# UNIVERSITY<sup>OF</sup> BIRMINGHAM University of Birmingham Research at Birmingham

# A comparison of carbon dioxide (CO<sub>2</sub>) emission trends among provinces in China

Du, Kerui; Xie, Chunping; Ouyang, Xiaoling

DOI: 10.1016/j.rser.2017.01.102

License: Creative Commons: Attribution-NonCommercial-NoDerivs (CC BY-NC-ND)

Document Version Peer reviewed version

#### Citation for published version (Harvard):

Du, K, Xie, C & Ouyang, X 2017, 'A comparison of carbon dioxide (CO) emission trends among provinces in China', *Renewable and Sustainable Energy Reviews*, vol. 73, pp. 19-25. https://doi.org/10.1016/j.rser.2017.01.102

Link to publication on Research at Birmingham portal

Publisher Rights Statement: Checked for eligibility 23/10/2018

https://doi.org/10.1016/j.rser.2017.01.102

#### **General rights**

Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

•Users may freely distribute the URL that is used to identify this publication.

•Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.

•User may use extracts from the document in line with the concept of 'fair dealing' under the Copyright, Designs and Patents Act 1988 (?) •Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

#### Take down policy

While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact UBIRA@lists.bham.ac.uk providing details and we will remove access to the work immediately and investigate.

# A comparison of carbon dioxide (CO<sub>2</sub>) emission trends among provinces in China

Kerui Du<sup>a</sup>, Chunping Xie<sup>b\*</sup>, Xiaoling Ouyang<sup>c\*\*</sup>

<sup>a</sup> Center for Economic Research, Shandong University, Jinan 250100, China.

<sup>b</sup> Birmingham Centre for Energy Storage, School of Chemical Engineering,

University of Birmingham, Edgbaston, Birmingham B15 2TT, UK.

<sup>c</sup> Department of Economics, School of Economics, Faculty of Economics and

Management, East China Normal University, Shanghai 200062, China.

\* Corresponding author at: Birmingham Centre for Energy Storage, School of

Chemical Engineering, University of Birmingham, Edgbaston, Birmingham B15 2TT, UK.

E-mail address: <u>susulovedog@hotmail.com</u>

\*\* Corresponding author at: Department of economics, School of economics, Faculty

of economics and management, East China Normal University, Shanghai 200062, China. E-mail address: <u>xlouyang@jjx.ecnu.edu.cn</u>

## Abstract

As the world leader in CO<sub>2</sub> emissions, China is a key focus for climate change mitigation. In this paper, we conducted a cross-province comparison of CO<sub>2</sub> emission trends in China from 2006 to 2012. We determined effects of CO<sub>2</sub> emission factor (EMF), energy mix change (EMX), potential energy intensity change (PEI), industrial structure (STR), economic activity (EAT), technological change (BPC) and energy efficiency change (EC) as underlying forces of  $CO_2$  emission changes with production-based decomposition. Compared other to production-theory decomposition analyses (PDA), the method used in this paper can overcome the weakness of PDA on the measurement of structural changes and energy mix effect. The results provided strong evidence that EAT is the main driver behind rising emissions, while changes in PEI, EMX and EC have led to CO<sub>2</sub> emission reductions in most provinces/municipalities in China. In particular, we introduced the global benchmark technology to establish the relationship between CO2 emissions and energy use technology. The potential CO<sub>2</sub> reductions in China were further measured under the scenarios of contemporaneous technology and global technology. The principal empirical implication is that the promotion of energy conservation technology and reductions in inter-regional technological disparity would be effective in reducing CO<sub>2</sub> emissions in technically inefficient regions.

*Keywords:* Decomposition; Shephard distance function; Production-theory decomposition analysis; Data envelopment analysis.

# Highlights

- A combination of IDA and PDA is developed to investigate CO<sub>2</sub> emissions in China.
- $\blacktriangleright$  Economic activity is the main driver behind China's rising CO<sub>2</sub> emissions.
- $\succ$  The less developed regions show large potential reduction of CO<sub>2</sub> emissions.

#### 1 1. Introduction

As the world leader in CO<sub>2</sub> emissions from fossil fuel combustion, China has 2 3 attracted worldwide attention with its accelerating CO<sub>2</sub> emissions over the past three decades. Considering its critical role in global CO<sub>2</sub> emissions, China becomes a key 4 focus for effects in emission mitigations. In this context, a lot of efforts have been 5 made to identify and quantify the underlying driving forces that affect CO<sub>2</sub> emission 6 changes in China. In literature, factors that influence changes of China's CO<sub>2</sub> 7 emissions have been widely discussed in previous studies ([1]; [2]; [3]; [4]; [5]). 8 9 However, CO<sub>2</sub> emission trends among different provinces in China have been less systematically investigated ([6]). 10

11 It should be noted that significant diversity exists among eastern, central and 12 western areas in China ([7]). For example, indicators such as per capita GDP, carbon emission intensity and energy efficiency differ greatly across regions in China ([8]), 13 14 and the differences are most prominent between the developed regions in eastern area 15 and the less developed regions in western area of China. In order to control greenhouse gas emissions, the Chinese government established a set of carbon 16 emission reduction targets for different regions in the 11<sup>th</sup> and 12<sup>th</sup> Five-Year Plans 17 (FYP) for national economic and social development. However, how to reasonably 18 allocate regional CO<sub>2</sub> reduction targets based on the actual situations and reduction 19 potential of various regions is still worthy of discussion ([9]). Therefore, 20 21 understanding the key drivers behind China's growing CO<sub>2</sub> emissions and developing regional emission reduction policies in China have theoretical and practical values for 22

23 decision makers.

