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Du, Kerui; Xie, Chunping; Ouyang, Xiaoling

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# **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: [susulovedog@hotmail.com](mailto:susulovedog@hotmail.com)*

\*\* Corresponding author at: *Department of economics, School of economics, Faculty  
of economics and management, East China Normal University, Shanghai 200062,  
China. E-mail address: [xlouyang@jjx.ecnu.edu.cn](mailto:xlouyang@jjx.ecnu.edu.cn)*

## **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<sub>2</sub> emission changes with production-based decomposition. Compared to other 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 CO<sub>2</sub> 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.
- Economic activity is the main driver behind China's rising CO<sub>2</sub> emissions.
- The less developed regions show large potential reduction of CO<sub>2</sub> emissions.

1 **1. Introduction**

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

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  
13 emission intensity and energy efficiency differ greatly across regions in China ([8]),  
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  
16 greenhouse gas emissions, the Chinese government established a set of carbon  
17 emission reduction targets for different regions in the 11<sup>th</sup> and 12<sup>th</sup> Five-Year Plans  
18 (FYP) for national economic and social development. However, how to reasonably  
19 allocate regional CO<sub>2</sub> reduction targets based on the actual situations and reduction  
20 potential of various regions is still worthy of discussion ([9]). Therefore,  
21 understanding the key drivers behind China's growing CO<sub>2</sub> emissions and developing  
22 regional emission reduction policies in China have theoretical and practical values for

23 decision makers.

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

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<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.

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

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

66 expected that such improvement would promote energy intensity reduction or at least  
67 would not have a negative impact on energy intensity reduction. However, results from  
68 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  
71 industries and energies cannot be reflected in the PDA model. Specifically, the lower  
72 energy consumption feature of the tertiary industry sector compared to the second  
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  
75 the PDA model, the output proportions of three sectors (primary, secondary, and  
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  
78 share of secondary industry declined, while the share of tertiary increased  
79 correspondingly. On one hand, the declined proportion of secondary industry in  
80 output would make the value of output distance function smaller; on the other hand,  
81 the increased proportion of tertiary industry in output would make the value of output  
82 distance function bigger. If the effect of the latter were bigger than the former, the  
83 industrial structure transformation would have a negative impact on energy intensity  
84 reduction, which is contrary to fact.

85 Based on the above analysis, we combined the advantages of IDA and PDA to  
86 examine the influencing factors of China's CO<sub>2</sub> emission changes and compare CO<sub>2</sub>  
87 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<sub>2</sub> 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.

103 The remainder of this article is organized as follows: [Section 2](#) describes  
104 methodology and data; [Section 3](#) presents and discusses the empirical results; [Section](#)  
105 [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  $n = 1, \dots, N$  can be expressed as:

$$\begin{aligned}
C_t^n &= \sum_{ij} C_{ij,t}^n \\
109 \quad &= \sum_{ij} \frac{C_{ij,t}^n}{E_{ij,t}^n} \frac{E_{ij,t}^n}{E_{i,t}^n} \frac{E_{i,t}^n / Y_{i,t}^n}{D_i^s(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)} \frac{Y_{i,t}^n}{Y_t^n} \frac{D_i^s(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{D_i^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)} D_{i,t}^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n) \quad (1)
\end{aligned}$$

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  $E_{ij,t}^n$ ;  $D_i^s(\cdot)$   
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  $i = 1, \dots, I$  at time period  $t = 1, \dots, T$  can be expressed as:

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

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

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

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

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

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

125 Using DEA-type linear programming technique, the Shepard energy distance  
126 function can be estimated through the following optimization problems.

