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CO_2 emission reduction potential in China from combined effects of structural adjustment of economy and efficiency improvement

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ABSTRACT

China has committed to decreasing its emission intensity by 60% to 65% by 2030 compared to 2005 levels and achieving carbon neutrality by 2060. It is of great importance to evaluate the CO_2 emission reduction potential to quantify the amount of CO_2 emissions that can be less generated and the amount that should be balanced out. Economic structure adjustment and CO_2 emission efficiency improvement will contribute to mitigating CO_2 emissions, which always happen simultaneously in the real world. However, few studies consider these issues simultaneously, which can lead to inaccurate estimation. A scenario analysis framework is proposed to estimate their combined effects, and an indicator is proposed to measure the technical feasibility of achieving the reduction potential. A set of scenarios are designed based on this framework and we find that: (1) to achieve carbon neutrality, 6161.16 Mt of CO_2 emissions of China can be less generated compared to 2017 levels by significantly increasing its tertiary industry share to high-income entities' level and adopting the most advanced technology to improve emission efficiency; the remaining 2732.40 Mt of CO_2 emissions should be removed by carbon offsetting. Regarding emission intensity, 81.39% can be reduced compared with the 2005 level; and (2) Technical feasibility analysis shows Sichuan, Chongqing, and Anhui have the largest technical barriers in achieving the reduction potential. The proposed scenario analysis framework can provide a reference not only for China to achieve the emission mitigation pledges, but for countries with significant technological differences and structure adjustment to formulate mitigation strategies.

List of abbreviations including units and nomenclature

AD:	Activity data of fossil fuel consumption, Million tonnes of standard coal equivalent
AE:	Actual CO_2 emissions, Million tonnes
AEI:	Actual CO_2 emission intensity, Tonnes /10^4 RMB
AGDP:	Actual gross domestic product, 10^4 RMB
AIS:	Actual industry structure, %
C:	CO_2 emissions, Million tonnes
CC:	Carbon content per calorie, Tonnes CO_2/J
DEA:	Data envelopment analysis
DMU:	Decision-making unit
E:	Energy, Million tonnes of standard coal equivalent
EF:	Emission factor, Tonnes CO_2/J
K:	Capital, 100 million RMB
L:	Labour, 10^4 persons
NCV:	Net caloric value, J/tonnes fossil fuel consumption
NDDF:	Non-radial directional distance function
O:	Carbon oxidation ratio, %
PCE:	Potential change in CO_2 emissions, Million tonnes
PCEI:	Potential change in emission intensity, Tonnes /10^4 RMB
PE:	Potential CO_2 emissions, Million tonnes
PEI_i^G:	Potential emission intensity of i industry under group-frontier technology, Tonnes /10^4 RMB
PEI_i^M:	Potential emission intensity of i industry under meta-frontier technology, Tonnes /10^4 RMB

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PGDP: Potential gross domestic product, 10^4 RMB
PIS: Potential industry structure, %
T_i^G: The group-frontier production technology of i industry
T_i^M: The meta-frontier production technology of i industry
TFRE: Technical feasibility of reducing emissions
TRP: Technological reduction potential, Million tonnes
Y: Gross domestic product, 100 million RMB

1. Introduction

The rapid economic growth in China has led to high energy consumption, resulting in accompanying high CO_2 emissions. Since 2007, China has been the world's top CO_2 emitter (Guan et al., 2009). China formally joined the Paris Agreement in 2016 (The Chinese Government, 2016), which tries to keep global warming below 2°C, with best efforts to limit warming to 1.5°C. To limit global warming to 1.5 °C, the world should achieve net-zero emissions around the second half of the century (Intergovernmental Panel on Climate Change, 2018). China has taken on its share of responsibility for the mitigation of global climate change and has designed a range of CO_2 emission reduction targets (The Chinese Government, 2017). In 2015, China committed to decreasing its emission intensity by 60% to 65% compared to 2005 levels by 2030 (The Chinese Government, 2015). In 2020, China further pledged to achieve carbon neutrality by 2060 (The Chinese Government, 2020). Carbon neutrality indicates having a balance between producing CO_2 emissions and absorbing CO_2 emissions from the atmosphere (Guo et al., 2017; Lausselet et al., 2017). CO_2 emission reduction potential analysis can quantify the amount of CO_2 emissions that can be less produced and the amount that should be offset, which helps to facilitate the achievement of the carbon-neutral target (Fang et al., 2018; Hilton and Kerr, 2017).

