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Abstract

As the world leader in CO_2 emissions, China is a key focus for climate change mitigation. In this paper, we conducted a cross-province comparison of CO_2 emission trends in China from 2006 to 2012. We determined 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) as underlying forces of CO_2 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_2 emission reductions in most provinces/municipalities in China. In particular, we introduced the global benchmark technology to establish the relationship between CO_2 emissions and energy use technology. The potential CO_2 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_2 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_2 emissions in China.
- Economic activity is the main driver behind China's rising CO_2 emissions.
- The less developed regions show large potential reduction of CO_2 emissions.

1. Introduction

As the world leader in CO_2 emissions from fossil fuel combustion, China has attracted worldwide attention with its accelerating CO_2 emissions over the past three decades. Considering its critical role in global CO_2 emissions, China becomes a key focus for effects in emission mitigations. In this context, a lot of efforts have been made to identify and quantify the underlying driving forces that affect CO_2 emission changes in China. In literature, factors that influence changes of China's CO_2 emissions have been widely discussed in previous studies ([1]; [2]; [3]; [4]; [5]). However, CO_2 emission trends among different provinces in China have been less systematically investigated ([6]).

It should be noted that significant diversity exists among eastern, central and 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]), and the differences are most prominent between the developed regions in eastern area 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 emission reduction targets for different regions in the 11^{th} and 12^{th} Five-Year Plans (FYP) for national economic and social development. However, how to reasonably allocate regional CO_2 reduction targets based on the actual situations and reduction potential of various regions is still worthy of discussion ([9]). Therefore, understanding the key drivers behind China's growing CO_2 emissions and developing regional emission reduction policies in China have theoretical and practical values for decision makers.

CO_2 emissions in China have attracted increasing attentions in light of China's decisive role in the global carbon emission mitigation. Technically, CO_2 emission changes can be analyzed by attributing the changes in CO_2 emissions into several pre-defined factors by adopting decomposition analysis ([10]). In literature, the structural decomposition analysis (SDA) and the index decomposition analysis (IDA) are the most commonly used decomposition techniques ([11]; [12]; [13]; [14]; [15]; [16]; [17]; [18]; [19]; [20])[1]. In terms of data and methodologies, the SDA uses the 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 more flexible, easy to use, and has relatively lower data requirements for empirical models. As a result, IDA has been widely used to decompose CO_2 emissions in different countries and various time periods ([21]; [22]; [23]; [24]; [25]). Under the framework of IDA, factors such as the carbon intensity of energy use, energy intensity, structural change and economic activity were identified as the major factors affecting CO_2 emissions, and the decline in energy intensity was identified as the driving force for the considerable decrease in China's CO_2 emissions ([26]; [27]; [28]). However, IDA could not provide a quantitive analysis for the impacts of technological change effect, substitutions between energy and other inputs (i.e., capital and labor), and the effect of technical efficiency change on sectoral intensity change, because it simply regards the energy/emission intensity change as the effect

[1] 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, decomposition analysis was improved and conducted within the production theory framework. [33] proposed production-theoretical decomposition analysis (PDA) based on Shephard output distance functions, which can be computed using data envelopment analysis (DEA) techniques. Empirical analyses of CO_2 emission changes 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 efficiency change". The former measures the effect of best practice technology, and the latter measures the effect of changes in production efficiency. PDA provides detailed information about the influence of production technologies, which could be used to evaluate the degree of "energy efficiency paradox" ([36]). However, its measurement on energy mix effect and the industrial structure effect, which are regarded as important factors of emission change, is possibly inconsistent with reality. For example, when industrial structure transforms from energy intensive industries to less energy intensive industries, it is expected that the industrial structure change would reduce an economy's overall energy intensity. However, results from PDA indicates that such an industrial structure transformation has a negative effect on energy intensity reduction ([39]). PDA has a similar problem for the measurement of energy mix effect. When energy consumption structure has been improved, it is 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.

