts on DEA

This study summarizes previous DEA efforts, returning to the first DEA journal publication by Charnes, Cooper and Rhodes (1978). After their effort, many researchers have explored many concepts, methodologies and applications on the method. The book (Sueyoshi & Goto, 2018) has discussed the history of DEA after returning to the science of the 18th century. See also Glover and Sueyoshi (2009) and Ijiri and Sueyoshi (2010) that discussed the history from the perspective of Professor W.W. Cooper who was the father of DEA. Sueyoshi and Sekitani (2009) mathematically examined strengths and drawbacks of all DEA models. Sueyoshi and Goto (2012) discussed how to apply DEA to environmental assessment. They considered a computational framework that separated outputs into desirable (e.g. electricity) and undesirable (e.g. CO_2 emission) categories. The two groups of outputs had opposite directions for improvement and they were unified into a single efficiency measure. Recently, Sueyoshi and Goto (2019) and Sueyoshi et al. (2017b) have extended the original work toward a new unification process for environmental assessment. The book (Sueyoshi & Goto, 2018) has provided about 700 articles on the DEA environmental assessment. Their description included how to select production factors (inputs and outputs) and how apply the DEA method for environmental assessment for specific industries such as agriculture, transportation, electricity distribution, energy and others. See also Sueyoshi, Yuan and Goto (2017a) for the literature survey.

In addition to the above previous works on DEA, we summarize previous studies that applied DEA to energy and environmental protection. For example, Bruno and Manello (2015), Li et al. (2017), Sueyoshi et al. (2017a, 2017b), Tan and Lin (2018) and T. Sueyoshi, Li and Gao (2018) have applied the DEA approach to assess energy usage and environmental protection. Many other studies evaluated energy efficiency, eco-efficiency or environmental efficiency, where the potential contributors were explored. For example, Picazo-Tadeo, Gmez-Limn and Reig-Martnez (2011) assessed farming eco-efficiency in Spain and found that eco-inefficiency was highly linked with operational inefficiency in input management. Martini, Manello and Scotti (2013) evaluated airport inefficiency, after considering environmental externality (noise and air pollutions) in Italy. Falavigna, Manello and Pavone (2013) assessed environmental efficiency in Italian agriculture and found that public funds were generally assigned to disadvantaged areas. Mahlberg and Luptacik (2014) examined the contributors to eco-efficiency. Ignatius, Ghasemi, Zhang, Emrouznejad and Hatami-Marbini (2016) evaluated energy efficiency of 23 EU member countries, after dealing with asymmetric fuzzy numbers. Kuosmanen and Johnson (2017) examined the performance of electricity distribution firms in Finland. Sueyoshi and Wang (2018) applied DEA environmental assessment to examine US petroleum industry by using a non-radial approach with the property of translation invariance in a time horizon. The property makes it possible to handle a negative value(s) in the environmental assessment.

2.2. Previous efforts on decomposition analysis

We first focus upon the existing studies on decomposition analysis that will be further explored in this research. In reviewing the previous works, we identified the six types of effects, which were the driving forces of energy (or carbon) related targets. As summarized in the right hand side of Table 1, these effects were *AE*, *IE*, *OE*, *STRE*, *SUBE* and *TE* (e.g. Yao et al., 2015; Wang & Zhou, 2018, 2018; Wang, Hang, Su & Zhou, 2018). First, *AE* implied an effect on economy by its activity changes (e.g. growth in GDP or sector value added). Second, *IE* was measured by the ratio of GDP (or sector value-added) to energy consumption (or CO_2 emission). Changes in potential (or actual) energy (or carbon) intensity directly influence operational or environmental efficiencies. Third, *OE* stands for operational efficiency. Fourth, *STRE* indicated effects due to energy consumption mix or structure of

Table 1
Recent DEA environmental studies on PDA and IDA.

Article	Desirable output	Undesirable output	Inputs	Methods	Country, sector and periods	Decomposition target	Main decomposed factors
Tan and Lin (2018)	Sector output		*K*, *E*, *L*	PDA and IDA	China, energy–intensive sectors, 2000–2013	Energy intensity	*AE*, *IE*, *OE*, *STRE*, *SUBE*, *TE*.
Wang and Zhou (2018)	Sector output	CO_2	*K*, *E*, *L*	PDA and spatial decomposition	14 world countries, 33 economic sectors, 2007	Regional disparities in carbon intensity	*AE*, *IE*, *STRE*, *SUBE*.
Liu, Zhou, Zhou and Wang (2018)	GDP		*K*, *E*, *L*	PDA and IDA	China, provinces, 2007–2012	Energy consumption	*AE*, *IE*, *OE*, *STRE*, *SUBE*, *TE*.
Wang et al. (2018)	Industrial GDP	CO_2	*K*, *E*, *L*	PDA, IDA and attribution analysis	China, industry, 2006–2014	Carbon intensity	*AE*, *OE*, *STRE*, *SUBE*, *TE*.
Kwon, Cho and Sohn (2017)	GDP	CO_2	*E*, *L*, patent	IDA	12 European countries, 2007–2010	CO_2 emission	*AE*, *IE*, *STRE*.
Wang and Feng (2017)	Industrial GDP	CO_2	*K*, *E*, *L*	PDA and IDA	China, industry, 2000–2015	CO_2 emission	*AE*, *IE*, *OE*, *STRE*, *TE*.
Li et al. (2017)	GDP	CO_2	*K*, *E*, *L*	PDA and IDA	China, provinces, 2001–2011	CO_2 emission	*AE*, *IE*, *OE*, *STRE*, *TE*.
Du, Xie and Ouyang (2017)	GDP	CO_2	*E*	PDA and IDA	China, provinces, 2006–2012	Carbon intensity	*AE*, *IE*, *OE*, *STRE*, *TE*.
Du and Lin (2015)	GDP		*K*, *E*, *L*	PDA and IDA	China, provinces, 2003–2010	Energy consumption	*AE*, *IE*, *OE*, *STRE*, *SUBE*, *TE*.
Wang et al. (2015)	GDP	CO_2	*E*	PDA	China, provinces, 2005–2010	CO_2 emission	*AE*, *IE*, *OE*, *TE*.
Lin and Du (2014)	Sector output		*K*, *E*, *L*	PDA and IDA	China, provinces, 2005 and 2010	Energy intensity	*AE*, *IE*, *OE*, *STRE*, *SUBE*, *TE*.
Guo et al. (2014)	Sector output	CO_2	*K*, *E*, *L*	IDA	China, transportation sector, 1997–2012	CO_2 emission	*AE*, *IE*, *STRE*.
Xu, Fan and Yu (2014)	Sector output	CO_2	*E*	IDA	China, 2005–2010	Energy consumption, CO_2 emission	*AE*, *IE*, *OE*, *STRE*.
Zhang, Zhang and Tan (2013)	GDP	CO_2	*K*, *E*, *L*	PDA	25 *OE*CD counties and China, 1998–2007	CO_2 emission	*AE*, *IE*, *OE*, *STRE*, *TE*.
Kim and Kim (2012)	Sector output	CO_2	*K*, *E*, *L*	PDA and IDA	World countries, 1990–2006	CO_2 emission	*AE*, *IE*, *OE*, *STRE*, *TE*.
Zhang, Tan, Tan and Yuan (2012)	GDP	CO_2	*K*, *E*, *L*	PDA	World countries, 1995–2005	CO_2 emission	*AE*, *IE*, *OE*, *TE*.

(a) GDP: gross domestic product. *K*: capital. *L*: labor. *E*: energy. PDA: Production-theoretical Decomposition Analysis. IDA: Index decomposition analysis. *AE*: activity effect; *IE*: intensity effect; *OE*: operational (or technical) efficiency change effect; *STRE*: structure effect; *SUBE*: substitution effect; *TE*: technological change effect.

economy. There were differences between energy-intensive and energy-extensive sectors. Fifth, *SUBE* was an effect due to inter-factor substitution between energy and non-energy inputs. The substitution may directly influence input combination in production process, thus affecting production performance (e.g. Wang & Zhou, 2018). Finally, the effect of different technology advancement is measured by technology changes or operational efficiency changes. Thus, PDA was used to measure the effect of *OE* and *TE* by comparing inefficient organizations with the best practice ones (e.g. Wang & Zhou, 2018, Wang et al., 2018).