Different methods have been used to evaluate CO_2 emission reduction potential. One popular method is the Logarithmic Mean Divisia Index, which can be used to evaluate the influencing factors of CO_2 emissions and to measure the reduction potential based on the change rates of determinants (Li et al., 2019; Lin and Ouyang, 2014; Song et al., 2019). For example, Lin and Ouyang (2014) decomposed the change of CO_2 emissions of the Chinese non-metallic mineral products industry into five determinants and suggested that the reduction potential can be 99.02 Mt if the growth rate of each determinant is 2% lower. The Conservation Supply Curve method has also been adopted in several studies to evaluate the reduction potential (Hasanbeigi et al., 2013), whose main idea is substituting traditional production technology with energy efficiency technologies and measures (Hasanbeigi et al., 2010). For instance, Hasanbeigi et al. (2013) pointed out that the reduction potential regarding technical fuel saving in the Chinese iron and steel industry can be 1205 Mt considering 23 energy efficiency technologies and measures. Single-indicators are normally used to describe the proportional relationship between two factors, such as emission intensity and energy intensity (Shan et al., 2018a; Yu et al., 2015). To measure emission reduction potential, single-factor analysis typically assumed that the efficiency can reach a certain percentile level or average level of single-indicator of the sampled objects (Ang et al., 2011; Graus et al., 2007; Shan et al., 2018a). Although the above methods can evaluate the emission reduction potential with the improvement of specific factors (e.g., change rates of determinants and partial technology substitution), they are limited in measuring the reduction potential under the most advanced production technology at present. The data envelopment analysis (DEA) method can measure the emission reduction potential by constructing a total-factor production technology frontier, which is the best-practice level a decision-making unit (DMU) can achieve (Sun et al., 2019; Zhang et al., 2018; Zhang et al., 2016)). Thus, the DEA method can be employed to measure CO_2 emission efficiency within a total-factor production framework and gain more insights into emission potential reduction (Hu et al., 2019; Shao, 2017; Wang and Wei, 2014; Zhang et al., 2016).

However, there are some challenges in emission reduction potential analysis. First, most studies regarding reduction potential analysis have just focused on the evaluation through emission efficiency improvement based on the DEA method and do not simultaneously consider the mitigation effects of economic structure change, which further limits the understanding of their combined effects. Economic structure adjustment and improvement of CO_2 emission efficiency always happen simultaneously in the real world. Many studies have found that economic structure adjustment is a significant contributor to CO_2 emission mitigation (Guan et al., 2018; Zhang et al., 2014) and the neglect of the significant role of economic structure change can lead to inaccurate estimation of CO_2 emission reduction potential (Chang, 2015; Guan et al., 2014; Zhou et al., 2013). Second, the technical feasibility of achieving the emission reduction potential has not been explored previously, even though emission reduction potential in terms of its level (Bian et al., 2013; Guo et al., 2011; Zhang et al., 2016), sources (Du et al., 2014; Fei and Lin, 2017), abatement costs (Choi et al., 2012; Wang and Wei, 2014; Xie et al., 2017), and mitigation strategies (Feng et al., 2017; Guo et al., 2011) have been explored in many studies. The technical feasibility can vary among regions because of large regional diversities in the levels of low-carbon technology. For example, it may take a longer time and more effort for a region with a lower technology level to achieve the CO_2 emission reduction potential. An indicator used to measure the technical feasibility is thus badly needed, which can help to set more feasible and practical emission mitigation targets.