The main reason for the above problems of PDA is that the structural components 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 energy consumption feature of the tertiary industry sector compared to the second industry sector is not reflected in the distance function. Therefore, the PDA model cannot provide information on the real effect of industrial structure transformation. In the PDA model, the output proportions of three sectors (primary, secondary, and tertiary) are all included in the output distance functions. The industrial structure was assumed to change as follows: the share of primary industry remained constant, the share of secondary industry declined, while the share of tertiary increased correspondingly. On one hand, the declined proportion of secondary industry in output would make the value of output distance function smaller; on the other hand, the increased proportion of tertiary industry in output would make the value of output 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 reduction, which is contrary to fact.

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 model based on the Shephard energy distance function to disaggregate the provincial level changes of CO_2 emissions in China during 2006-2012, and then introduce the global benchmark technology to establish the relationship between CO_2 emissions and energy use technologies. The central idea of the combination is introducing Shephard energy distance functions which captures the impacts from production technology in the expression of the aggregate CO_2 emissions, and then conducting IDA (e.g., LMDI) for this equation to identify the influencing factors driving change in the aggregate CO_2 emissions. In this sense, PDA and IDA are embodied together to provide the mechanism of CO_2 emission change. **The contributions of this paper lie in the following aspects:** First, the decomposition method used in this paper can overcome the weakness of PDA on the measurement of structural changes, and thus can produce more reasonable results; Second, the proposed approach has been applied in the field of investigating CO_2 emission trends among provinces in China; Third, from the methodological perspective, this paper specifies a different production technology 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.

2. Methodology and Data

2.1 The decomposition model

The CO_2 emissions of country $n = 1, ..., N$ can be expressed as:

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

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

where $E_{ij,t}^{n}$ denotes the consumption of the type-j energy in the sub-sector i of country n at the period t, and $C_{ij,t}^{n}$ represents the CO_2 emissions from $E_{ij,t}^{n}$; $D_{\mathrm{i}}^{g}(\cdot)$ and $D_{\mathrm{i}}^{\mathrm{c}}(\cdot)$ are the Shepard energy distance functions defined on the contemporaneous benchmark technology and the global benchmark technology, respectively. Specifically, the contemporaneous production technology for the industrial sub-sector $i = 1,...,I$ at time period $t = 1,...,T$ can be expressed as:

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

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

$$T_{i}^{\mathrm{g}} = \{T_{i,1}^{\mathrm{c}} \cup T_{i,2}^{\mathrm{c}} \cup ... \cup T_{i,T}^{\mathrm{c}}\} \quad (3)$$

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.

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

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

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

$$
\begin{aligned}
&\left[D_{i,t}^{c}(E_{i,t},Y_{i,t},C_{i,t})\right]^{-1}=\min\theta\\
&\quad s.t.\quad \sum_{n=1}^{N}\lambda_n E_{i,t}^{n}\le\theta E_{i,t}\\
&\qquad\quad \sum_{n=1}^{N}\lambda_n Y_{i,t}^{n}\ge\theta Y_{i,t}\\
&\qquad\quad \sum_{n=1}^{N}\lambda_n C_{i,t}^{n}=\theta C_{i,t}\\
&\qquad \lambda_n\ge 0, n=1,\ldots,N, t=1,\ldots,T
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
&\left[D_{i}^{g}(E_{i,t},Y_{i,t},C_{i,t})\right]^{-1}=\min\theta\\
&\quad s.t.\quad \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t} E_{i,t}^{n}\le\theta E_{i,t}\\
&\qquad\quad \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t} Y_{i,t}^{n}\ge\theta Y_{i,t}\\
&\qquad\quad \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t} C_{i,t}^{n}=\theta C_{i,t}\\
&\qquad \lambda_{n,t}\ge 0, n=1,\ldots,N, t=1,\ldots,T
\end{aligned}
\tag{7}
$$

Using the LMDI method, the change in CO_2 emissions between time period t and time period τ can be decomposed as:

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

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

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

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

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

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

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

$$D_{EC}=\exp\left\{\frac{L(C^{n}_{ij,\tau},C^{n}_{ij,t})}{L(C^{n}_{\tau},C^{n}_{t})}\ln\frac{D^{c}_{i,\tau}(E^{n}_{i,\tau},Y^{n}_{i,\tau},C^{n}_{i,\tau})}{D^{c}_{i,t}(E^{n}_{i,t},Y^{n}_{i,t},C^{n}_{i,t})}\right\}.$$