To extend the research efforts in Table 1, this study utilizes a combined approach between PDA and IDA to investigate potential sources on CO_2 emission changes in China.

Until now, decomposition analysis has been often utilized to investigate potential sources of energy or environmental indicators (e.g. energy productivity and carbon intensity). Those previous studies have utilized IDA and SDA as decomposition methods, along with PDA. A detailed methodological comparison among them can be found in Hoekstra, Bergh and C.J.M. (2003), Su and Ang (2012) and Zaim, Gazel and Akkemik (2017), Zhou and Ang (2008). A problem is that no research has clearly explored a mathematical justification on the decomposition analysis. The theoretical justification will be an important future extension of this study.

The main differences among the three decomposition methods explored in this study are as follows. First, their foundations are significantly different. The IDA was linked to the index number theory, which decomposed a value change index into price and quantity change indices. The SDA was based upon the input-output analysis in quantitative economics and thus it was applied to analyze the factors affecting energy or carbon related indicators. Meanwhile, PDA depended upon the production theory, which incorporated both desirable and undesirable outputs. Second, the SDA was usually more data demanding than the other two methods, since it relied on input-output relationship. In comparison, the IDA needed data with sector disaggregation, while the PDA was less data-demanding and involved computation by linear programming. Finally, as for desirable properties, the PDA satisfied factor-reversal and time reversal properties. The method was robust to an occurrence of zero in values. In comparison, some IDA or SDA methods satisfy the three properties and the other methods do not. See Zhou and Ang (2008) for a detailed discussion.

Returning to the fifth column of Table 1, including the previous studies related to PDA and IDA, this study identifies four interesting findings. First, among 16 studies, 12 studies were related to China at various disaggregated levels. China was an important research focus because it had large energy consumption and CO_2 emission. Second, among these studies, there were two types of decomposition targets, i.e. energy-related targets and CO_2-related targets. The former targets contained energy consumption, energy efficiency, energy intensity and energy productivity. This type of research contained 5 studies. Meanwhile, the latter targets included carbon intensity and CO_2 emissions as examined in 12 studies. In this aspect, it was a research focus regarding how to reduce CO_2 emissions and carbon intensity. Third, methodologically, 9 studies adopted the combined approach of PDA with IDA, 4 studies adopted PDA and 3 studies adopted IDA. In this regard, the combined approach of PDA and IDA had several methodological advantages, because it investigated the potential sources (e.g. substitution between production factors, efficiency and technology changes) by comparing the approach with traditional IDA studies (e.g. Du & Lin, 2015; Kim & Kim, 2012; Lin & Du, 2014). Meanwhile, this approach overcomes the inconsistency of PDA. See Lin and Du (2014) for a detailed description on the inconsistency. Finally, the existing studies mainly focused upon five types of effects, which were due to the driving forces of energy (or carbon) related targets. They examined five types of effects. All the 16 studies discussed economic activity, 15 studies examined intensity effect, 14 studies considered structure effect, and the 13 studies, adopting PDA, discussed the effect of operational efficiency and technology changes. By comparison, only 6 studies considered a substitution effect.

The position of this study is that we propose a new combination between PDA and IDA to investigate potential sources on CO_2 emission changes in China. We use DEA to measure decomposed components of the combined approach. It is true that DEA cannot measure the decomposed potential sources of CO_2 emission, but it can provide the level of these decomposed components by measuring these efficiencies and indexes. Thus, this study documents a new DEA-based decomposition analysis to reduce the amount of CO_2 emission in China.

3. Models and data set

This study utilizes the DEA approaches proposed in Du and Lin (2015)), Kim and Kim (2012) and Ang and Choi (1997), Li et al. (2017), Zhou and Ang (2008).

3.1. Environmental production technology

DMUs (e.g. Chinese provinces) use inputs to produce outputs. This study considers n DMUs ($j = 1,.., n$). Three inputs are specified by the vector $X = (x_E, x_C, x_L)$, where the three subscripts stand for energy (E), capital (C) and labor (L), respectively. A desirable output (g) is GDP (Gross Domestic Product), while an undesirable output (b) is the amount of CO_2 emission.

The production technology set (T) can be specified in the following manner:

$$T = \left\{ (x_E, x_C, x_L, g, b) : \sum_{j=1}^{n} x_{Ej}\lambda_j \le x_E, \quad \sum_{j=1}^{n} x_{Cj}\lambda_j \le x_C, \right.$$
$$\left. \sum_{j=1}^{n} x_{Lj}\lambda_j \le x_L, \quad \sum_{j=1}^{n} g_j\lambda_j \ge g, \quad \sum_{j=1}^{n} b_j\lambda_j \le b, \lambda_j \ge 0 \right\}. \qquad (1)$$

where the technology (T) assumes constant RTS and constant DTS because Eq. (1) excludes $\sum_{j=1}^{n} \lambda_j = 1$ from the formulation. The assumption is important for avoiding an infeasible solution on (1). Sueyoshi and Goto (2018) provided a detailed description on RTS and DTS.

Meanwhile, a distance function measures either minimization of a production input or maximization of a desirable output, when other production variables remain unchanged. Thus, it determines an efficiency level by comparing between an observed DMU and an efficiency frontier. For the specific period t, the distance functions for the energy input (x_E^t) and the desirable output (g^t) become as follows:

$$D_E^t(x_E^t, x_C^t, x_L^t, g^t, b^t) = \min\{\theta : (\theta x_E^t, x_C^t, x_L^t, g^t, b^t) \in T^t\} \text{ and} \qquad (2)$$

$$D_G^t(x_E^t, x_C^t, x_L^t, g^t, b^t) = \max\{\eta : (x_E^t, x_C^t, x_L^t, \eta g^t, b^t) \in T^t\}. \qquad (3)$$

Here, $\theta \le 1$ and $\eta \ge 1$, related to the level of efficiency, are maintained in the two equations.

Suppose there are two periods (*t-1* and t) to be examined in this study. To handle the existence of production variables in a time horizon, we define the distance functions as follows:

$$D_E^{t-1}\left(x_E^t, x_C^t, x_L^t, g^t, b^t\right) = \min\left\{\theta : \left(\theta x_E^t, x_C^t, x_L^t, g^t, b^t\right) \in T^{t-1}\right\}, \qquad (4)$$

$$D_G^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t) = \max\{\eta : (x_E^t, x_C^t, x_L^t, \eta g^t, b^t) \in T^{t-1}\}, \qquad (5)$$

$$D_E^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1}) = \min\{\theta : (\theta x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1}) \in T^t\} \text{ and} \qquad (6)$$

$$D_G^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1}) = \max\{\eta : (x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, \eta g^{t-1}, b^{t-1}) \in T^t\}. \qquad (7)$$

In the above equations, D^{t-1} indicates the technology set at the *t-1* th period, while D^t indicates the same set for the t th period. Eq. (4) minimizes the energy input under the technology set of the *t-1* th period, where all production variables are at the t th period. On the other hand, Eq. (6) minimizes the energy input under the technology set of the t th period, where all production variables are at the *t-1* th period. Eqs. (5) and (7) can be explained by a similar manner.

3.2. Decomposition approach

This study uses PDA to conduct decomposition analysis of CO_2 emission. See Yao et al. (2015), Zhou and Ang (2008) and Kim and Kim (2012) on their descriptions on the PDA. Based upon these previous studies, this study conducts further decomposition analysis by introducing three new indexes of technology changes.

In the s th period, we decompose the total amount of CO_2 emission (b^s) as follows:

$$b^s = \sum_j b_j^s = \sum_j \frac{b_j^s}{x_{Ej}^s} \times \frac{x_{Ej}^s}{x_E^s} \times \frac{x_E^s}{g^s} \times g^s \text{ for } s \in \{t-1, t\}, \qquad (8)$$

where the subscript (j) stands for the j th DMU. The total sum of these DMUs drops the subscription. The s stands for the s th period, containing either the t-1 th or the t th period.