CO<sub>2</sub> emissions in China have attracted increasing attentions in light of China's 24 25 decisive role in the global carbon emission mitigation. Technically, CO<sub>2</sub> emission changes can be analyzed by attributing the changes in CO<sub>2</sub> emissions into several 26 27 pre-defined factors by adopting decomposition analysis ([10]). In literature, the structural decomposition analysis (SDA) and the index decomposition analysis (IDA) 28 are the most commonly used decomposition techniques ([11]; [12]; [13]; [14]; [15]; 29 [16]; [17]; [18]; [19]; [20])<sup>1</sup>. In terms of data and methodologies, the SDA uses the 30 31 input-output framework and data, while the IDA uses only sector level data to decompose changes in indicators. Therefore, compared to SDA, the method of IDA is 32 more flexible, easy to use, and has relatively lower data requirements for empirical 33 34 models. As a result, IDA has been widely used to decompose CO<sub>2</sub> emissions in different countries and various time periods ([21]; [22]; [23]; [24]; [25]). Under the 35 framework of IDA, factors such as the carbon intensity of energy use, energy 36 37 intensity, structural change and economic activity were identified as the major factors affecting CO<sub>2</sub> emissions, and the decline in energy intensity was identified as the 38 driving force for the considerable decrease in China's CO<sub>2</sub> emissions ([26]; [27]; 39 [28]). However, IDA could not provide a quantitive analysis for the impacts of 40 technological change effect, substitutions between energy and other inputs (i.e., 41 capital and labor), and the effect of technical efficiency change on sectoral intensity 42 43 change, because it simply regards the energy/emission intensity change as the effect

<sup>&</sup>lt;sup>1</sup> A useful summary of the various methods of IDA can be found in Ang and Zhang (2000). In addition, Ang et al. (2010) also provides a systematic review on the existing IDA-based energy efficiency accounting systems. Additionally, Hoekstra and Van den Bergh (2003) provided a comparison between SDA and IDA.

of production technology ([29]; [30]). Therefore, the method of IDA is difficult to
provide reasonable explanations on the mechanism of sectoral energy/emission
intensity changes based on economic theories ([31]; [32] ).

More recently, in order to analyze the impact of production technology, 47 decomposition analysis was improved and conducted within the production theory 48 framework. [33] proposed production-theoretical decomposition analysis (PDA) 49 based on Shephard output distance functions, which can be computed using data 50 envelopment analysis (DEA) techniques. Empirical analyses of CO<sub>2</sub> emission changes 51 52 based on the method of PDA include [34]; [35]; [36]; [37]; [38], etc. The proposed methodologies can assess the effects of "technological change" and "technical 53 efficiency change". The former measures the effect of best practice technology, and 54 55 the latter measures the effect of changes in production efficiency. PDA provides detailed information about the influence of production technologies, which could be 56 used to evaluate the degree of "energy efficiency paradox" ([36]). However, its 57 measurement on energy mix effect and the industrial structure effect, which are 58 regarded as important factors of emission change, is possibly inconsistent with reality. 59 For example, when industrial structure transforms from energy intensive industries to 60 less energy intensive industries, it is expected that the industrial structure change 61 would reduce an economy's overall energy intensity. However, results from PDA 62 indicates that such an industrial structure transformation has a negative effect on 63 energy intensity reduction ([39]). PDA has a similar problem for the measurement of 64 energy mix effect. When energy consumption structure has been improved, it is 65

expected that such improvement would promote energy intensity reduction or at least
would not has a negative impact on energy intensity reduction. However, results from
PDA demonstrate the inconsistency.

69 The main reason for the above problems of PDA is that the structural components 70 in output distance function are symmetrical. In other words, different properties of industries and energies cannot be reflected in the PDA model. Specifically, the lower 71 energy consumption feature of the tertiary industry sector compared to the second 72 73 industry sector is not reflected in the distance function. Therefore, the PDA model 74 cannot provide information on the real effect of industrial structure transformation. In the PDA model, the output proportions of three sectors (primary, secondary, and 75 76 tertiary) are all included in the output distance functions. The industrial structure was 77 assumed to change as follows: the share of primary industry remained constant, the share of secondary industry declined, while the share of tertiary increased 78 correspondingly. On one hand, the declined proportion of secondary industry in 79 output would make the value of output distance function smaller; on the other hand, 80 the increased proportion of tertiary industry in output would make the value of output 81 82 distance function bigger. If the effect of the latter were bigger than the former, the industrial structure transformation would have a negative impact on energy intensity 83 reduction, which is contrary to fact. 84

Based on the above analysis, we combined the advantages of IDA and PDA to examine the influencing factors of China's  $CO_2$  emission changes and compare  $CO_2$ emissions among provinces in China. Specifically, we establish the decomposition

88	model based on the Shephard energy distance function to disaggregate the provincial
89	level changes of $CO_2$ emissions in China during 2006-2012, and then introduce the
90	global benchmark technology to establish the relationship between CO <sub>2</sub> emissions and
91	energy use technologies. The central idea of the combination is introducing Shephard
92	energy distance functions which captures the impacts from production technology in
93	the expression of the aggregate CO <sub>2</sub> emissions, and then conducting IDA (e.g., LMDI)
94	for this equation to identify the influencing factors driving change in the aggregate
95	CO <sub>2</sub> emissions. In this sense, PDA and IDA are embodied together to provide the
96	mechanism of CO <sub>2</sub> emission change. The contributions of this paper lie in the
97	following aspects: First, the decomposition method used in this paper can overcome
98	the weakness of PDA on the measurement of structural changes, and thus can produce
99	more reasonable results; Second, the proposed approach has been applied in the field
100	of investigating CO <sub>2</sub> emission trends among provinces in China; Third, from the
101	methodological perspective, this paper specifies a different production technology
102	setting which could be extended to other application areas.

The remainder of this article is organized as follows: Section 2 describes
methodology and data; Section 3 presents and discusses the empirical results; Section
4 is conclusions and implications.