Motivated by this, this study fills the first gap by exploring the combined effects of economic structure adjustment and emission efficiency improvement to measure CO_2 emission reduction potential (including reduction potential in CO_2 emissions and emission intensity). To increase the predictivity of emission reduction potential, eight scenarios are designed, of which two scenarios examine the mitigation effect of economic structure adjustment, three examine emission efficiency improvement, and a further three scenarios measure their combined effects. To address the second gap, an indicator is proposed to measure the technical feasibility of realizing the reduction potential. This indicator reflects the components of the emission reduction potential, a part of which is straightforward to achieve, while another part caused by technology gaps requires more time and effort. These scenarios and the indicator are then applied to Chinese 30 provinces. The most significant contribution of this paper is proposing a scenario analysis framework that can not only examine the combined effects of economic structure adjustment and emission efficiency improvement on reduction potential, but also quantify the amount of CO_2 emissions that should be balanced out for the 2060 carbon-neutral target. This proposed analysis framework and thinking in this study also provide a basis for countries with large technological differences that are undergoing significant structure adjustment to formulate precise mitigation targets towards carbon neutrality.

2. Methodology and data

2.1. NDDF based on group- and meta-frontier technologies

The non-radial directional distance function (NDDF), a kind of DEA method, has been widely used to measure total-factor CO_2 emission efficiency and reduction potential (Sueyoshi and Goto, 2012; Zhou et al., 2012). Zhou et al. (2012) provided a formal definition of NDDF with undesirable outputs to measure the CO_2 emission efficiency of electricity generation of 126 countries in 2005. Traditionally, all the DMUs are assumed to have common production technology and share the same production frontier (Du et al., 2014). However, in reality, the homogenous production technology assumption may be too strong and lose rationality when there are significant technological differences among different types of DMUs (Molinos-Senante et al., 2015; Yu and Choi, 2015). To solve this heterogeneity problem, some studies have taken technology heterogeneities among groups into consideration (Chiu et al., 2012; Oh, 2010). However, some studies pointed out that when using NDDF to include technological heterogeneity among different groups, meta-frontier technology cannot always envelop all group-frontier technology (Cheng et al., 2018b; Du et al., 2014). This can lead to the efficiency measured under meta-frontier technology being larger than that under group-frontier technology. Cheng et al. (2018b) proposed an improved NDDF to solve this problem. Because of the advantages of this improved NDDF, this study also adopted this model to measure the potential emission intensity under group- and meta-frontier technology.

2.1.1. Group- and meta-frontier technologies

Assume that *K, L, E* are respectively capital stock, labour force, and energy consumption, which represent inputs of the production process. *Y* denotes gross domestic product (GDP) and *C* indicates CO_2 emissions. The group-frontier technology of a group (T^G) can be obtained as follows:

$$T^G = \{(K,L,E,Y,C) : (K,\ L,\ E)\ can\ produce\ (Y,\ C) \tag{1}$$

where *T* satisfies the standard axioms of production theory, including the strong disposability of inputs and desirable outputs, weak disposability of undesirable outputs, and null-jointness assumptions (Färe and Grosskopf, 2006). In addition, T is also assumed to be a closed and bounded set, indicating that a finite amount of inputs can only produce a finite amount of outputs (Färe et al., 1989). According to Battese et al. (2004) and O'Donnell et al. (2008), meta-frontier technology is further defined by incorporating all group-frontier technologies. Suppose there are *H* groups, the meta-frontier technology can be expressed as follow.

$$T^M = \{T^{G1} \cup T^{G2} \cup \cdots T^{GH}\} \tag{2}$$

Because there are provincial diversities in socio-economic development, technology heterogeneities among regions are thought to exist and are significant (Du et al., 2014). The same production frontier constructed by all provinces cannot accurately reflect the technological differences among different regions. Therefore, the 30 provinces are divided into four groups according to the National Bureau of Statistics of China, namely Eastern region, Central region, Western region, and Northeast region (**Table A.1**). The production frontier of each group can be expressed as T^G, while the production frontier that envelops these four groups can be expressed as T^M. Due to different industries using various focus of technology during the production process, secondary and tertiary industries are assumed to have different meta-frontier technology, and each of them envelops their own group-frontier technologies, as shown in **Fig. A.1**.