For further decomposition, the geometric mean is used to avoid the arbitrariness of selecting the referenced technology in a time horizon. This study introduces indexes concerning technology changes which need further decomposition as follows:

$$\begin{aligned}
b^{t-1} = & \sum_j \frac{b_j^{t-1}}{x_{Ej}^{t-1}} \times \frac{x_{Ej}^{t-1}}{x_E^{t-1}} \\
& \times \frac{x_E^{t-1}/\left[D_E^{t-1}(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})D_E^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})\right]^{1/2}}{g^{t-1}/\left[D_G^{t-1}(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})D_G^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})\right]^{1/2}} \\
& \times D_E^{t-1}(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1}) \\
& \times \left[D_E^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})/D_E^{t-1}(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})\right]^{1/2} \\
& \times g^{t-1} \\
& \times \left[D_G^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})/D_G^{t-1}(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})\right]^{1/2} \\
& \times \frac{1}{D_G^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})} \\
& \times \left[\frac{D_G^{t-1}(x_E^t, x_C^{t-1}, x_L^{t-1}, g^t, b^{t-1})D_G^t(x_E^t, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})}{D_G^t(x_E^t, x_C^{t-1}, x_L^{t-1}, g^t, b^{t-1})D_G^{t-1}(x_E^t, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})}\right]^{1/2} \\
& \times \left[\frac{D_G^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})D_G^{t-1}(x_E^t, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})}{D_G^{t-1}(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})D_G^t(x_E^t, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})}\right]^{1/2} \\
& \times \left[\frac{D_G^t(x_E^t, x_C^{t-1}, x_L^{t-1}, g^t, b^{t-1})D_G^{t-1}(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})}{D_G^{t-1}(x_E^t, x_C^{t-1}, x_L^{t-1}, g^t, b^{t-1})D_G^t(x_E^{t-1}, x_C^{t-1}, x_L^{t-1}, g^{t-1}, b^{t-1})}\right]^{1/2}
\end{aligned} \qquad (9)$$

$$\begin{aligned} b^t &= \sum_j \frac{b_j^t}{x_{Ej}^t} \times \frac{x_{Ej}^t}{x_E^t} \\ &\times \frac{x_E^t/\left[D_E^t(x_E^t, x_C^t, x_L^t, g^t, b^t) D_E^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t)\right]^{1/2}}{g^t/\left[D_G^t(x_E^t, x_C^t, x_L^t, g^t, b^t) D_G^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t)\right]^{1/2}} \\ &\times D_E^t(x_E^t, x_C^t, x_L^t, g^t, b^t) \\ &\times \left[D_E^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t)/D_E^t(x_E^t, x_C^t, x_L^t, g^t, b^t)\right]^{1/2} \\ &\times g^t \\ &\times \left[D_G^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t)/D_G^t(x_E^t, x_C^t, x_L^t, g^t, b^t)\right]^{1/2} \\ &\times \frac{1}{D_G^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t)} \\ &\times \left[\frac{D_G^t(x_E^{t-1}, x_C^t, x_L^t, g^{t-1}, b^t) D_G^{t-1}(x_E^{t-1}, x_C^t, x_L^t, g^t, b^t)}{D_G^{t-1}(x_E^{t-1}, x_C^t, x_L^t, g^{t-1}, b^t) D_G^t(x_E^{t-1}, x_C^t, x_L^t, g^t, b^t)}\right]^{1/2} \\ &\times \left[\frac{D_G^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t) D_G^t(x_E^{t-1}, x_C^t, x_L^t, g^t, b^t)}{D_G^t(x_E^t, x_C^t, x_L^t, g^t, b^t) D_G^{t-1}(x_E^{t-1}, x_C^t, x_L^t, g^t, b^t)}\right]^{1/2} \\ &\times \left[\frac{D_G^{t-1}(x_E^{t-1}, x_C^t, x_L^t, g^{t-1}, b^t) D_G^t(x_E^t, x_C^t, x_L^t, g^t, b^t)}{D_G^t(x_E^{t-1}, x_C^t, x_L^t, g^{t-1}, b^t) D_G^{t-1}(x_E^t, x_C^t, x_L^t, g^t, b^t)}\right]^{1/2} \end{aligned} \quad (10)$$

Eqs. (9) and (10) have eleven decomposed indexes as listed in these right hand sides. The ten indexes are variables and the one index (*EMF*) is assumed to be unchanged. These indexes are specified by the following manner:

(a) *EMF*: The index indicates the change in CO_2 emission factor due to energy. Following Kim and Kim (2012), the index is assumed to be unchanged, so indicating that it does not produce any effect on CO_2 emission.
(b) *EMX*: The index measures the structure effect that results from an energy mix change.
(c) *PEI*: The index measures the effect caused by a potential energy intensity change. The index is different from actual observed-energy intensity, where operational inefficiency is assumed to be eliminated. See Zhou and Ang (2008) and Kim and Kim (2012) for their detailed discussions.
(d) *EUEF*: The index indicates the effect due to an energy-based *OE* change.
(e) *ESTC*: The index shows the effect originated from an energy saving technology change.
(f) *EA*: The index accounts for the effect induced by an economic activity change. The economic activity is expected to make a profound effect on the economic system.
(g) *GTC*: The index measures the effect due to a desirable output (e.g. GDP) technology change.
(h) *GEF*: The index stands for the effect caused by a desirable output-based *OE* change.
(i) *GBTC*: The index is measured as a desirable output-based technology change. This index explains the effect of a technology change in GDP across periods in which the other inputs and desirable output are assumed to be unchanged.
(j) *EBTC*: The index is measured by an energy based technology change. The index measures the effect of a technology change in energy across periods, when the other inputs and outputs are assumed to be unchanged.
(k) *CBTC*: The index is referred to as a combined technology change. This index indicates the effect of a technology change for a desirable output and an input, across periods when the other inputs and undesirable output are assumed to be fixed.

It is important to note that there are two differences between *GTC* and *GBTC* which are related to technology changes. One of them is that *GTC* is an ordinary technology index (e.g. information technology development which influences all industries), while *GBTC* belongs to biased technology index where "biased" means specific technology development such as solar energy. The other is that time horizons on production factors are different between them. For example, *GTC* does not cover production factors in two periods, while *GBTC* covers their economic activities in the two periods.

Index classification: The previous studies have discussed six indexes, as summarized in the right hand side of Table 1. Meanwhile, this study uses eleven indexes which are classified into five groups. The first index contains activity effect (*AE* in Table 1), which is measured by *EA* in this study. The second index has intensity effect (*IE* in Table 1), which is measured by *PEI*. The third index indicates a structure effect (*STRE* and *SUBE* in Table 1), which are measured by *EMX*. The fourth index (*OE* in Table 1) examines the effect caused by operational efficiency change that are measured by *EUEF* and *GEF*. The fifth index (*TE* in Table 1) shows the effect of technology change that is measured by *ESTC* and *GTC*. Note that *EMF* is assumed to be unchanged, so not corresponding to indexes listed in Table 1.

Three New Indexes: This study proposes *GBTC*, *EBTC* and *CBTC* as new indexes. The proposed indexes are derived from *TE* (technological change effect). The previous technology index does not cover production variables between two periods. Thus, we measure a technology progress.

Based on the above descriptions, the decomposition of CO_2 emission can be expressed as follows:

$$b^s = \sum_j b_j^s = \begin{pmatrix} \sum_j EMF_j^s \times EMX_j^s \times PEI \times EUEF \times ESTC \times EA \\ \times GTC \times GEF \times GBTC \times EBTC \times CBTC \end{pmatrix} \quad \text{for } s \in \{t-1, t\} \quad (11)$$

This study uses the following multiplicative logarithmic mean, or the Divisia index method (LMDI). This method was initially proposed by Ang and Choi (1997). It has the advantage of performing perfect decomposition without unexplained residual terms.