106

# 2. Methodology and Data

# 107 *2.1 The decomposition model*

108 The CO<sub>2</sub> emissions of country n = 1,...,N can be expressed as:

 $C_{\rm t}^n = \sum_{ii} C_{\rm ij,t}^n$ 

$$=\sum_{ij} \frac{C_{ij,t}^{n}}{E_{ij,t}^{n}} \frac{E_{ij,t}^{n}}{E_{i,t}^{n}} \frac{E_{i,t}^{n}/Y_{i,t}^{n}}{D_{i}^{g}(E_{i,t}^{n},Y_{i,t}^{n},C_{i,t}^{n})} \frac{Y_{i,t}^{n}}{Y_{t}^{n}} Y_{t}^{n} \frac{D_{i}^{g}(E_{i,t}^{n},Y_{i,t}^{n},C_{i,t}^{n})}{D_{i,t}^{c}(E_{i,t}^{n},Y_{i,t}^{n},C_{i,t}^{n})} D_{i,t}^{c}(E_{i,t}^{n},Y_{i,t}^{n},C_{i,t}^{n})$$
(1)

110 where  $E_{ij,t}^n$  denotes the consumption of the type-*j* energy in the sub-sector *i* of 111 country *n* at the period *t*, and  $C_{ij,t}^n$  represents the CO<sub>2</sub> emissions from  $E_{ij,t}^n$ ;  $D_i^g(\cdot)$ 112 and  $D_i^c(\cdot)$  are the Shepard energy distance functions defined on the 113 contemporaneous benchmark technology and the global benchmark technology, 114 respectively. Specifically, the contemporaneous production technology for the 115 industrial sub-sector i = 1,...,I at time period t = 1,...,T can be expressed as:

116 
$$T_{i,t}^{c} = \left\{ (E_{i,t}, Y_{i,t}, C_{i,t}) : E_{i,t} \text{ can produce}(Y_{i,t}, C_{i,t}) \right\}$$
(2)

117 The global benchmark technology for the industrial sub-sector i is defined as 118 ([40] and [41]):

119 
$$T_i^{g} = \{T_{i,1}^{c} \cup T_{i,2}^{c} \cup \dots \cup T_{i,T}^{c}\}$$
(3)

According to [42], the Shepard energy distance function relative to the contemporaneous benchmark technology and the global benchmark technology can be described as Eq. (4) and Eq. (5), respectively.

123 
$$D_{i,t}^{c}(E_{i,t}, Y_{i,t}, C_{i,t}) = \sup\{\theta : (E_{i,t} / \theta, Y_{i,t}, C_{i,t}) \in T_{i,t}^{c}\}$$
(4)

124 
$$D_i^g(E_{i,t}, Y_{i,t}, C_{i,t}) = \sup\{\theta : (E_{i,t} / \theta, Y_{i,t}, C_{i,t}) \in T_i^g\}$$
(5)

Using DEA-type linear programming technique, the Shepard energy distancefunction can be estimated through the following optimization problems.

$$\begin{bmatrix} D_{i,i}^{c}(E_{i,i}, Y_{i,i}, C_{i,i}) \end{bmatrix}^{1} = \min \theta$$

$$st. \quad \sum_{n=1}^{N} \lambda_{n} E_{i,i}^{n} \leq \theta E_{i,i}$$

$$\sum_{n=1}^{N} \lambda_{n} Y_{i,i}^{n} \geq \theta Y_{i,i}$$

$$\sum_{n=1}^{N} \lambda_{n} C_{i,i}^{n} = \theta C_{i,i}$$

$$\lambda_{n} \geq 0, n = 1, ..., N, t = 1, ..., T$$

$$\begin{bmatrix} D_{i}^{g}(E_{i,i}, Y_{i,i}, C_{i,i}) \end{bmatrix}^{1} = \min \theta$$

$$st. \quad \sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} E_{i,t}^{n} \leq \theta E_{i,t}$$

$$\sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} Y_{i,t}^{n} \geq \theta Y_{i,t}$$

$$\sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} Y_{i,t}^{n} = \theta C_{i,t}$$

$$\sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} Y_{i,t}^{n} = \theta C_{i,t}$$

$$\sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} Y_{i,t}^{n} = \theta C_{i,t}$$

$$\sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} Z_{i,t}^{n} = \theta C_{i,t}$$

$$\sum_{t=1}^{N} \sum_{n=1}^{N} \lambda_{n,t} C_{i,t} = \partial C_{i,t}$$
  
 $\lambda_{n,t} \ge 0, n = 1, ..., N, t = 1, ..., T$ 

# 129 Using the LMDI method, the change in $CO_2$ emissions between time period *t* and

130 time period 
$$\tau$$
 can be decomposed as:

131 
$$C_{\tau}^{n} / C_{t}^{n} = D_{EMF} \times D_{EMX} \times D_{PEI} \times D_{STR} \times D_{EAT} \times D_{BPC} \times D_{EC}$$
(8)

132 where 
$$D_{EMF} = \exp\left\{\frac{L(C_{ij,\tau}^{n}, C_{ij,t}^{n})}{L(C_{\tau}^{n}, C_{t}^{n})}\ln\frac{C_{ij,\tau}^{n}/E_{ij,\tau}^{n}}{C_{ij,t}^{n}/E_{ij,t}^{n}}\right\};$$

133 
$$D_{EMX} = \exp\left\{\frac{L(C_{ij,\tau}^{n}, C_{ij,t}^{n})}{L(C_{\tau}^{n}, C_{t}^{n})}\ln\frac{E_{ij,\tau}^{n} / E_{i,\tau}^{n}}{E_{ij,t}^{n} / E_{i,t}^{n}}\right\};$$

134 
$$D_{PEI} = \exp\left\{\frac{L(C_{ij,\tau}^{n}, C_{ij,t}^{n})}{L(C_{\tau}^{n}, C_{t}^{n})}\ln\frac{[E_{i,\tau}^{n} / D_{i,\tau}^{c}(E_{i,\tau}^{n}, Y_{i,\tau}^{n}, C_{i,\tau}^{n})] / Y_{i,\tau}^{n}}{[E_{i,t}^{n} / D_{i,t}^{c}(E_{i,\tau}^{n}, Y_{i,\tau}^{n}, C_{i,t}^{n})] / Y_{i,t}^{n}}\right\};$$

135 
$$D_{STR} = \exp\left\{\frac{L(C_{ij,\tau}^{n}, C_{ij,t}^{n})}{L(C_{\tau}^{n}, C_{t}^{n})}\ln\frac{Y_{i,\tau}^{n}/Y_{\tau}^{n}}{Y_{i,t}^{n}/Y_{t}^{n}}\right\};$$