$$\begin{aligned}
& [D_{i,t}^c(E_{i,t}, Y_{i,t}, C_{i,t})]^{-1} = \min \theta \\
& \text{s.t. } \sum_{n=1}^N \lambda_n E_{i,t}^n \leq \theta E_{i,t} \\
& \sum_{n=1}^N \lambda_n Y_{i,t}^n \geq \theta Y_{i,t} \\
& \sum_{n=1}^N \lambda_n C_{i,t}^n = \theta C_{i,t} \\
& \lambda_n \geq 0, n=1, \dots, N, t=1, \dots, T
\end{aligned} \tag{6}$$

$$\begin{aligned}
& [D_i^g(E_{i,t}, Y_{i,t}, C_{i,t})]^{-1} = \min \theta \\
& \text{s.t. } \sum_{t=1}^T \sum_{n=1}^N \lambda_{n,t} E_{i,t}^n \leq \theta E_{i,t} \\
& \sum_{t=1}^T \sum_{n=1}^N \lambda_{n,t} Y_{i,t}^n \geq \theta Y_{i,t} \\
& \sum_{t=1}^T \sum_{n=1}^N \lambda_{n,t} C_{i,t}^n = \theta C_{i,t} \\
& \lambda_{n,t} \geq 0, n=1, \dots, N, t=1, \dots, T
\end{aligned} \tag{7}$$

Using the LMDI method, the change in CO<sub>2</sub> emissions between time period  $t$  and time period  $\tau$  can be decomposed as:

$$C_{\tau}^n / C_t^n = D_{EMF} \times D_{EMX} \times D_{PEI} \times D_{STR} \times D_{EAT} \times D_{BPC} \times D_{EC} \tag{8}$$

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

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

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

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

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

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

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

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

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

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 into seven components. The first component  $D_{EMF}$  is the CO<sub>2</sub> emission factor effect. 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 energy inefficiency relative to the global technology. Following [42] and [36], we 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 change. The fifth component  $D_{EAT}$  refers to the impact from output scale change which is usually regarded 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 ( $T_i^g$ ) and the contemporaneous technology ( $T_{i,t}^c$ ) measured along energy direction.

$\frac{D_i^c(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n) / D_i^g(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)}{D_i^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n) / D_i^g(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}$  indicates the contemporaneous technology gets

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

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

166 In summary, the change in CO<sub>2</sub> emissions over time can be attributed into seven  
167 indexes: emission factor change, energy mix change, potential energy intensity  
168 change, output structure change, economic activity effect, the effect of energy  
169 technological change and the effect of energy efficiency change. For any one of them,  
170 it will contribute to the increase of (decline in) CO<sub>2</sub> emissions if its value is greater  
171 (less) than one.

## 172 2.2 Data

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

---

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

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

### 188 **3. Results and discussion**

#### 189 *3.1 Empirical results of decomposition*

190 [Table 1](#) reports changes in China's CO<sub>2</sub> emissions and contributions to CO<sub>2</sub>  
191 emission changes from effects of CO<sub>2</sub> emission factor (EMF), energy mix change  
192 (EMX), potential energy intensity change (PEI), industrial structure (STR), economic  
193 activity (EAT), technological change (BPC) and energy efficiency change (EC) in  
194 different provinces in China during 2006-2012.

195 As shown in column (1), we can see that CO<sub>2</sub> emissions in all  
196 provinces/municipalities in China increased during 2006-2012 except for Beijing. As  
197 a political and economic center of China, Beijing is one of the world's most polluted  
198 cities. Beijing made great efforts to reduce energy-related CO<sub>2</sub> emissions. For

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

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

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

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

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

217 The effect of potential energy intensity ( $D_{PEI}$ ) in column (4) measures the impact  
218 of energy intensity change on CO<sub>2</sub> emissions under the scenario without energy  
219 inefficiency relative to the global technology. The values of  $D_{PEI}$  in this paper are  
220 almost less than one. The results are basically consistent with the findings of [38],

221 indicating that the change of energy intensity will contribute to the decline of CO<sub>2</sub>  
222 emissions when inefficiency of the energy-usage technology relative to the global  
223 technology has been improved as much as possible. In particular, provinces such as  
224 Hunan, Jilin and Anhui have experienced larger impacts of D<sub>PEI</sub> compared to other  
225 provinces. In contrast, provinces such as Hainan and Xinjiang have experienced  
226 increased potential energy intensity that leads to increasing CO<sub>2</sub> emissions.