The ratio between the two (*t-1* and *t*) periods is specified by

$$D_{TOT} = \frac{b^t}{b^{t-1}} = \begin{pmatrix} D_{EMF} \times D_{EMX} \times D_{PEI} \times D_{EUEF} \times D_{ESTC} \times D_{EA} \\ \times D_{GTC} \times D_{GEF} \times D_{GBTC} \times D_{EBTC} \times D_{CBTC} \end{pmatrix} \quad (12)$$

We measure all the potential sources of CO_2 emission by the following equations:

$$D_{EMF} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{EMF_j^t}{EMF_j^{t-1}}\right)\right\} \quad (13)$$

$$D_{EMX} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{EMX_j^t}{EMX_j^{t-1}}\right)\right\} \quad (14)$$

$$D_{PEI} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{PEI^t}{PEI^{t-1}}\right)\right\} \quad (15)$$

$$D_{EUEF} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{EUEF^t}{EUEF^{t-1}}\right)\right\} \quad (16)$$

$$D_{ESTC} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{ESTC^t}{ESTC^{t-1}}\right)\right\} \quad (17)$$

$$D_{EA} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{EA^t}{EA^{t-1}}\right)\right\} \quad (18)$$

$$D_{GTC} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{GTC^t}{GTC^{t-1}}\right)\right\} \quad (19)$$

$$D_{GEF} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{GEF^t}{GEF^{t-1}}\right)\right\} \quad (20)$$

$$D_{GBTC} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{GBTC^t}{GBTC^{t-1}}\right)\right\} \quad (21)$$

$$D_{EBTC} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{EBTC^t}{EBTC^{t-1}}\right)\right\} \quad (22)$$

$$D_{CBTC} = \exp\left\{\sum_j \frac{(b_j^t - b_j^{t-1})/(\ln b_j^t - \ln b_j^{t-1})}{(b^t - b^{t-1})/(\ln b^t - \ln b^{t-1})} \cdot \ln\left(\frac{CBTC^t}{CBTC^{t-1}}\right)\right\} \quad (23)$$

This study assumes no occurrence of zero in the denominators measured by Eqs. (13)–(23). See Wang and Feng (2017) have discussed a mathematical rationale on the above equations.

Assessment Rule: The ratio (i.e. a total influence on CO_2 emission) between the two (*t-1* and *t*) periods measures an increasing rate via $D_{TOT} = b^t/b^{t-1}$. The assessment is classified by the following rule:

(a) If $b^t/b^{t-1} > 1$, then the CO_2 emission "increases" in the amount from the *t-1* th to the *t* period. This situation is "undesirable".
(b) If $b^t/b^{t-1} = 1$, then the CO_2 emission shows "no change" on the amount between the two periods.
(c) If $b^t/b^{t-1} < 1$, then the CO_2 emission "decreases" in the amount between the two periods. This situation is "desirable".

It is important to specify the two additional treatments on the assessment rule. One of the two treatments is that we may take a natural logarithm (ln) on the ratio in the manner of $\ln(b^t/b^{t-1}) = \ln(b^t) - \ln(b^{t-1})$.The above classification is separated into (a) positive (increasing, so being undesirable), (b) zero (no change), or (c) negative (decreasing, so being desirable), respectively. The other treatment is that we measure the annual average of rate changes in the observed annual periods. This study will determine our assessment on Chinese provinces by their annual averages.

3.3. DEA models

To measure the decomposed indexes of the k th DMU, this study solves the following DEA model:

$$\begin{aligned}
&\left[D_E^s(x_E^{s'}, x_C^{s'}, x_L^{s'}, g^{s'}, b^{s'})\right]^{-1} = \min \theta_E \\
&s.t. \quad \sum_{j=1}^n x_{Ej}^s \lambda_j - \theta_E x_{Ek}^{s'} \le 0, \\
&\qquad \sum_{j=1}^n x_{Cj}^s \lambda_j \le x_{Ck}^{s'}, \\
&\qquad \sum_{j=1}^n x_{Lj}^s \lambda_j \le x_{Lk}^{s'}, \\
&\qquad \sum_{j=1}^n g_j^s \lambda_j \ge g_k^{s'}, \\
&\qquad \sum_{j=1}^n b_j^s \lambda_j \le b_k^{s'}, \\
&\lambda_j \ge 0\ (\mathrm{j} = 1, \cdots, n), \theta_E : URS, s \in \{t-1, t\}\ \&\ s' \in \{t-1, t\}.
\end{aligned} \quad (24)$$

Model (24) represents the distance function with energy minimization. The model incorporates symbols to represent the two periods, i.e. *s* and *s'*. The level of operational efficiency (θ_E^*) is measured on the optimality of Model (24).

Meanwhile, the distance function with a desirable output is maximized. The maximization is structured by the following model:

$$\begin{aligned}
&\left[D_G^s(x_E^{s'}, x_C^{s'}, x_L^{s'}, g^{s'}, b^{s'})\right]^{-1} = \max \eta \\
&s.t. \quad \sum_{j=1}^n x_{Ej}^s \lambda_j \le x_{Ek}^{s'}, \\
&\qquad \sum_{j=1}^n x_{Cj}^s \lambda_j \le x_{Ck}^{s'}, \\
&\qquad \sum_{j=1}^n x_{Lj}^s \lambda_j \le x_{Lk}^{s'}, \\
&\qquad \sum_{j=1}^n g_j^s \lambda_j - \eta g_k^{s'} \ge 0, \\
&\qquad \sum_{j=1}^n b_j^s \lambda_j \le b_k^{s'}, \\
&\lambda_j \ge 0\ (\mathrm{j} = 1, \cdots, n), \eta : URS, s \in \{t-1, t\}\ \&\ s' \in \{t-1, t\}.
\end{aligned} \quad (25)$$

Here, the level of operational efficiency (θ_g^*) is measured by $1/\eta^*$ on the optimality of Model (25).

At the end of this subsection, we need to mention five assumptions on Models (24) and (25) that make a linkage to the proposed decomposition analysis. (a) First, DEA models belong to the radial measurement because they contain efficiency scores (θ_E^* and θ_g^*) in their objective functions. However, the objective functions do not have any influence from slacks. As discussed by Sueyoshi and Goto (2018), their multipliers (i.e. dual variables) become often zero in their dual formulations. In the occurrence of zero in the multipliers, the DEA measurements by Models (24) and (25) cannot fully use information (i.e. data) on production factors. This study assumes that all multipliers are positive so that they can fully utilize all production factors in the proposed assessments. (b) Second, Models (24) and (25) often suffer from an occurrence of multiple solutions (e.g. multiple projection and multiple reference sets). See Sueyoshi and Sekitani (2009). The use of those models

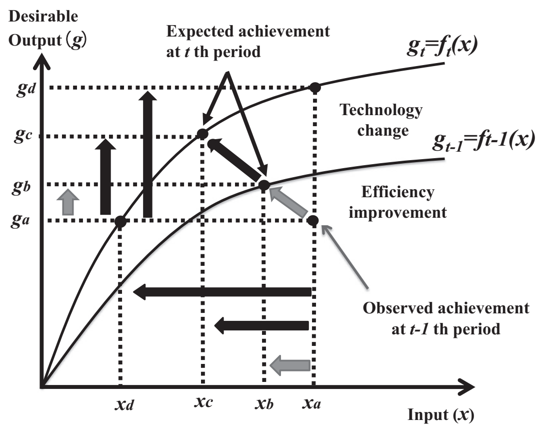

Fig. 1. An illustration of decomposed indexes.

requires the assumption on a "unique" solution on optimality for the decomposition analysis. See Sueyoshi and Goto (2018) that provided a detailed description on how to handle multiple solutions. (c) Third, this study assumes no occurrence of frontier cross-over, implying that efficiency frontiers in *t-1* th and *t* th periods make a crossover or the *t* period retreats from the *t*-1 period in the worst case. To handle the difficulty, Models (24) and (25) need to incorporate production factors in multiple periods (e.g. *t-2*, *t-1* and *t* periods) in the left hand sides of those formulations. See Sueyoshi and Goto (2018). (d) Fourth, the DEA efficiency scores depend upon L1-norm distance measurement. However, the proposed decomposition approach depends upon L2-norm distance measurement. The two distance measures may be approximately similar to each other in the proposed approach. See Sueyoshi and Goto (2018) that has described a historical difference between the two distance norms. (e) Finally, this study assumes that the unique solutions are produced by Models (24) and (25) and the assumption is applicable to all the computational processes for the proposed decomposition process (12)-(23).

It is clear that the proposed decomposition approach does not function as we expect if any of the four assumptions is violated. The proposed approach provides just an approximated result for decomposition in the case. We will discuss how to handle the difficulty in a future research extension.