136 
$$D_{EAT} = \exp\left\{\frac{L(C_{ij,\tau}^{n}, C_{ij,t}^{n})}{L(C_{\tau}^{n}, C_{t}^{n})}\ln\frac{Y_{\tau}^{n}}{Y_{t}^{n}}\right\};$$

137 
$$D_{BPC} = \exp\left\{\frac{L(C_{ij,\tau}^{n}, C_{ij,t}^{n})}{L(C_{\tau}^{n}, C_{t}^{n})}\ln\frac{D_{i}^{g}(E_{i,\tau}^{n}, Y_{i,\tau}^{n}, C_{i,\tau}^{n})/D_{i}^{c}(E_{i,\tau}^{n}, Y_{i,\tau}^{n}, C_{i,\tau}^{n})}{D_{i}^{g}(E_{i,t}^{n}, Y_{i,\tau}^{n}, C_{i,t}^{n})/D_{i}^{c}(E_{i,t}^{n}, Y_{i,\tau}^{n}, C_{i,t}^{n})}\right\};$$

138 
$$D_{EC} = \exp\left\{\frac{L(C_{ij,\tau}^{n}, C_{ij,t}^{n})}{L(C_{\tau}^{n}, C_{t}^{n})}\ln\frac{D_{i,\tau}^{c}(E_{i,\tau}^{n}, Y_{i,\tau}^{n}, C_{i,\tau}^{n})}{D_{i,t}^{c}(E_{i,\tau}^{n}, Y_{i,\tau}^{n}, C_{i,\tau}^{n})}\right\}.$$

139  $L(\cdot, \cdot)$  is a weighting scheme called logarithmic mean weight which is expressed 140 as follows:

141 
$$L(x, y) = \begin{cases} (x - y)/(\ln x - \ln y), & x \neq y \\ x, & x = y \end{cases}$$
(9)

The decomposition model presented above is a modification of [36]. Unlike [36], we introduce the global benchmark technology to establish the relationship between CO<sub>2</sub> emissions and energy use technology. Our formulation avoids the introduction of the cross-period distance functions so that it can be free from the infeasibility issue.

Eq. (8) shows that the change in CO<sub>2</sub> emissions over times can be decomposed 146 into seven components. The first component  $D_{EMF}$  is the CO<sub>2</sub> emission factor effect. 147 148 The second component  $D_{EMX}$  refers to the effect of energy mix change. The third component  $D_{PEI}$  captures the energy intensity change under the scenario without 149 energy inefficiency relative to the global technology. Following [42] and [36], we 150 151 term this component as the potential energy intensity change. The fourth component  $D_{STR}$  is industrial structure effect, accounting for the impact from output composition 152 change. The fifth component  $D_{EAT}$  refers to the impact from output scale change 153 which is regarded 154 usually as economic activity effect.  $D_i^c(E_i^n, Y_i^n, C_i^n) / D_i^g(E_i^n, Y_i^n, C_i^n)$  is a best practice gap between the global technology 155  $(T_i^g)$  and the contemporaneous technology  $(T_{i,t}^c)$  measured along energy direction. 156  $\frac{D_i^c(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)/D_i^g(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)}{D_i^c(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)/D_i^g(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)}$  indicates the contemporaneous technology gets 157

158 closer to (shifts further away from) the global benchmark technology. In other words,

the value of this ratio means technological change. Thus, the sixth component  $D_{BPC}$ which is the weighting sum of the reciprocal of  $\frac{D_i^c(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)/D_i^s(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)}{D_i^c(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)/D_i^s(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)}$ describes the impact from technological change in energy use.  $1/D_{i,\tau}^c(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)$  is the ratio of the minimum energy input (under the contemporaneous technology) to the real energy input, which is usually defined as energy use efficiency (denoted as EC). The last component  $D_{EC}$  is the weighting sum of the reciprocal of EC, thereby indicating the effect of energy efficiency change.

In summary, the change in  $CO_2$  emissions over time can be attributed into seven indexes: emission factor change, energy mix change, potential energy intensity change, output structure change, economic activity effect, the effect of energy technological change and the effect of energy efficiency change. For any one of them, it will contribute to the increase of (decline in)  $CO_2$  emissions if its value is greater (less) than one.

172 *2.2 Data* 

A panel data set including China's 30 provinces/municipalities during the period of 2006-2012 is collected for the empirical study<sup>1</sup>. The whole economy for each province is divided into six subsectors: "agriculture", "industry", "construction", "transport, storage and post", "wholesale, retail, hotels and catering services", and "financial intermediation, real estate and other tertiary industries". The output variable is represented by value-added of the economic subsector. Data on value-added are

<sup>&</sup>lt;sup>1</sup> Due to data unavailability, Tibet is not included in this study.

collected from China Premium Database<sup>1</sup>. Data on different types of energy are 179 obtained from China Energy Statistical Yearbook (CESY)<sup>2</sup>. Data on energy-related 180 CO<sub>2</sub> emissions are estimated by the method described in [43]. In addition, our 181 calculation of energy-related CO<sub>2</sub> emissions also includes the indirect emissions from 182 183 heat and power consumption of each subsector. Electricity emission factor is obtained by dividing energy-related CO<sub>2</sub> emissions from electricity generation by the power 184 output. Heat emission factor is obtained by dividing energy-related CO<sub>2</sub> emissions 185 from heat generation by the heat output. Data in value terms are measured at the 2005 186 real 10<sup>8</sup> Chinese Yuan (CNY). 187

- 188 **3. Results and discussion**
- 189 *3.1 Empirical results of decomposition*

Table 1 reports changes in China's  $CO_2$  emissions and contributions to  $CO_2$ emission changes from effects of  $CO_2$  emission factor (EMF), energy mix change (EMX), potential energy intensity change (PEI), industrial structure (STR), economic activity (EAT), technological change (BPC) and energy efficiency change (EC) in different provinces in China during 2006-2012.

As shown in column (1), we can see that  $CO_2$  emissions in all provinces/municipalities in China increased during 2006-2012 except for Beijing. As a political and economic center of China, Beijing is one of the world's most polluted cities. Beijing made great efforts to reduce energy-related  $CO_2$  emissions. For

<sup>&</sup>lt;sup>1</sup> Available at: http://www.ceicdata.com.