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

241 As shown in column (6), the values of economic activity change (D<sub>EAT</sub>) in all  
242 provinces in China are greater than one in this paper. Results indicated that D<sub>EAT</sub> has



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

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

265 CO<sub>2</sub> emission changes. Results indicated that most provinces decreased CO<sub>2</sub>  
 266 emissions due to the improved energy efficiencies. Meanwhile D<sub>EC</sub> in  
 267 provinces/municipalities such as Hebei, Hubei, Qinghai, Shaanxi, Shanghai, Sichuan,  
 268 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

272 This subsection further measures the potential CO<sub>2</sub> reduction (PCR) in China.  
 273 Under the contemporaneous technology scenario, the PCR for region  $n$  at the time  
 274 period  $t$  can be calculated as:

$$\begin{aligned}
 PCR_{t,c}^n &= C_t^n - C_{t,bpc}^n \\
 C_{t,bpc}^n &= \sum_{ij} \frac{C_{ij,t}^n E_{ij,t}^n}{E_{ij,t}^n E_{i,t}^n} \frac{E_{i,t}^n / D_i^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{Y_{i,t}^n} Y_{i,t}^n
 \end{aligned}
 \tag{12}$$

276 We obtain the potential of nationwide CO<sub>2</sub> emission reduction by summing up  
 277 the potentials of CO<sub>2</sub> emission reduction in different regions in China. Results of the  
 278 potential CO<sub>2</sub> reduction under the contemporaneous technology scenario are shown in  
 279 [Table 2](#).

280 **Table 2 here**

281

282 As shown in [Table 2](#), the nationwide potential CO<sub>2</sub> reductions (PCR) under the  
 283 contemporaneous technology scenario showed an increasing trend overall.  
 284 Specifically, the nationwide PCR increased from 15.70 billion tons in 2006 to 20.81  
 285 billion tons in 2012 with an average growth rate of 4.93 per annum. The smaller the

286 numerical value of PCR is, the closer the technological gap between each  
287 province/municipality's actual technology and the contemporaneous technology is. In  
288 other words, PCR indicates the successfulness of the adoption of the  
289 contemporaneous technology of each province/municipality. Therefore, results  
290 showed that China's capabilities to improve production technical efficiency through  
291 introducing international advanced technologies and international cooperation on  
292 technological innovation have been weakened over the years.

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

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

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

$$\begin{aligned}
 PCR_{t,g}^n &= C_t^n - C_{t,bpg}^n \\
 C_{t,bpg}^n &= \sum_{ij} \frac{C_{ij,t}^n}{E_{ij,t}^n} \frac{E_{ij,t}^n}{E_{i,t}^n} \frac{E_{i,t}^n / D_i^g(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{Y_{i,t}^n} Y_{i,t}^n
 \end{aligned} \tag{13}$$

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

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

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

351 reductions in inter-regional technological disparity would be effective in reducing  
352 carbon emissions in technically inefficient regions.

353 **Table 3 here**

354

#### 355 **4. Conclusions and implications**

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

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

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

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

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

395 Based on the analysis of the potential of CO<sub>2</sub> emission reductions (PCR), we  
396 determined that China have experienced higher potential for mitigation over time.  
397 Additionally, the numerical values of PCR were larger under the global technology  
398 scenario compared to those under the contemporaneous technology scenario.  
399 However, the PCRs of economically developed regions located in East China were  
400 relatively lower than the less economically developed regions located in central and  
401 western China. This means that the diffusions of production technologies of  
402 economically developed regions were more efficient. Results indicated that research  
403 and development investment in production technology as well as the spread of  
404 advanced technologies through international cooperation can effectively reduce the  
405 potential for CO<sub>2</sub> emissions mitigation. In particular, the results revealed that energy  
406 conservation technology (ECT) promotion and reductions in inter-regional  
407 technological disparity would be effective in reducing carbon emissions in technically  
408 inefficient regions. Therefore, this paper also provided insights into how the  
409 underdeveloped regions in western area of China may develop a low emissions future.

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