3.4. A graphical illustration on decomposed indexes

To visually describe the relationship among different decomposed indexes, Fig. 1 depicts one input (or undesirable output), a desirable output and two frontiers across periods (i.e. *t-1* and *t*). In the figure, the horizontal axis represents the input (*x*: energy), while the vertical axis represents the desirable output (*g*: GDP). The functional form *f(x)* stands for a production function at each time period. In the figure, we assume that an increase in *x* enhances the amount of *b*. Thus, Fig. 1 does not specify *b* (i.e. CO_2 emission) on the horizontal axis.

There are two observations in the manner that DMU (x_a, g_a) at period *t-1* shifts to DMU (x_c, g_c) at period *t*. The shift may include multiple projections from the *t-1* th period to the *t* th period. For example, (x_a, g_d) and (x_d, g_a) are such horizontally and vertically projected DMUs on the efficient frontier at the *t* th period.

This study begins with the indexes for depicting technology changes, which can be visually expressed by a frontier shift across periods. Conventionally, technology changes (i.e. frontier changes) are expressed in terms of energy saving technology changes (*ESTC*) by measuring $x_b - x_c$ and desirable output technology changes (*GTC*) by $g_c - g_b$. Both occur within each period. Those ratios between the two periods are measured by D_{ESTC} and D_{GTC}.

In addition to those representing frontier changes, there is an index to measure an efficiency change, i.e. a desirable output operational efficiency change (*GEF*). The index is measured by $g_b - g_a$. The ratio between the two periods is measured by D_{GEF}. The index for measuring an energy use efficiency change (*EUEF*) is specified by $x_b - x_a$. The ratio between the two periods is measured by D_{EUEF}.

The energy related indexes examined in this study incorporate *EMF*, *EMX* and *PEI*. The *EMF* indicates how a use of energy influences the amount of CO_2 emission. Fig. 1 does not depict the index because it does not specify the axis for *b*. It also assumes that the relationship is unchanged on a specific point in the horizontal axis. The degree of D_{EMF} indicates the ratio between the two periods (so, two different points on the horizontal axis). In a similar manner, the *EMX* indicates the effect of an energy mix (e.g. a fuel mix among oil, gas, nuclear and renewable energy sources). The *PEI* indicates the level of energy intensity (e.g. a portion of energy sources) that determines an effective allocation of the input (energy). Both indicate a shift from x_a to x_d in Fig. 1. Their contributions are measured by D_{EMX} and D_{PEI} in the proposed decomposition. Meanwhile, the *EA* indicates an economic activity change due to a scale change. For example, it is possible for a DMU to shift from g_a to g_d by focusing on its economic development. The contribution is measured by D_{EA} in the two periods.

Besides the above existing technology change indexes, this study incorporates three new indexes related to technology changes. These indexes contain *GBTC*, *EBTC* and *CBTC*. The feature of these technology changes is that they capture frontier changes due to specific input and/or desirable output, given that the others are "unchanged" across periods. This study considers the three types of such indexes, where only energy, desirable output or their combination are assumed to be unchanged. Fig. 1 visually illustrates *GBTC* where a desirable output change across two periods and inputs are assumed to be unchanged. So, the distance between $g_c - g_b$ indicates such a case along with a horizontal (input specific) projection. The degree of D_{GBTC} indicates the ratio between the two periods. The measurement is applicable to *EBTC*. In the case, given *g*, the distance is measured by $x_c - x_b$ along with a vertical (desirable output specific) projection. The degree of D_{EBTC} indicates the ratio between the two periods. The *CBTC* combines the analytical feature of *GBTC* and that of *EBTC*. Thus, given specific *x* and *g*, it measures the shift in the horizontal and vertical coordinates. The degree of D_{CBTC} indicates the ratio between the two periods.

3.5. Data set

In this study, each province in China is regarded as a DMU. Due to data accessibility, this study incorporates the data set concerning 30 provinces (or province-equivalents, provinces hereafter, excluding Tibet) only in China mainland. The periods are from 2008 to 2016.

In the proposed model, the inputs contain capital (*C*, in 10^8 RMB), labor (*L*, in 10^4 persons) and energy (*E*, in 10^4 tce). In terms of capital, this study utilizes the method of the perpetual inventory (stock) and the result of Zhang, Wu and Zhang (2002), with the base year of 2000. The data source is National Bureau of Statistics of China (2009a-2017a).

Labor is calculated as the sum of urban unit employment and the number of engaged persons in private enterprises and self-employed individuals at year-end, where the data source is National Bureau of Statistics of China (2009b-2017b). Energy is measured as total energy consumption and the data source is National Bureau of Statistics of China (2009c-2017c).

Table 2
Descriptive statistics of production variables from 2008 to 2016.

Indicator [1]	Production inputs [2]			Outputs	
	Capital 10^8 RMB	Labor 10^4 persons	Energy 10^4 tce	GDP 10^8 RMB	CO_2 10^4 tons
Mean	15,681.07	1216.21	13,779.60	12,933.14	29,527.75
Standard deviation	10,888.46	933.37	8315.68	10,596.60	20,899.23
Minimum	1852.72	101.67	1135.00	640.35	1578.56
Maximum	48,590.68	5595.37	38,899.00	52,310.95	98,768.67

(a) Sources: National Bureau of Statistics of China (2009a, 2017a, 2009b, 2017b, 2009c, 2017c, and 2018).
(b) Production inputs include labor (L, 10^4 persons), capital (K, 10^8 RMB) and energy (E, 10^4 tce). Desirable output is GDP (G, 10^8 RMB). Undesirable output is CO_2 (B, 10^4 tons).

The desirable output includes GDP and an undesirable output is CO_2. The data source of GDP is National Bureau of Statistics of China (2018). The amount of CO_2 is calculated according to the method proposed by Du (2010) and the data source is National Bureau of Statistics of China (2009c, 2017c), IPCC (2006) and National Coordination Committee on Climate Change (2007). Table 2 summarizes the descriptive statistics of the above production variables.

3.6. CO_2 emission changes in China

Fig. 2 illustrates an average growth rate of CO_2 emission across Chinese provinces from 2008 to 2016. The average annual growth rate is listed in the legend by measuring $((b^t - b^{t-1})/b^{t-1})$. The figure visually indicates that there are significant differences in an average growth rate across Chinese provinces.

To explain such regional differences in CO_2 emission changes, Fig. 2 separates our empirical findings by the following three groups: (a) The 1st group (yellow marked) includes the provinces with a negative growth in CO_2 emission. The group contains the three provinces such as Beijing, Shanghai and Yunnan. These results are not surprising to us because Beijing and Shanghai are already well-developed with significant economic restructuring from industry to service. Their pollution levels are saturated in the increase of CO_2 emission. In contrast, Yunnan has a small-sized economy with slow economic growth. (b) The 2nd group (green-marked) contains the provinces with rapid growth in CO_2 emission. The group contains 2 provinces such as Shaanxi (10.37%) and Xinjiang (15.57%) in their annual growth rates. (c) The 3rd group (red-marked) includes provinces with moderate growth in CO_2 emission. They contain 25 provinces in total. The average growth rates range from zero to 9% in their annual growth. Currently, China is still in the process of industrialization and urbanization. Their CO_2 emissions are expected to grow in those provinces.

Next, comparing between our empirical findings and the existing literature, this study notes a comment on the three new potential contributors to CO_2 emission changes. These contributors include (a) *GBTC* as a previously proposed index, (b) *EBTC* and (c) *CBTC*; all are newly proposed in this study. These contributors can provide us with information for guiding environmental policy. It is easily envisioned that the proposed approach is extendable to examining other decomposition targets (e.g. carbon intensity and energy productivity). To document such research importance, this study investigates the effect of different technology changes on CO_2 emission. Thus, this study provides detail information on potential sources to produce China's CO_2 emission changes at a provincial level. Such information is important to policy makers, especially for local governments.