<sup>&</sup>lt;sup>2</sup> Available at: http://tongji.cnki.net/overseas/engnavi/NaviDefault.aspx

example, Beijing raised emission standards and promoted the use of electric 199 automobiles during the preparation for the Olympic Games in 2008. In 2011, Beijing 200 201 was identified as one of the pilots of the first batch of national carbon emission trading, and its carbon emission trading scheme was launched in the late 2012. 202 Additionally, the local government used a series of measures to reduce CO<sub>2</sub> emissions: 203 first, shutting down or moving highly polluted factories to neighboring provinces (e.g., 204 Hebei, Tianjin); second, promoting the emission reduction policies such as "using 205 electricity instead of coal" and "burning natural gas instead of coal"; third, 206 207 encouraging the transfer of energy saving technologies in energy intensive industries, 208 etc.

The values of CO<sub>2</sub> emission factor effect (D<sub>EMF</sub>) in column (2) are almost smaller
than 1 except for those in provinces of Gansu, Hainan, Inner Mongolia and Xinjiang.
However, it can be seen that D<sub>EMF</sub> has a trifling effect on emission changes.

The effect of energy mix change ( $D_{EMX}$ ) in column (3) has led to the decline of CO<sub>2</sub> emissions in 13 provinces in China. However, the energy mix change for 17 provinces contributes to their increase in CO<sub>2</sub> emissions. The findings are a little different from the results of [44] which shows that the effect of energy mix change play a negative role in CO<sub>2</sub> emissions in most of China's provinces.

The effect of potential energy intensity ( $D_{PEI}$ ) in column (4) measures the impact of energy intensity change on CO<sub>2</sub> emissions under the scenario without energy inefficiency relative to the global technology. The values of  $D_{PEI}$  in this paper are almost less than one. The results are basically consistent with the findings of [38], indicating that the change of energy intensity will contribute to the decline of  $CO_2$ emissions when inefficiency of the energy-usage technology relative to the global technology has been improved as much as possible. In particular, provinces such as Hunan, Jilin and Anhui have experienced larger impacts of  $D_{PEI}$  compared to other provinces. In contrast, provinces such as Hainan and Xinjiang have experienced increased potential energy intensity that leads to increasing  $CO_2$  emissions.

The values of industrial structure effect  $(D_{STR})$  in column (5) were smaller than 227 228 one for most provinces/municipalities including Beijing, Gansu, Guangdong, Guizhou, 229 Hainan, Hebei, Heilongjiang, Jiangsu, Ningxia, Shandong, Shanxi, Shaanxi, Shanghai, Tianjin, Xinjiang, Yunnan and Zhejiang. In which, 9 provinces/municipalities are 230 economically developed regions located in the eastern coast of China; 6 provinces are 231 232 the less economically developed regions located in the western China; and 2 provinces are from central China. It indicated that the industrial structure change has 233 changed such that CO<sub>2</sub> emissions have decreased in these provinces. However, the 234 values of D<sub>STR</sub> were larger than one for provinces such as Anhui, Guangxi, Henan, 235 Hubei, Hunan, Jilin, Jiangxi, Liaoning, Inner Mongolia, Qinghai, Sichuan and so on. 236 It can be seen that most of the listed provinces are less economically developed 237 regions located in the central and western China. In addition, the economic transfer 238 (the transfer of energy-intensive industries) between East and West China may 239 accelerate the transfer of pollution between the two regions. 240

As shown in column (6), the values of economic activity change ( $D_{EAT}$ ) in all provinces in China are greater than one in this paper. Results indicated that  $D_{EAT}$  has

played the most dominant role in increasing CO<sub>2</sub> emissions in all provinces in China. 243 The changes for provinces/municipalities such as Anhui, Fujian, Guangxi, Guizhou, 244 245 Hubei, Hunan, Jiangxi, Liaoning, Inner Mongolia, Qinghai, Shaanxi, Sichuan, Tianjin and Chongqing are greater than the geometric mean (2.0343), indicating that these 246 provinces have experienced higher increases in CO<sub>2</sub> emissions by economic activity 247 expansion. It can be seen that most of listed provinces are located in the central and 248 western China. These findings are in line with most previous studies, e.g., [35]; [38]; 249 [44]. 250

251 Columns (7) in Table 1 described the effect of technological change ( $D_{BPC}$ ) on CO<sub>2</sub> emission changes. The indicator reflected the capabilities for innovating new and 252 253 advanced technologies. In general, the impacts of technological improvement on CO<sub>2</sub> 254 emission reductions were insignificant, implying that technological change has a weaker influence on the reduction of CO<sub>2</sub> emissions compared to other indicators. 255 However, for China's wealthy coastal provinces or rich municipalities including 256 257 Beijing, Guangdong, Shanghai and Tianjin, the contributions of D<sub>BPC</sub> to the abatement of CO<sub>2</sub> emissions were significant. As the most developed metropolises in China, the 258 top research institutions were concentrated in Beijing and Shanghai. With the 259 advantage of location close to Beijing, Tianjin has recorded China's highest per-capita 260 GDP since 2013. Additionally, Tianjin was transforming into a hub city for research 261 and development ([45]). As the richest province which borders on Hong Kong, 262 263 Guangdong has experienced rapid technological progress in recent years ([35]).

264 Columns (8) in Table 1 described the effect of energy efficiency change  $(D_{EC})$  on

CO<sub>2</sub> emission changes. Results indicated that most provinces decreased CO<sub>2</sub> emissions due to the improved energy efficiencies. Meanwhile  $D_{EC}$  in provinces/municipalities such as Hebei, Hubei, Qinghai, Shaanxi, Shanghai, Sichuan, Tianjin and Chongqing slightly affected growing CO<sub>2</sub> emissions.