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

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

The decomposition model presented above is a modification of [36]. Unlike [36], we introduce the global benchmark technology to establish the relationship between CO_2 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_2 emissions over times can be decomposed into seven components. The first component D_{EMF} is the CO_2 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. $D^{c}_{i}(E^{n}_{i},Y^{n}_{i},C^{n}_{i})/D^{g}_{i}(E^{n}_{i},Y^{n}_{i},C^{n}_{i})$ is a best practice gap between the global technology (T^{g}_{i}) and the contemporaneous technology ($T^{c}_{i,t}$) measured along energy direction. $\dfrac{D^{c}_{i}(E^{n}_{i,\tau},Y^{n}_{i,\tau},C^{n}_{i,\tau})/D^{g}_{i}(E^{n}_{i,\tau},Y^{n}_{i,\tau},C^{n}_{i,\tau})}{D^{c}_{i}(E^{n}_{i,t},Y^{n}_{i,t},C^{n}_{i,t})/D^{g}_{i}(E^{n}_{i,t},Y^{n}_{i,t},C^{n}_{i,t})}$ indicates the contemporaneous technology gets 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 $\frac{D_i^c(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n) / D_i^g(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n)}{D_i^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n) / D_i^g(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}$ describes the impact from technological change in energy use. $1/D_{i,t}^c\left(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n\right)$ 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.

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[1]. 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

[1] Due to data unavailability, Tibet is not included in this study.

collected from China Premium Database[1]. Data on different types of energy are obtained from China Energy Statistical Yearbook (CESY)[2]. Data on energy-related CO_2 emissions are estimated by the method described in [43]. In addition, our calculation of energy-related CO_2 emissions also includes the indirect emissions from heat and power consumption of each subsector. Electricity emission factor is obtained by dividing energy-related CO_2 emissions from electricity generation by the power output. Heat emission factor is obtained by dividing energy-related CO_2 emissions from heat generation by the heat output. Data in value terms are measured at the 2005 real 10^8 Chinese Yuan (CNY).

3. Results and discussion

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

[1] Available at: http://www.ceicdata.com.

[2] Available at: http://tongji.cnki.net/overseas/engnavi/NaviDefault.aspx

example, Beijing raised emission standards and promoted the use of electric automobiles during the preparation for the Olympic Games in 2008. In 2011, Beijing 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. Additionally, the local government used a series of measures to reduce CO_2 emissions: first, shutting down or moving highly polluted factories to neighboring provinces (e.g., Hebei, Tianjin); second, promoting the emission reduction policies such as “using electricity instead of coal” and “burning natural gas instead of coal”; third, encouraging the transfer of energy saving technologies in energy intensive industries, etc.

The values of CO_2 emission factor effect (D_{EMF}) 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_{EMF} 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_2 emissions in 13 provinces in China. However, the energy mix change for 17 provinces contributes to their increase in CO_2 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_2 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_2 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 one for most provinces/municipalities including Beijing, Gansu, Guangdong, Guizhou, Hainan, Hebei, Heilongjiang, Jiangsu, Ningxia, Shandong, Shanxi, Shaanxi, Shanghai, Tianjin, Xinjiang, Yunnan and Zhejiang. In which, 9 provinces/municipalities are economically developed regions located in the eastern coast of China; 6 provinces are 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 changed such that CO_2 emissions have decreased in these provinces. However, the values of D_{STR} were larger than one for provinces such as Anhui, Guangxi, Henan, Hubei, Hunan, Jilin, Jiangxi, Liaoning, Inner Mongolia, Qinghai, Sichuan and so on. It can be seen that most of the listed provinces are less economically developed regions located in the central and western China. In addition, the economic transfer (the transfer of energy-intensive industries) between East and West China may accelerate the transfer of pollution between the two regions.