2.1.2. Potential emission efficiency under group- and meta-frontier technologies

A formal definition of NDDF with undesirable outputs was proposed by Zhou et al. (2012). Following Zhou et al. (2012), the NDDF can be expressed as:

$$\overrightarrow{ND}(K,L,E,Y,C;g) = \sup\{w^T\beta : (K,L,E,Y,C+g\times \mathrm{diag}(\beta)) \in T\} \tag{3}$$

$w = (w_K, w_L, w_E, w_Y, w_c)^T$ is the normalized weight vector, which was set as (1/9,1/9,1/9,1/3,1/3). $g = (-g_K, -g_L, -g_E, g_Y - g_C)$ indicates the directional vector. The negative symbol in *g* indicates decreasing direction (good outputs), while the positive symbol indicates increasing direction (inputs and bad outputs). The symbol *diag* means the diagonal matrices, and $\beta = (\beta_K, \beta_L, \beta_E, \beta_Y,\ \beta_C) \geq 0$ is the scaling factor used to describe the inefficiency of inputs and outputs.

The NDDF of a group can be denoted as $\overrightarrow{ND}^G(K,L,E,Y,C;g)$ and the value for $\overrightarrow{ND}^G(K,L,E,Y,C;g)$ can be obtained following equation (4) (Zhou et al., 2012):

$$\overrightarrow{ND}^G(K,L,E,Y,C;g) = \max\ w_K\beta_K^G + w_L\beta_L^G + w_E\beta_E^G + w_Y\beta_Y^G + w_C\beta_C^G,$$

$$s.t.\quad \sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t K_n^t \leq (1-\beta_K^G)K\ ,$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t L_n^t \leq (1-\beta_L^G)L\ ,$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t E_n^t \leq (1-\beta_E^G)E\ ,$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t Y_n^t \geq (1+\beta_Y^G)Y\ ,$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t C_n^t = (1-\beta_C^G)C\ ,$$

$$\lambda_n^t \geq 0,\ \ \beta_Y^G \geq 0,\ \ 0 \leq \beta_K^G,\ \beta_L^G,\ \ \beta_E^G,\ \beta_C^G < 1,\ \mathrm{t} = 1,2,\ \ldots\mathrm{T},\ \ n = 1,2,\ldots N, h = 1,2,\ldots,H \tag{4}$$

where K_n^t indicates capital stock of *n* province in *t* period. N^h indicates N DUMs in group *h*. Based on Kuosmanen (2005) and Podinovski and Kuosmanen (2011), the production technology was set to be constant returns to scale ($\lambda_n^t \geq 0$). PEI_i^G is used to represent potential emission intensity under the group-frontier technology of *i* industry, as follows:

$$PEI_i^G = \frac{(1-\beta_C^G)C}{(1+\beta_Y^G)Y} \tag{5}$$

Meta-frontier NDDF is denoted as $\overrightarrow{ND}^M(K,L,E,Y,C;g)$. Following Cheng et al. (2018b), The value for $\overrightarrow{ND}^M(K,L,E,Y,C;g)$ can be obtained as follows:

$$\overrightarrow{ND}^M(K,L,E,Y,C;g) = \max\ w_K\beta_K^M + w_L\beta_L^M + w_E\beta_E^M + w_Y\beta_Y^M + w_C\beta_C^M$$

$$s.t.\quad \sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t K_n^t \leq (1-\beta_K^M)(1-\beta_K^G)K\ ,$$

$$\sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t L_n^t \leq (1-\beta_L^M)(1-\beta_L^G)L\ ,$$

$$\sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t E_n^t \leq (1-\beta_E^M)(1-\beta_E^G)E\ ,$$