269

# Table 1 here

- 270
- 271 *3.2 The potential of CO*<sub>2</sub> *emission reductions*

This subsection further measures the potential  $CO_2$  reduction (PCR) in China. Under the contemporaneous technology scenario, the PCR for region *n* at the time period *t* can be calculated as:

$$PCR_{t,c}^{n} = C_{t}^{n} - C_{t,bpc}^{n}$$

$$C_{t,bpc}^{n} = \sum_{ij} \frac{C_{ij,t}^{n}}{E_{ij,t}^{n}} \frac{E_{ij,t}^{n}}{E_{i,t}^{n}} \frac{E_{i,t}^{n} / D_{i}^{c}(E_{i,t}^{n}, Y_{i,t}^{n}, C_{i,t}^{n})}{Y_{i,t}^{n}} Y_{i,t}^{n}$$
(12)

We obtain the potential of nationwide  $CO_2$  emission reduction by summing up the potentials of  $CO_2$  emission reduction in different regions in China. Results of the potential  $CO_2$  reduction under the contemporaneous technology scenario are shown in Table 2.

280

## Table 2 here

281

As shown in Table 2, the nationwide potential  $CO_2$  reductions (PCR) under the contemporaneous technology scenario showed an increasing trend overall. Specifically, the nationwide PCR increased from 15.70 billion tons in 2006 to 20.81 billion tons in 2012 with an average growth rate of 4.93 per annum. The smaller the numerical value of PCR is, the closer the technological gap between each province/municipality's actual technology and the contemporaneous technology is. In other words, PCR indicates the successfulness of the adoption of the contemporaneous technology of each province/municipality. Therefore, results showed that China's capabilities to improve production technical efficiency through introducing international advanced technologies and international cooperation on technological innovation have been weakened over the years.

The PCRs of provinces/municipalities including Beijing, Hainan, Shanghai, 293 294 Tianjin, Zhejiang and so on were relatively lower. This means that the diffusion of production technologies of these provinces/municipalities were more efficient. Most 295 of the above provinces were economically developed regions located in East China. 296 297 Among which, the PCR of Hainan was the lowest, the average value of which was 0.0973 billion tons during 2006-2012. Particularly, the PCR of Beijing dropped 298 significantly from 0.2442 billion tons in 2010 to 0.0973 billion tons in 2011, 299 equivalent to a decrease of 60.16%. Moreover, Beijing, Guangdong and Shanghai 300 have experienced lower potential for mitigation over time. The results are consistent 301 302 with the analysis in section 3.1.

303 On the contrary, the PCRs of provinces such as Hebei, Henan, Liaoning, 304 Shandong and Shanxi were relatively higher. This means that the diffusions of 305 production technologies of these provinces/municipalities were less efficient. In 306 particular, the PCR of Hebei was the highest among provinces, the average value of 307 which was 2.0082 billion tons during 2006-2012, accounting for 40.69% of the

15

nationwide average value of PCR. In preparation for the 2008 Olympics, Beijing
moved some highly polluted and high energy-consuming industries out of the city to
Hebei province to control industrial pollution. With the integration of
Beijing-Tianjin-Hebei, more energy intensive industries have been relocated in Hebei
province. The simply relocation of these industries without technological upgrades
might be the possible reason for the high PCR of Hebei.

Similarly, the PCR for region n at the time period t under the global technology scenario can be calculated as:

316  

$$C_{t,bpg}^{n} = \sum_{ij} \frac{C_{ij,t}^{n}}{E_{ij,t}^{n}} \frac{E_{ij,t}^{n}}{E_{i,t}^{n}} \frac{E_{i,t}^{n} / D_{i}^{g}(E_{i,t}^{n}, Y_{i,t}^{n}, C_{i,t}^{n})}{Y_{i,t}^{n}} Y_{i,t}^{n}$$
(13)

 $C^n$ 

 $C^n$ 

317 Results of the potential CO<sub>2</sub> reduction under the global technology scenario are 318 shown in Table 3. Under the global technology scenario, PCR indicated the successfulness of the adoption of the global technology, which also reflected the 319 degree of international cooperation on technological innovation and development. 320 321 Results indicated that the nationwide potential CO<sub>2</sub> reduction (PCR) under the global technology scenario also showed an increasing trend overall. These can be interpreted 322 to mean that the gaps between China's actual technology and the global technology 323 have become larger over the years. In other words, China's capabilities to improve 324 production technological efficiency through introducing international advanced 325 technologies or international cooperation on technological innovation and 326 development have been weakened in recent years, and thus resulted in the production 327 technological efficiency of China trailed far behind the world. Although China has 328

become a global manufacturing center, most products made in China have low added 329 value. According to China statistical yearbooks, the dominant technological intensity 330 331 level of the Chinese manufacturing industry was low-tech (more than 40%). In the current state of the global supply chain, China's manufacturing industry mainly plays 332 333 the role of "manufacturing, processing and assembly". In addition, the development of the secondary industry was relatively extensive during the rapid urbanization process, 334 and the introduction of international advanced technology was relatively limited. 335 336 Therefore, upgrading manufacturing technology levels would be a big challenge faced 337 by China in a new phase of economic development.

Comparatively, the numerical values of PCR were larger under the global 338 technology scenario than those under the contemporaneous technology scenario. It 339 340 indicated that the technological diffusion under the global technology scenario among provinces in China would be slower than that under the contemporaneous technology. 341 This means that the abilities of provinces/municipalities in China to adopting global 342 technologies related to energy usage were even weaker. Specially, provinces such as 343 Hainan, Beijing, Gansu, Ningxia, Qinghai, Tianjin, Shanghai and so on have lower 344 potentials for emission mitigation than provinces including Hebei, Henan, Hubei, 345 Liaoning, Shandong, Shanxi and Sichuan. On one hand, these can be interpreted to 346 mean that provinces/municipalities such as Hainan, Beijing, Gansu, Ningxia, Qinghai, 347 Tianjin, Shanghai and so on have made efforts to adopt the relatively latest production 348 349 technologies through international cooperation. On the other hand, these can also be interpreted to mean that the spread of energy conservation technologies and 350

351	reductions in	n inter-regional	technological	disparity	would	be	effective	in	reducing
352	carbon emiss	sions in technica	lly inefficient 1	regions.					