Here, it is important to summarize analytical features of the newly proposed approach from identifying the change of CO_2 emission. Using the new indexes, we understand how carbon emission has grown in the past. The ratio indicates a growth rate on CO_2 emission from the *t-1* th period to the *t* th period. It is an average annual growth rate. After comparing growth rates of CO_2 emissions between the two consecutive years, we take an average across periods. If the ratio is larger than zero, the amount is increasing on CO_2 emission. The opposite (i.e. decreasing) case can be found if it is less than zero (so, becoming better). If the ratio is

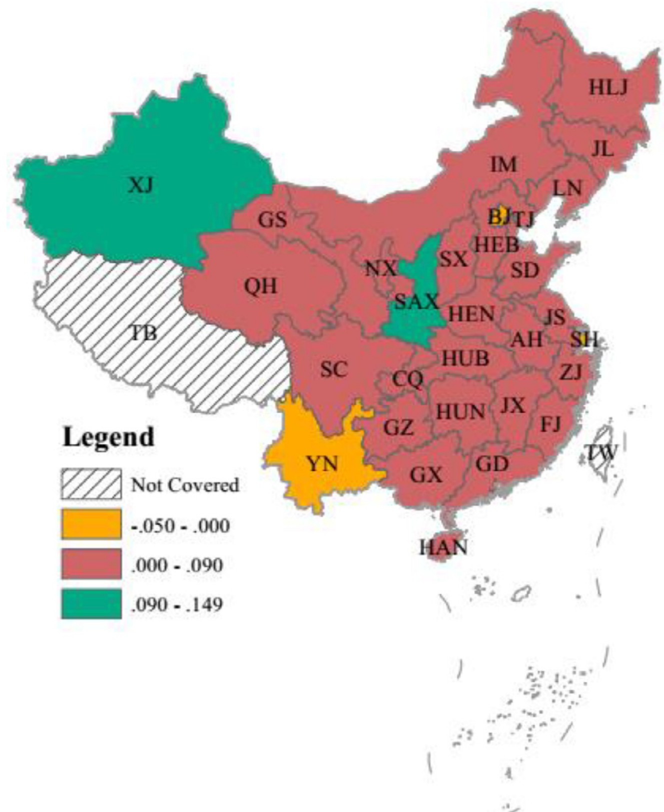

Fig. 2. Average growth rates of CO_2emissions from 2008 to 2016.
(a) BJ, Beijing; TJ, Tianjin; HEB, Hebei; SX, Shanxi; IM, Inner Mongolia; LN, Liaoning; JL, Jilin; HLJ, Heilongjiang; SH, Shanghai; JS, Jiangsu; AH, Anhui; CQ, Chongqing; FJ, Fujian; GS, Gansu; GD, Guangdong; GX, Guangxi; GZ, Guizhou; HAN, Hainan; HEN, Henan; HUB, Hubei; HUN, Hunan; JX, Jiangxi; NX, Ningxia; QH, Qinghai; SAX, Shaanxi; SC, Sichuan; YN, Yunnan; SD, Shandong; XJ, Xinjiang; ZJ, Zhejiang. For simplicity, this study does not cover all geographical regions of China.
(b) If the growth rates are larger than zero, they exhibit an increase in the CO_2 emission. The opposite (i.e. decrease) case can be found if they are less than zero. If they are zero, then no change is found on the emission increase or decrease.
(c) Section 3 describes how to compute growth rates. This study measures the rate by $((b^t - b^{t-1})/b^{t-1})$. The high growth rate (0.090–0.149) is green-colored and the next (0.000–0.090) is red-colored. Both have increased the amount of CO_2 emission. In contrast, the yellow-colored provinces have negative growth (−0.050–0.000), so that their industrialization did not increase the amount of CO_2 emission.
(d) The CO_2 emissions are calculated as the product of energy consumption and emission factors. The obtained CO_2 emissions are used to compute the annual growth rates. The decomposition is used to compute the forces determining the CO_2 emission changes across periods. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Effects of various contributors to CO_2 emissions changes.

Provinces	D_{EMX}	D_{PEI}	D_{EUEF}	D_{ESTC}	D_{EA}	D_{GTC}	D_{GEF}	D_{GBTC}	D_{EBTC}	D_{CBTC}
Beijing	0.938	1.097	1.000	0.945	1.081	1.106	0.820	1.000	1.001	1.000
Tianjin	0.965	1.061	1.000	0.955	1.131	1.085	0.851	1.000	1.009	0.991
Hebei	1.001	1.021	0.989	0.968	1.089	1.070	0.905	1.000	1.000	1.000
Liaoning	0.998	1.135	1.011	0.878	1.080	1.048	0.923	1.000	1.000	1.000
Shanghai	0.982	1.017	1.003	0.971	1.078	1.053	0.905	1.000	1.000	1.000
Jiangsu	1.005	1.025	1.000	0.973	1.101	1.055	0.901	1.000	1.000	1.000
Zhejiang	0.975	1.021	1.008	0.973	1.087	1.057	0.903	1.000	1.000	1.000
Fujian	0.969	1.022	1.000	0.977	1.110	1.055	0.901	1.000	1.000	1.000
Shandong	1.012	1.020	1.048	0.925	1.099	1.054	0.911	1.000	1.000	1.000
Guangdong	0.986	1.034	1.011	0.959	1.090	1.056	0.900	1.000	1.007	0.993
Hainan	1.001	0.991	1.041	0.967	1.103	1.064	0.918	1.000	1.002	0.998
Shanxi	0.997	1.000	1.005	0.973	1.080	1.053	0.925	1.000	1.001	0.999
Jilin	1.001	1.021	0.971	0.973	1.101	1.050	0.909	1.000	1.000	1.000
Heilongjiang	0.999	1.040	0.984	0.968	1.090	1.049	0.907	1.000	1.000	1.000
Anhui	0.994	1.034	1.000	0.973	1.113	1.050	0.898	1.000	1.000	1.000
Jiangxi	0.993	1.024	1.010	0.973	1.111	1.049	0.906	1.000	1.000	1.000
Henan	0.992	1.014	0.984	0.973	1.100	1.049	0.916	1.000	1.000	1.000
Hubei	0.987	1.013	0.982	0.973	1.112	1.050	0.915	1.000	1.000	1.000
Hunan	0.993	1.030	0.974	0.973	1.110	1.049	0.908	1.000	1.000	1.000
Inner Mongolia	1.016	1.072	1.000	0.923	1.112	1.050	0.909	1.000	1.003	0.997
Guangxi	0.999	1.023	1.008	0.973	1.107	1.049	0.908	1.000	1.000	1.000
Chongqing	0.979	1.051	0.974	0.973	1.133	1.051	0.882	1.000	1.000	1.000
Sichuan	0.976	1.040	0.984	0.973	1.114	1.061	0.883	1.000	1.000	1.000
Guizhou	0.998	1.027	0.986	0.973	1.122	1.052	0.901	1.000	1.000	1.000
Yunnan	0.954	1.019	0.993	0.973	1.111	1.048	0.912	1.000	1.000	1.000
Shaanxi	1.030	1.025	1.008	0.973	1.114	1.050	0.906	1.000	1.000	1.000
Gansu	1.000	1.005	0.996	0.973	1.103	1.051	0.922	1.000	1.000	1.000
Qinghai	0.987	1.015	1.026	0.973	1.109	1.068	0.899	1.000	1.000	1.000
Ningxia	1.009	1.001	1.025	0.973	1.104	1.060	0.918	1.000	1.000	1.000
Xinjiang	1.033	1.001	1.067	0.973	1.100	1.071	0.908	1.000	0.999	1.001
China's average	0.992	1.030	1.003	0.964	1.103	1.057	0.902	1.000	1.001	0.999
# of Provinces >1	9	28	13	0	30	30	0	0	6	1
# of Provinces =1	1	1	6	0	0	0	0	30	23	24
# of Provinces <1	20	1	11	30	0	0	30	0	1	5

(a) # denotes the number of provinces whose values are greater than, equal to, or less than unity, respectively.

Table 4
Comparison of decomposed results between this study and some previous studies.