$$\sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t Y_n^t \geq (1+\beta_Y^M)(1+\beta_Y^G)Y\ ,$$

$$\sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{n=1}^{N^h}\lambda_n^t C_n^t = (1-\beta_C^M)(1-\beta_C^G)C\ ,$$

$$\lambda_n^t \geq 0,\ \beta_Y^M \geq 0,\ \ 0 \leq \beta_K^M,\ \beta_L^M,\ \ \beta_E^M,\ \beta_C^M < 1,\ \mathrm{t} = 1,2,\ \ldots\mathrm{T},\ \ n = 1,2,\ldots,\mathrm{N},\ h = 1,2,\ldots,H \tag{6}$$

The production technology is assumed to exhibit constant returns to scale by setting $\lambda_n^t \geq 0$ (Kuosmanen, 2005; Podinovski and Kuosmanen, 2011).

PEI_i^M is used to represent potential emission intensity of *i* industry under meta-frontier technology, as follows:

$$PEI_i^M = \frac{\left(1-\beta_C^M\right)\left(1-\beta_C^G\right)C}{\left(1+\beta_Y^M\right)\left(1+\beta_Y^G\right)Y} \tag{7}$$

When PEI_i^G or PEI_i^M becomes lower, it indicates CO_2 emission efficiency improvement because a DMU can produce less CO_2 emissions per unit of GDP.

2.2. Framework of reduction potential scenario analysis

In this subsection, a framework is proposed to obtain the reduction potential under different scenarios by economic structure change and CO_2 emission efficiency improvement as well as the feasibility of achieving the reduction potential. As shown in **Fig. 1**, the design of appropriate scenarios includes three components, baseline, CO_2 emission efficiency change, and economic structure change. The first component, baseline, is the level used for comparisons with the emissions under a range of scenarios. The second component, efficiency change, can be divided into two phases and is obtained through the DEA method shown in section 2.1. The third component, economic structure change, can be designed based on the economic structure of an economic entity in the future. Based on this framework, potential changes in CO_2 emissions (PCE) and potential changes in emission intensity (PCEI) can be evaluated. An indicator is also proposed to measure the technical feasibility of reducing CO_2 emissions (TFRE). In the following paragraphs, the derivation processes of PCE, PCEI, and TFRE are presented.

The first part of the scenario analysis framework is to evaluate the reduction potential of emission intensity. Emission intensity indicates CO_2 emissions per unit of GDP. In this study, two driving factors of emission intensity are considered, including industry structure and CO_2 emission efficiency. Here, CO_2 emission efficiency indicates CO_2 emissions per unit of GDP of a specific industry. When an industry improves its emission efficiency, it suggests this industry can produce less CO_2 emissions per unit of GDP. Therefore, *AEI*, *PEI*, and *PCEI* can be obtained following equations (8), (9), and (10), respectively. In the case where the industry structure is the only factor that changes and the emission intensity of all industries is the same, the overall emission intensity will remain unchanged ($PCEI = 0$).

$$AEI = \sum_{i=1}^{n} AIS_i \times AEI_i, \quad \sum_{i=1}^{n} PIS_i = 1 \tag{8}$$

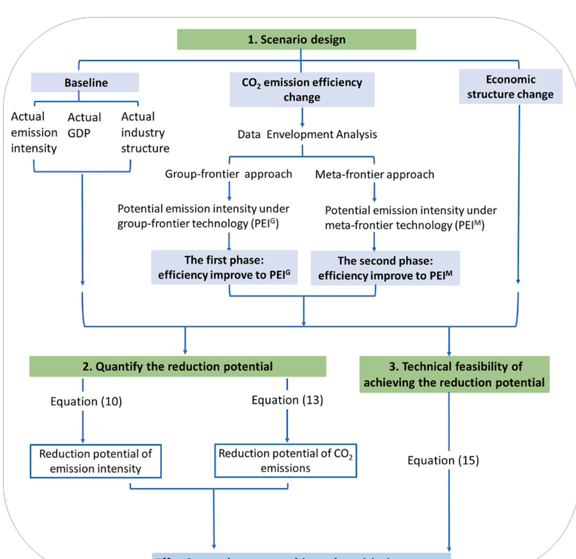

Fig. 1. The framework of CO2 emission reduction potential scenario analysis.