353

## Table 3 here

354

# **4. Conclusions and implications**

As the public concerns about environmental pollution increase and the global 356 concern about the increasing CO<sub>2</sub> emissions from China, how to control and mitigate 357 CO<sub>2</sub> emissions have become the priority of the Chinese government at the stage of 358 359 "new normal" economic development. Although the government has set reduction targets of CO<sub>2</sub> emissions for different regions in China, the reasonable allocation of 360 regional CO<sub>2</sub> reduction targets based on the actual situations and reduction potentials 361 362 as well as the differentiated reduction strategies among regions still need further research. 363

With a production-based decomposition approcah ([36]), this study identified the 364 365 emission trends among different provinces/municipalities in China, discussed the 366 impacts of the driving forces behind CO<sub>2</sub> emissions, and evaluated the mitigation potential of each province/municipality under the scenarios of contemporaneous 367 technology and global technology. Specifically, this paper introduced the global 368 benchmark technology to establish the relationship between CO2 emissions and 369 energy use technology. Additionally, we combined the advantages of IDA and PDA to 370 371 examine the impacts of energy mix effect and the industrial structure effect on China's CO<sub>2</sub> emission changes, which made up for the defects of PDA that may result in 372

373 unreasonable results in the measurement of the above two kinds of effects.

The changes of CO<sub>2</sub> emissions for China's 30 provinces/municipalities were 374 375 decomposed into seven components for the time period 2006-2012. The decomposition results showed that CO<sub>2</sub> emissions in all provinces/municipalities in 376 377 China increased during 2006-2012 except for Beijing. The results provided strong evidence that the economic activity effect is the main driver behind rising emissions, 378 which is consistent with the conclusions of the existing literature, while changes in 379 380 potential energy intensity, energy mix and energy efficiency change have led to CO<sub>2</sub> 381 emission reductions in most provinces/municipalities in China. In general, the impacts of technological improvement on CO<sub>2</sub> emission reductions were trifling. However, for 382 provinces/municipalities including Beijing, Guangdong, Shanghai and Tianjin, the 383 384 contributions of technological change to the abatement of CO<sub>2</sub> emissions were significant. These can be interpreted to mean that the above provinces/municipalities 385 showed stronger capabilities for innovating new and advanced energy saving 386 387 technologies.

Because of the increase in the service sector and a decrease in the secondary sector, industrial structure changes have reduced  $CO_2$  emissions in many economically developed regions located in the eastern coast of China. However, the growing proportion of secondary industry due to the economic transfer between East and West China, the changes of industrial structure have resulted in the increase in CO<sub>2</sub> emissions in many less economically developed regions located in western CO<sub>2</sub> emissions in many less economically developed regions located in western China.

Based on the analysis of the potential of  $CO_2$  emission reductions (PCR), we 395 determined that China have experienced higher potential for mitigation over time. 396 397 Additionally, the numerical values of PCR were larger under the global technology scenario compared to those under the contemporaneous technology scenario. 398 399 However, the PCRs of economically developed regions located in East China were relatively lower than the less economically developed regions located in central and 400 western China. This means that the diffusions of production technologies of 401 economically developed regions were more efficient. Results indicated that research 402 403 and development investment in production technology as well as the spread of advanced technologies through international cooperation can effectively reduce the 404 405 potential for  $CO_2$  emissions mitigation. In particular, the results revealed that energy 406 conservation technology (ECT) promotion and reductions in inter-regional technological disparity would be effective in reducing carbon emissions in technically 407 inefficient regions. Therefore, this paper also provided insights into how the 408 409 underdeveloped regions in western area of China may develop a low emissions future.

410 Acknowledgements

This paper is supported by National Natural Science Foundation of China (No.
71603148; No. 71472065), China Postdoctoral Science Foundation (No.
2016M590627), Overseas Published Project for Humanities and Social Science of
East China Normal University (2015HW006).

# 415 **References**

416 [1] Fan Y, Liu L-C, Wu G, Tsai H-T, Wei Y-M. Changes in carbon intensity in China:

417 empirical findings from 1980–2003. Ecological Economics. 2007;62:683-91.

- [2] Dhakal S. Urban energy use and carbon emissions from cities in China and policy
  implications. Energy Policy. 2009;37:4208-19.
- 420 [3] Tian X, Chang M, Tanikawa H, Shi F, Imura H. Structural decomposition analysis
- 421 of the carbonization process in Beijing: A regional explanation of rapid increasing
- 422 carbon dioxide emission in China. Energy Policy. 2013;53:279-86.
- 423 [4] Du K, Lu H, Yu K. Sources of the potential CO 2 emission reduction in China: a
- 424 nonparametric metafrontier approach. Applied Energy. 2014;115:491-501.
- [5] Ouyang X, Lin B. An analysis of the driving forces of energy-related carbon
  dioxide emissions in China's industrial sector. Renewable and Sustainable Energy
  Reviews. 2015;45:838-49.
- [6] Lin B, Du K. Energy and CO 2 emissions performance in China's regional
  economies: Do market-oriented reforms matter? Energy Policy. 2015;78:113-24.
- 430 [7] Meng L, Guo Je, Chai J, Zhang Z. China's regional CO 2 emissions:
- characteristics, inter-regional transfer and emission reduction policies. Energy Policy.
  2011;39:6136-44.
- [8] Lin B, Du K. Technology gap and China's regional energy efficiency: A parametric
  metafrontier approach. Energy Economics. 2013;40:529-36.
- 435 [9] Yi W-J, Zou L-L, Guo J, Wang K, Wei Y-M. How can China reach its CO 2
- 436 intensity reduction targets by 2020? A regional allocation based on equity and
  437 development. Energy Policy. 2011;39:2407-15.
- [10] Ang BW. Decomposition analysis for policymaking in energy:: which is thepreferred method? Energy policy. 2004;32:1131-9.
- [11] Rose A, Casler S. Input–output structural decomposition analysis: a critical
  appraisal. Economic Systems Research. 1996;8:33-62.
- [12] Ang B, Choi K-H. Decomposition of aggregate energy and gas emission
  intensities for industry: a refined Divisia index method. The Energy Journal.
  1997:59-73.
- [13] Sun J. Changes in energy consumption and energy intensity: a completedecomposition model. Energy economics. 1998;20:85-100.
- 447 [14] Ang BW, Zhang F. A survey of index decomposition analysis in energy and