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_2 emissions in all provinces in China. The changes for provinces/municipalities such as Anhui, Fujian, Guangxi, Guizhou, Hubei, Hunan, Jiangxi, Liaoning, Inner Mongolia, Qinghai, Shaanxi, Sichuan, Tianjin and Chongqing are greater than the geometric mean (2.0343), indicating that these provinces have experienced higher increases in CO_2 emissions by economic activity expansion. It can be seen that most of listed provinces are located in the central and western China. These findings are in line with most previous studies, e.g., [35]; [38]; [44].

Columns (7) in Table 1 described the effect of technological change (D_{BPC}) on CO_2 emission changes. The indicator reflected the capabilities for innovating new and advanced technologies. In general, the impacts of technological improvement on CO_2 emission reductions were insignificant, implying that technological change has a weaker influence on the reduction of CO_2 emissions compared to other indicators. However, for China's wealthy coastal provinces or rich municipalities including Beijing, Guangdong, Shanghai and Tianjin, the contributions of D_{BPC} to the abatement of CO_2 emissions were significant. As the most developed metropolises in China, the top research institutions were concentrated in Beijing and Shanghai. With the advantage of location close to Beijing, Tianjin has recorded China's highest per-capita GDP since 2013. Additionally, Tianjin was transforming into a hub city for research and development ([45]). As the richest province which borders on Hong Kong, Guangdong has experienced rapid technological progress in recent years ([35]).

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

CO_2 emission changes. Results indicated that most provinces decreased CO_2 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_2 emissions.

Table 1 here

3.2 The potential of CO_2 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:

$$\begin{aligned} &PCR^{n}_{\mathrm{t,c}} = C^{n}_{\mathrm{t}} - C^{n}_{\mathrm{t,bpc}} \\ &C^{n}_{\mathrm{t,bpc}} = \sum_{ij} \frac{C^{n}_{\mathrm{ij,t}}}{E^{n}_{\mathrm{ij,t}}} \frac{E^{n}_{\mathrm{ij,t}}}{E^{n}_{\mathrm{i,t}}} \frac{E^{n}_{\mathrm{i,t}} / D^{c}_{i}(E^{n}_{\mathrm{i,t}}, Y^{n}_{\mathrm{i,t}}, C^{n}_{\mathrm{i,t}})}{Y^{n}_{\mathrm{i,t}}} Y^{n}_{\mathrm{i,t}} \end{aligned} \quad (12)$$

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.

Table 2 here

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, Tianjin, Zhejiang and so on were relatively lower. This means that the diffusion of production technologies of these provinces/municipalities were more efficient. Most of the above provinces were economically developed regions located in East China. 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 significantly from 0.2442 billion tons in 2010 to 0.0973 billion tons in 2011, equivalent to a decrease of 60.16%. Moreover, Beijing, Guangdong and Shanghai have experienced lower potential for mitigation over time. The results are consistent with the analysis in section 3.1.

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

$$\begin{aligned} PCR^{n}_{\mathrm{t,g}} &= C^{n}_{\mathrm{t}} - C^{n}_{\mathrm{t,bpg}} \\ C^{n}_{\mathrm{t,bpg}} &= \sum_{ij} \frac{C^{n}_{\mathrm{ij,t}}}{E^{n}_{\mathrm{ij,t}}} \frac{E^{n}_{\mathrm{ij,t}}}{E^{n}_{\mathrm{i,t}}} \frac{E^{n}_{\mathrm{i,t}} / D^{g}_{i}(E^{n}_{\mathrm{i,t}}, Y^{n}_{\mathrm{i,t}}, C^{n}_{\mathrm{i,t}})}{Y^{n}_{\mathrm{i,t}}} Y^{n}_{\mathrm{i,t}} \end{aligned} \tag{13}$$

Results of the potential CO_2 reduction under the global technology scenario are shown in Table 3. Under the global technology scenario, PCR indicated the successfulness of the adoption of the global technology, which also reflected the degree of international cooperation on technological innovation and development. Results indicated that the nationwide potential CO_2 reduction (PCR) under the global technology scenario also showed an increasing trend overall. These can be interpreted to mean that the gaps between China's actual technology and the global technology have become larger over the years. In other words, China's capabilities to improve production technological efficiency through introducing international advanced technologies or international cooperation on technological innovation and development have been weakened in recent years, and thus resulted in the production technological efficiency of China trailed far behind the world. Although China has become a global manufacturing center, most products made in China have low added value. According to China statistical yearbooks, the dominant technological intensity 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 the role of "manufacturing, processing and assembly". In addition, the development of the secondary industry was relatively extensive during the rapid urbanization process, and the introduction of international advanced technology was relatively limited. Therefore, upgrading manufacturing technology levels would be a big challenge faced by China in a new phase of economic development.