$$PEI = \sum_{i=1}^{n} PIS_i \times PEI_i, \quad \sum_{i=1}^{n} AIS_i = 1 \tag{9}$$

$$PCEI = AEI - PEI = \sum_{i=1}^{n} (AIS_i \times AEI_i - PIS_i \times PEI_i) \tag{10}$$

where i refers to industry. AIS_i and PIS_i indicate actual and potential industry structure of i industry (the ratio of value added of i industry to total GDP), respectively. AEI_i and PEI_i indicate actual and potential emission intensity, respectively. The improvement of AEI_i can be divided into two phases. The first phase is improving to PEI_i^G, while the second phase is further improving to PEI_i^M ($PEI_i^G \geq PEI_i^M$), as shown in Fig.1. PEI_i^G and PEI_i^M can be obtained based on equations (5) and (7), respectively.

The second part of the scenario analysis framework is to evaluate the reduction potential of CO_2 emissions. Three driving factors of emissions are considered, including GDP, industry structure, and CO_2 emission efficiency. Based on these three factors, actual CO_2 emissions (*AE*), potential CO_2 emissions (*PE*) and *PCE*[1] can be obtained by calculating the equations (11), (12), and (13), respectively. Similarly, AEI_i can be first improved to PEI_i^G, and then improved to PEI_i^M ($PEI_i^G \geq PEI_i^M$), as shown in Fig.1.

$$AE = AGDP \times \sum_{i=1}^{n} AIS_i \times AEI_i, \quad \sum_{i=1}^{n} AIS_i = 1 \tag{11}$$

$$PE = PGDP \times \sum_{i=1}^{n} PIS_i \times PEI_i, \quad \sum_{i=1}^{n} PIS_i = 1 \tag{12}$$

$$PCE = AE - PE = AGDP \times \sum_{i=1}^{n} AIS_i \times AEI_i - PGDP \times \sum_{i=1}^{n} PIS_i \times PEI_i \tag{13}$$

An important contribution of this study is in proposing an indicator (*TFRE*) to measure the degree of difficulty in achieving the reduction potential, as shown in equation (16). Even with the knowledge of the reduction potential under a variety of scenarios for mitigating emissions, the technical feasibility of reducing CO_2 emissions can be different among the provinces because of significant regional diversities in technology levels. Many studies have found that technological diffusion can be an important channel to facilitate the achievement of a low-carbon economy (Danish et al., 2018; Jiang et al., 1998). The costs, attenuation patterns, and time for technology diffusion can be affected by the spatial and economic distance. A province is more likely to learn low-carbon technology from a province geographically and economically close to it (Li et al., 2019; Wang et al., 2018). Therefore, the reduction potential under group-frontier technology is easier to achieve by catching up with the best performers within this group. This kind of reduction potential is attributed to managerial inefficiency and is defined as managerial reduction potential (*MRP*), as shown in equation (15). The managerial inefficiency suggest the difference between currently available technology for a DMU and the technology available for the corresponding group (Battese and Rao, 2002). In comparison, potential CO_2 emissions caused by technology gaps among groups take more time and effort to be reduced since the technology diffusion is more difficult. Potential CO_2 emissions caused by technology gaps are defined as technological reduction potential (*TRP*), as shown in

[1] PE can be larger, the same as, or smaller than AE. In some cases, such as the introduction of backward technology and development of heavy manufacturing, may hinder the improvement of emission efficiency and industry structure adjustment towards low-carbon industries, and further lead to higher potential CO_2 emissions. Once PCE is negative, it indicates CO_2 emissions have the potential to increase instead of decrease.