- 448 environmental studies. Energy. 2000;25:1149-76.
- 449 [15] Ang BW, Liu FL. A new energy decomposition method: perfect in decomposition
- and consistent in aggregation. Energy. 2001;26:537-48.
- 451 [16] Hoekstra R, Van Den Bergh JC. Structural decomposition analysis of physical
- 452 flows in the economy. Environmental and resource economics. 2002;23:357-78.
- 453 [17] Hoekstra R, Van den Bergh JC. Comparing structural decomposition analysis and
- 454 index. Energy economics. 2003;25:39-64.
- [18] Lise W. Decomposition of CO 2 emissions over 1980–2003 in Turkey. Energy
  Policy. 2006;34:1841-52.
- 457 [19] Su B, Ang B. Structural decomposition analysis applied to energy and emissions:
- 458 some methodological developments. Energy Economics. 2012;34:177-88.
- 459 [20] Xu X, Ang BW. Index decomposition analysis applied to CO 2 emission studies.
- 460 Ecological Economics. 2013;93:313-29.
- 461 [21] Wang C, Chen J, Zou J. Decomposition of energy-related CO 2 emission in
  462 China: 1957–2000. Energy. 2005;30:73-83.
- [22] Wu L, Kaneko S, Matsuoka S. Driving forces behind the stagnancy of China's
  energy-related CO 2 emissions from 1996 to 1999: the relative importance of
  structural change, intensity change and scale change. Energy policy. 2005;33:319-35.
- 466 [23] Liu L-C, Fan Y, Wu G, Wei Y-M. Using LMDI method to analyze the change of
- 467 China's industrial CO 2 emissions from final fuel use: an empirical analysis. Energy
- 468 Policy. 2007;35:5892-900.
- [24] Donglan Z, Dequn Z, Peng Z. Driving forces of residential CO 2 emissions in
  urban and rural China: an index decomposition analysis. Energy Policy.
  2010;38:3377-83.
- 472 [25] Lin B, Ouyang X. Analysis of energy-related CO 2 (carbon dioxide) emissions
- and reduction potential in the Chinese non-metallic mineral products industry. Energy.2014;68:688-97.
- 475 [26] Zhang M, Mu H, Ning Y. Accounting for energy-related CO 2 emission in China,
- 476 1991–2006. Energy Policy. 2009;37:767-73.
- 477 [27] Zhao M, Tan L, Zhang W, Ji M, Liu Y, Yu L. Decomposing the influencing

478 factors of industrial carbon emissions in Shanghai using the LMDI method. Energy.

479 2010;35:2505-10.

- 480 [28] Kaivo-oja J, Luukkanen J, Panula-Ontto J, Vehmas J, Chen Y, Mikkonen S, et al.
- 481 Are structural change and modernisation leading to convergence in the CO 2 economy?
- 482 Decomposition analysis of China, EU and USA. Energy. 2014;72:115-25.
- [29] Kim Y, Worrell E. International comparison of CO 2 emission trends in the iron
  and steel industry. Energy policy. 2002;30:827-38.
- [30] Ma C, Stern DI. China's changing energy intensity trend: A decomposition
  analysis. Energy economics. 2008;30:1037-53.
- 487 [31] Lin B, Du K. Decomposing energy intensity change: A combination of index
- 488 decomposition analysis and production-theoretical decomposition analysis. Applied
- 489 Energy. 2014;129:158-65.
- 490 [32] Du K, Lin B. Understanding the rapid growth of China's energy consumption: A
- 491 comprehensive decomposition framework. Energy. 2015;90:570-7.
- 492 [33] Wang C. Decomposing energy productivity change: a distance function approach.
  493 Energy. 2007;32:1326-33.
- 494 [34] Zhou P, Ang B. Decomposition of aggregate CO 2 emissions: a
  495 production-theoretical approach. Energy Economics. 2008;30:1054-67.
- 496 [35] Li M. Decomposing the change of CO 2 emissions in China: a distance function
- 497 approach. Ecological Economics. 2010;70:77-85.
- [36] Kim K, Kim Y. International comparison of industrial CO 2 emission trends and
  the energy efficiency paradox utilizing production-based decomposition. Energy
  Economics. 2012;34:1724-41.
- 501 [37] Zhang Y-J, Da Y-B. Decomposing the changes of energy-related carbon 502 emissions in China: evidence from the PDA approach. Natural hazards. 503 2013;69:1109-22.
- 504 [38] Wang Q, Chiu Y-H, Chiu C-R. Driving factors behind carbon dioxide emissions
- in China: A modified production-theoretical decomposition analysis. Energy
  Economics. 2015;51:252-60.
- 507 [39] Wang C. Sources of energy productivity growth and its distribution dynamics in

- 508 China. Resource and Energy Economics. 2011;33:279-92.
- 509 [40] Pastor JT, Lovell CK. A global Malmquist productivity index. Economics Letters.510 2005;88:266-71.
- 511 [41] Oh D-h. A metafrontier approach for measuring an environmentally sensitive
- 512 productivity growth index. Energy Economics. 2010;32:146-57.
- 513 [42] Zhou P, Ang BW, Poh K-L. A survey of data envelopment analysis in energy and
- environmental studies. European Journal of Operational Research. 2008;189:1-18.
- 515 [43] Liu Z, Geng Y, Lindner S, Guan D. Uncovering China's greenhouse gas emission
- from regional and sectoral perspectives. Energy. 2012;45:1059-68.
- 517 [44] Li A, Zhang A, Zhou Y, Yao X. Decomposition analysis of factors affecting
- carbon dioxide emissions across provinces in China. Journal of Cleaner Production.
- 519 2017;141:1428-44.
- 520 [45] Shi H, Chertow M, Song Y. Developing country experience with eco-industrial
- 521 parks: a case study of the Tianjin Economic-Technological Development Area in
- 522 China. Journal of Cleaner Production. 2010;18:191-9.
- 523