Studies	Time coverage	Provinces	D_{EMX}	D_{PEI}	D_{EUEF}	D_{ESTC}	D_{EA}	D_{GTC}	D_{GEF}	D_{GBTC}	D_{EBTC}	D_{CBTC}
Zhou and Ang (2008)	1995–2005	China's average		0.6740	1.1372	0.9334	4.9117	0.6711	0.8864			
Kim and Kim (2012)	1990–2006	China's average	0.9771	0.3024	1.0092	1.0127	3.9648					
Li et al. (2017)	2001–2011	LCIP	1.0045	0.9450	1.0018	1.0078	1.2437	1.0319	1.0050			
		MCIP	0.9878	0.9624	1.0033	1.0046	1.2628	1.0339	1.0008			
		HCIP	0.9924	0.9793	1.0027	1.0018	1.2583	1.0300	0.9821			
This study	2008–2015	China's average	0.992	1.030	1.003	0.964	1.103	1.057	0.902	1.000	1.001	0.999

(a) Li et al. (2017) classified all China's provinces into three groups. In this regard, LCIP, MCIP and HCIP stand for low-carbon-intensity provinces, middle-carbon-intensity provinces and high-carbon-intensity provinces respectively.

zero, then no change is found in the ratio. We can discuss such a possibility on CO_2 emission prevention by measuring whether the ratio increases or decreases between the two periods. The ratio measurement is an initial step to understand on how we may reduce the amount of CO_2 emission in future energy planning.

4. Sources affecting CO_2 emission changes in China

4.1. Overall results

Table 3 summarizes the decomposition results of ten potential contributors in China's emission changes. As mentioned previously, if the number is larger than unity, then it indicates that the factor results in an increase in CO_2 emission. In contrast, if it is less than unity, then it implies an opposite case (i.e. decline in CO_2 emission). If it is equal to unity, then it indicates that the contributor makes no effect on CO_2 emission.

Table 4 compares our results with those of some previous studies. In the table, our results are close to those of some previous studies. For example, the fourth column indicates that China's average D_{EMX} (0.992) is slightly less than unity. This result implies that China has a potential to reduce the amount of CO_2 emission by changing the structure of an energy mix (e.g. a fuel mix change among coal, oil, nuclear and renewable energies).

The result is consistent with those of Kim and Kim (2012), whose average was 0.9771 with the analysis period from 1990 to 2006. In this study, the period was updated from 2008 to 2015. Furthermore, our obtained average is close to the three measures of Li et al. (2017). Meanwhile, in this study, China's D_{EUEF} on average is larger than unity (1.003) on the sixth column of Table 4. The result is consistent with that of Kim and Kim (2012) and Li et al. (2017). This result indicates that even if China increases the energy-based *OE* change, the effort may not reduce the CO_2 emission.

Returning to Table 3, all contributors can be classified into three groups. The first group has two factors (D_{GEF} and D_{ESTC}), whose averages are significantly less than unity. Here, the "average" indicates the annual mean of each factor from 2009 to 2016. Among

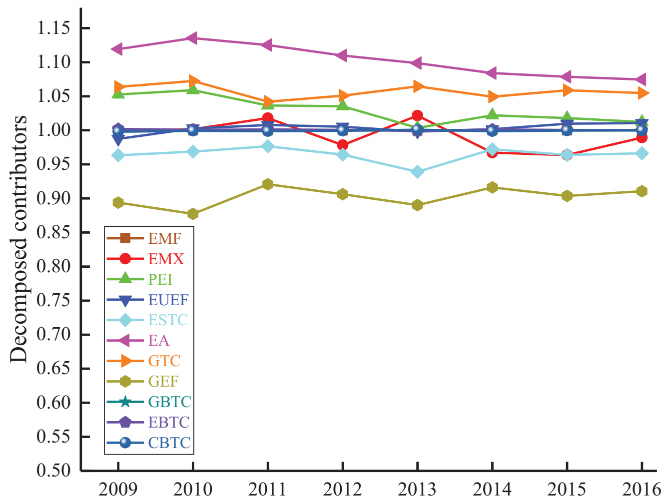

Fig. 3. Time trends of various decomposed contributors to CO_2emissions
(a) If the number is larger than unity, then it indicates that this factor results in an increase in CO_2 emission. In contrast, if it is less than unity, then it implies an opposite case (i.e. decline in CO_2 emission). In the case where it is equal to unity, it indicates that the contributor makes no effect on CO_2 emission.
(b) Since D_{ESTC} and D_{GEF} are less than unity, they can reduce the amount of CO_2 emission.

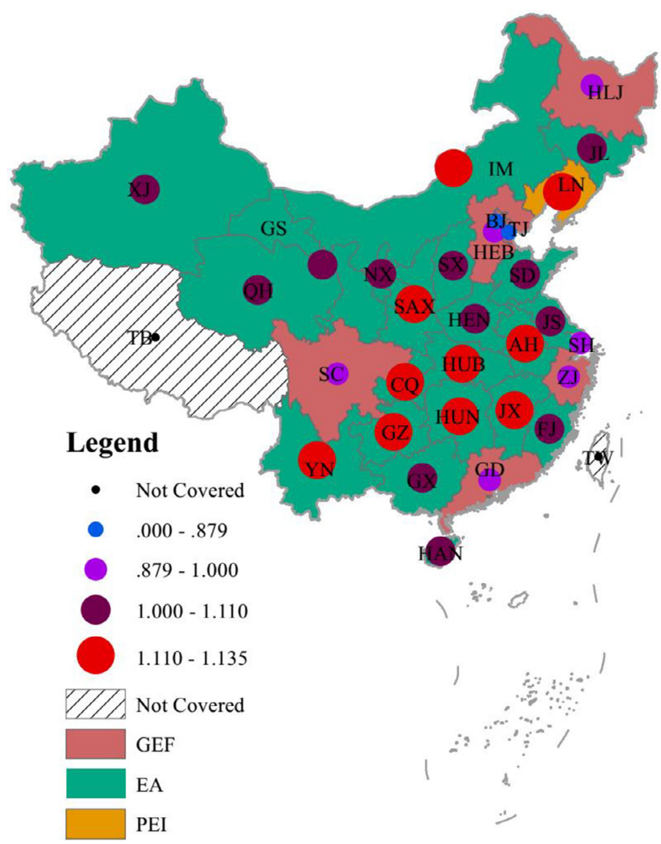

Fig. 4. Geographical distribution of the most important factor.
(a) *GEF* is the most important contributors for Beijing, Shanghai and Tianjin.

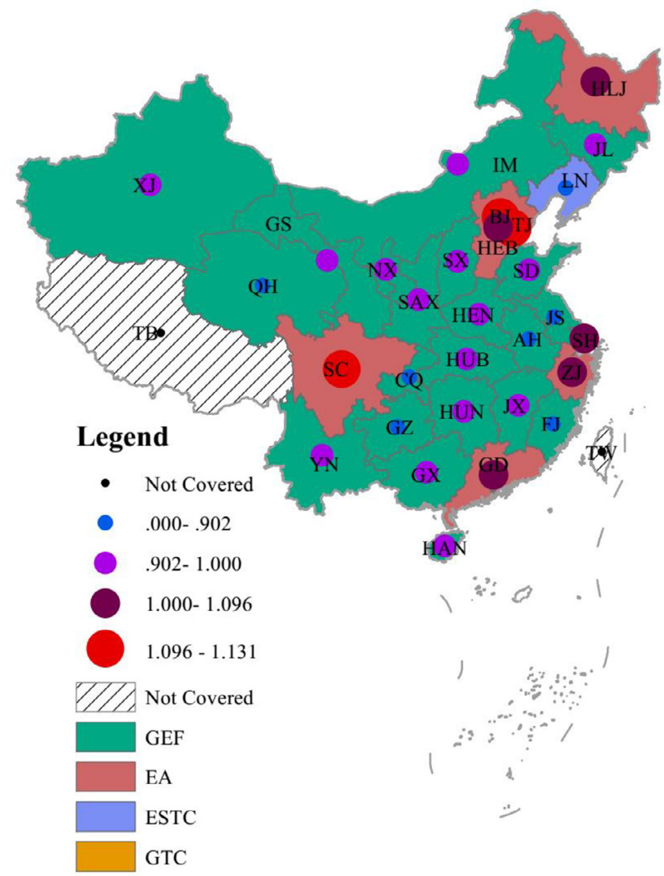

Fig. 5. Geographical distribution of the second most important factor.
(a) *GTC* is the second most important contributors for Beijing. *EA* is for Tianjin and Shanghai.

the two factors, D_{GEF} has the lowest values (0.902), implying that the operational efficiency change of the desirable output may result in the reduction of CO_2 emission. The numerical values of (D_{ESTC}) are less than unity (0.964). Thus, energy saving technology change causes mitigation of CO_2 emission. The second group contains three factors (D_{EA}, D_{GTC} and D_{PEI}), whose numerical values are considerably larger than unity. Among all contributors, D_{EA} has the largest numerical values (1.103), which means that economic activity brings about an increase in CO_2 emission. The numerical values of D_{GTC} are 1.057 and those of D_{PEI} are 1.030. Thus, the technology change of a desirable output and that of a potential energy intensity change contribute to increased CO_2 emission. Finally, the third group includes five contributors, whose numerical values are between 0.99 and 1.01. Thus, these factors play insignificant roles in determining changes in China's CO_2 emission.