equation (14). The technology gaps indicate the difference between available technology for a specific group and the technology available for all groups (Battese and Rao, 2002). The share of *TRP* in the maximum reduction potential is defined as *TFRE*. The maximum reduction potential indicates the total reduction potential when all industries adopt the most advanced low-carbon technology (PEI_i^M), which is equal to the summation of *TRP* and *MRP*, as shown in equation (16). *TFRE* ranges from 0 to 1. The higher *TFRE* is, the more difficult is to decrease CO_2 emissions.

$$TRP = GDP \times \sum_{i=1}^{n} IS_i \times \left(PEI_i^G - PEI_i^M\right), \quad \sum_{i=1}^{n} IS_i = 1 \tag{14}$$

$$MRP = GDP \times \sum_{i=1}^{n} IS_i \times \left(AEI_i - PEI_i^G\right), \quad \sum_{i=1}^{n} IS_i = 1 \tag{15}$$

$$TFRE = \frac{TRP}{TRP + MRP} = \begin{cases} \dfrac{\sum_{i=1}^{n} IS_i \times \left(PEI_i^G - PEI_i^M\right)}{\sum_{i=1}^{n} IS_i \times \left(AEI_i - PEI_i^M\right)}, & \sum_{i=1}^{n} IS_i \times \left(AEI_i - PEI_i^M\right) \neq 0 \\ 0, & \sum_{i=1}^{n} IS_i \times \left(AEI_i - PEI_i^M\right) = 0 \end{cases} \tag{16}$$

where PEI_i^G and PEI_i^M are obtained based on equations (5) and (7), respectively. IS_i indicate industry structure and can be AIS_i or PIS_i. If the study focuses on *TFRE* under an actual situation, AIS_i will be chosen. In the condition that $\sum_{i=1}^{n} IS_i \times (AEI_i - PEI_i^M) = 0$, all industries are located on the meta-frontier technology, indicating there is no reduction potential and $TFRE = 0$.

$$TFRE = \frac{TRP}{TRP + MRP} = \begin{cases} \dfrac{PEI^G - PEI^M}{AEI - PEI^M}, & AEI - PEI^M \neq 0 \\ 0, & AEI - PEI^M = 0 \end{cases} \tag{17}$$

In the case where all industries are treated as a completed economy entity, *TFRE* shown in equation (16) can be simplified to equation (17).

2.3. Variables selection and data sources

Various kinds of inputs and outputs can be chosen when evaluating environmental efficiency. For example, labour, capital, land, fossil fuel, renewable energy, and water can be selected as inputs, while GDP, CO_2 emissions, SO_2 emissions, and solid waste, can be treated as outputs. The selection of inputs and outputs primarily depends on the focus of the study. To evaluate eco-efficiency, Zhang et al. (2008) used water resource, raw mining resource, and energy as inputs and three kinds of water pollutants, three kinds of solid pollutants and value-added of industry as outputs. To evaluate the green growth efficiency, Zhao and Yang, (2017) chose employment, built-up areas, water, electricity, and fixed asset investment as inputs and a series of variables as outputs, such as GDP, SO_2 emissions, and $PM_{2.5}$. Zhou et al. (2012) evaluated the energy and CO_2 emission performance in electricity generation by using fossil fuel as input and electricity, heat, and CO_2 emissions as outputs. Since this study shed light on the evaluation of CO_2 emission efficiency and reduction potential, the same as Li and Lin (2015), Wang et al. (2013), and Du et al. 2014), the variables which have greater impacts on the evaluation were chosen; they are three inputs (labour, capital stock, and energy), one desirable output variable (GDP) and one bad output variable (CO_2 emissions).

The CO_2 emission calculation method used here has been introduced in our previous study (Shan et al., 2018b) and only the significant steps are shown here. CO_2 emissions can be considered in two parts: energy- and process-related emissions. Energy-related emissions are a result of 17 types of fossil fuel combustion from 45 sectors (**Table A.2**), while process-related emissions are generated because of chemical reactions during the production process.