Comparatively, the numerical values of PCR were larger under the global technology scenario than those under the contemporaneous technology scenario. It indicated that the technological diffusion under the global technology scenario among provinces in China would be slower than that under the contemporaneous technology. This means that the abilities of provinces/municipalities in China to adopting global technologies related to energy usage were even weaker. Specially, provinces such as Hainan, Beijing, Gansu, Ningxia, Qinghai, Tianjin, Shanghai and so on have lower potentials for emission mitigation than provinces including Hebei, Henan, Hubei, Liaoning, Shandong, Shanxi and Sichuan. On one hand, these can be interpreted to mean that provinces/municipalities such as Hainan, Beijing, Gansu, Ningxia, Qinghai, Tianjin, Shanghai and so on have made efforts to adopt the relatively latest production technologies through international cooperation. On the other hand, these can also be interpreted to mean that the spread of energy conservation technologies and reductions in inter-regional technological disparity would be effective in reducing carbon emissions in technically inefficient regions.

Table 3 here

4. Conclusions and implications

As the public concerns about environmental pollution increase and the global concern about the increasing CO_2 emissions from China, how to control and mitigate CO_2 emissions have become the priority of the Chinese government at the stage of “new normal” economic development. Although the government has set reduction targets of CO_2 emissions for different regions in China, the reasonable allocation of regional CO_2 reduction targets based on the actual situations and reduction potentials as well as the differentiated reduction strategies among regions still need further research.

With a production-based decomposition approcah ([36]), this study identified the emission trends among different provinces/municipalities in China, discussed the impacts of the driving forces behind CO_2 emissions, and evaluated the mitigation potential of each province/municipality under the scenarios of contemporaneous technology and global technology. Specifically, this paper introduced the global benchmark technology to establish the relationship between CO_2 emissions and energy use technology. Additionally, we combined the advantages of IDA and PDA to examine the impacts of energy mix effect and the industrial structure effect on China’s CO_2 emission changes, which made up for the defects of PDA that may result in unreasonable results in the measurement of the above two kinds of effects.

The changes of CO_2 emissions for China's 30 provinces/municipalities were decomposed into seven components for the time period 2006-2012. The decomposition results showed that CO_2 emissions in all provinces/municipalities in 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, which is consistent with the conclusions of the existing literature, while changes in potential energy intensity, energy mix and energy efficiency change have led to CO_2 emission reductions in most provinces/municipalities in China. In general, the impacts of technological improvement on CO_2 emission reductions were trifling. However, for provinces/municipalities including Beijing, Guangdong, Shanghai and Tianjin, the contributions of technological change to the abatement of CO_2 emissions were significant. These can be interpreted to mean that the above provinces/municipalities showed stronger capabilities for innovating new and advanced energy saving 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_2 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 determined that China have experienced higher potential for mitigation over time. Additionally, the numerical values of PCR were larger under the global technology scenario compared to those under the contemporaneous technology scenario. However, the PCRs of economically developed regions located in East China were relatively lower than the less economically developed regions located in central and western China. This means that the diffusions of production technologies of economically developed regions were more efficient. Results indicated that research and development investment in production technology as well as the spread of advanced technologies through international cooperation can effectively reduce the potential for CO_2 emissions mitigation. In particular, the results revealed that energy conservation technology (ECT) promotion and reductions in inter-regional technological disparity would be effective in reducing carbon emissions in technically inefficient regions. Therefore, this paper also provided insights into how the underdeveloped regions in western area of China may develop a low emissions future.

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