Fig. 3 illustrates the time trend of various contributors. Among all factors, the three have comparatively large variation across annual periods. These factors are D_{PEI}, D_{EMX} and D_{EA}. These results are not surprising, since China's rapid economic growth results in significant variations in D_{EA} and D_{PEI}. In addition, during the examined periods, there are considerable changes in energy consumption mix, thus causing variations of D_{EMX}. In the comparison, there are insignificant changes in other contributors.

4.2. Important contributors and provincial variations

Table 3 indicates that there are significant differences in the distribution of indexes concerning potential contributors. Let us consider the number of provinces whose indexes are larger than, equal to, or less than unity. See the last row of Table 3.

All the contributors can be classified into the following four groups: (a) The first group contains two contributors, i.e. D_{ESTC} and D_{GEF}, whose indexes are less than unity in all provinces. The results imply that all provinces may mitigate the amount of CO_2 emission by improving both an operational efficiency for a desirable output (i.e. GDP) and an energy saving technology change. (b)

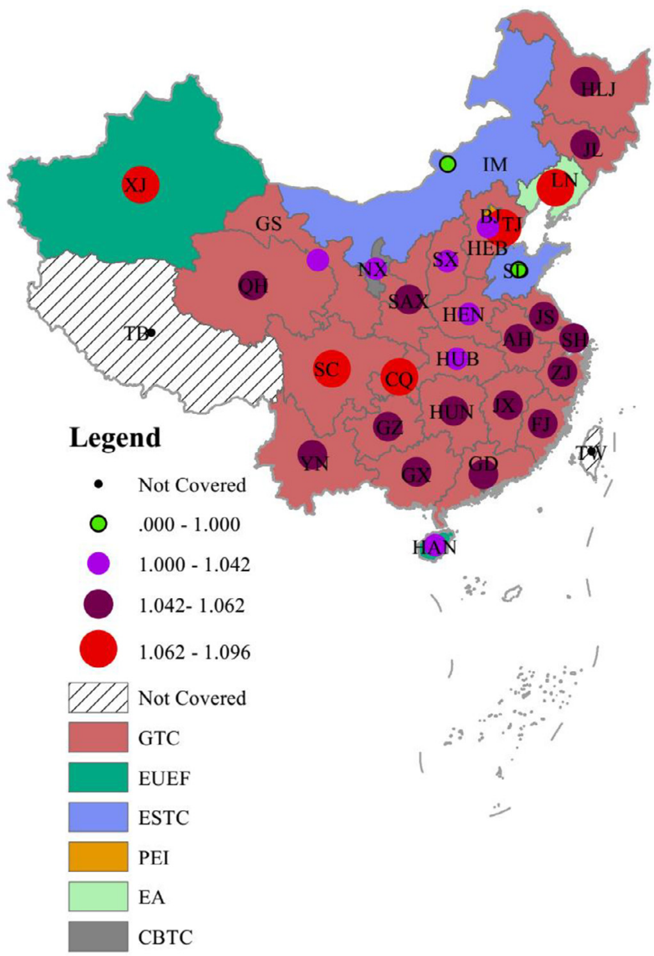

Fig. 6. Geographical distribution of the third most important factor
(a) *PEI* is the third most important contributors for Beijing. *GTC* is for Tianjin and Shanghai.

The second group includes one contributor (D_{GBTC}), whose indexes are close to unity in all provinces. Thus, a desirable output based technology change does not make any effect on changes in CO_2 emission. (c) The third group has two contributors (D_{EA} and D_{GTC}), whose indexes are greater than unity in almost all provinces. The results indicate that both economic activity (D_{EA}) and technology change (D_{GTC}) on GDP may increase the amount of CO_2 emission in all the provinces. (d) The fourth (last) group contains five contributors. They have mixed results across provinces in the manner that each contributor makes positive or negative effect on CO_2 emission. According to the results of D_{EMX}, an energy mix change decreased the amount of CO_2 emission in 20 provinces but it increased CO_2 emission in 9 provinces. The contributor shows an insignificant implication (i.e. index = 1) in one province (i.e. Gansu). There exist conflicting results in the effect of energy mix changes on CO_2 emission across provinces. Such mixed results are found in D_{EBTC}, D_{EUEF}, D_{CBTC} and D_{PEI}. Thus, provincial indexes (larger than, equal to or less than unity) on contributors provide policy makers with information for guiding provincial governments in guiding CO_2 reduction.

Figs. 4–6 also illustrate the geographical distribution of important decomposed factors. The three figures are for our illustrative descriptions. First, Fig. 4 depicts the *EA* is the most important contributor in 21 provinces in influencing the amount of CO_2 emission. These provinces exhibit the highest index ratio of EA among the eleven decomposition factors in terms of CO_2 reduction. This implies that the activity change on the economic system (e.g. a shift from manufacturing to service or high technology industry) may effectively reduce the amount of CO_2 emission. The economic activity change also includes the use of renewable energy sources in Chinese work places. The second important contributor of each province is listed in Fig. 5. The third important contributor of each province is listed in Fig. 6. The results indicate that economic activity is of crucial importance in increasing the amount of CO_2 emission. Meanwhile, *GEF* is the most important factor in eight provinces and it is the second important in 21 provinces. The results imply that a desirable output based operational efficiency change is important in reducing the amount of CO_2 emission. Moreover, *GTC* is the second important factor in one province and it is the third important one in 25 provinces. Thus, technology change of a desirable output is important in determining the amount of CO_2 emission at a provincial level.

5. Conclusion and future extensions

China has been the largest CO_2 emitter in the world. To prepare for the climate policy, it is a prerequisite for China to obtain detailed information on CO_2 emission sources. Under the policy direction, this study has proposed the three indexes regarding different technology changes that were incorporated into PDA and IDA. Those indexes measured technology changes across periods.

As an empirical application, the examined sources were used to decompose CO_2 emission across provinces in China from 2008 to 2015. The main findings were summarized as follows. First, several sources were important in increasing the amount of CO_2 emission in China. Among all decomposed factors, economic activity was the most important source of a large increase in China's CO_2 emission. In 21 provinces, the activity was the most important source in increasing the CO_2 emission. The technology change of a desirable output and potential energy intensity change followed the economic activity. The two factors played an important role in driving up the amount of CO_2 emission.

Second, two important sources decreased CO_2 emission. One of them was the operational efficiency change of desirable output. This source was the most important one for decreasing CO_2 emission in 8 provinces. In addition, the energy saving technology change was the second important source to reduce the CO_2 emission. The policy implication, obtained from the technology change, is that China should promote the energy saving technology progress to reduce CO_2 emission.

Finally, there were substantial provincial differences on the sources of CO_2 emission change. In terms of these potential contributors, there were conflicting results regarding their effect on CO_2 emission, since they decreased CO_2 emission in some provinces but increased CO_2 emission in the other provinces. They contained the energy mix change, the energy-based operational efficiency change, the potential energy intensity change, the energy based technology change and the combined technology change.

This study has drawbacks to be explored as future research tasks. First, we need to mathematically discuss on a linkage between decomposition and DEA formulation. Second, the proposed approach belongs to natural disposability because an efficiency frontier is identified by decreasing x_E (energy) and increasing g (GDP), so being not managerial disposability which finds an efficiency frontier by increasing energy and decreasing CO_2 emission. The proposed approach needs to incorporate the perspective of managerial disposability. Otherwise, we cannot perfectly identify the effect of CO_2 emission reduction. See Sueyoshi and Goto (2018) on the disposability concepts. Finally, we need to explore scale effects on the CO_2 emission reduction such as returns to scale and damages to scale (Sueyoshi & Goto, 2019). Those research issues will be the important future extensions of this study.

In conclusion, it is hoped that this research makes a contribution to Chinese environmental protection.

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