Energy-related CO_2 emissions:

$$C_{mj} = \sum_{m=1}^{17} \sum_{j=1}^{45} AD_{mj} \times NCV_m \times CC_m \times O_{mj} \tag{18}$$

where C_{mj} represents CO_2 emissions. *m* and *j* indicate fuel types and sectors, respectively. AD_{mj} indicates the amount of fossil fuel consumption, NCV_m, CC_m, and O_{mj} are the net caloric value, carbon content per calorie, and the carbon oxidation ratio, respectively. The emission factors are collected from Liu et al. (2015).

Process-related CO_2 emissions:

$$C_{process} = \sum_{z} AD_z \times EF_z\ ,\ z \in [1, 9] \tag{19}$$

where $C_{process}$ indicates CO_2 emissions from nine main industrial processes (Shan et al., 2018b), and *z* refers to an industrial process. AD_z indicates activity data. EF_z is the emission factor, as per Liu et al. (2015). Process-related CO_2 emissions are part of the emissions in secondary industry (**Table A.2**).

Energy consumption data were sourced from the China Energy Statistical Yearbooks and each province's statistical yearbooks, which were transformed into standard coal equivalents. Employed persons and GDP were taken from the China Statistical Yearbooks. Capital stock was estimated using the perpetual inventory method, as follows:

$$K_t = I_t + (1 - \delta)K_{t-1} \tag{20}$$

K_t, I_t and δ represent the capital stock, investment in fixed assets, and depreciation rate at period *t*, respectively. K_{t-1} refers to the capital stock in period $t-1$. The investment in fixed assets data was obtained from the China Statistical Yearbooks. Zhang (2008) suggested a depreciation rate at 9.6%, which has been widely adopted by many studies in the provincial capital analysis (Cheng et al., 2018a; Long et al., 2015; Meng et al., 2016). This study also used the depreciation rate given in Zhang (2008). The monetary variables were all converted into 2004 constant prices.

3. Design of scenarios

Based on the scenario analysis framework shown in section 2.2, eight scenarios are designed to investigate the mitigation effects of economic structure adjustment shifting from secondary industry towards tertiary industry and these two industries' emission efficiency improvement (**Table 1**). The baseline of the designed scenarios is CO_2 emissions/emission intensity in the year 2017. Scenarios A1 and A2 were designed to explore reduction potential via economic structure adjustment. Under scenarios A1 and A2, the emission efficiency is considered to be unchanged, that is $AEI_i = PEI_i$. Scenario A1 aims to explore the mitigation impacts of marginal change (1%) of economic structure adjustment in shifting from secondary industry towards tertiary industry. Scenario A2 is designed to provide greater predictability for the CO_2 emission reduction potential when China has reached a higher level of urbanization and industrialization.

Besides economic structure adjustment, CO_2 emission efficiency improvement is another significant factor that helps to mitigate CO_2 emissions (Guan et al., 2014, 2008; Xiao et al., 2019). Scenarios B1, B2, and B3 are designed to explore CO_2 emission reduction potential through efficiency improvement. Under scenarios B1, B2, and B3, the

[2] According to the World Bank, high-income economies are those in which 2017 gross national income per capita was US$12,055 or more. The share of the value added of tertiary industry to GDP of high-income economies in 2017 was 67.20% (constant 2010 US$), while the figure for secondary industry was 23.17%. China is categorized as an upper middle-income country.

Table 1
Description of the eight scenarios.[2]

	Secondary industry	Tertiary industry
Baseline	CO_2 emissions or emission intensity of secondary industry in 2017	CO_2 emissions or emission intensity of tertiary industry in 2017
Economic structure change		
Scenario A1	Decrease the share of the value added of secondary industry by 1%	Increase the share of the value added of tertiary industry by 1%
Scenario A2	Both industries: adjust economic structure to the level of high-income economics.	
CO_2 emission efficiency improvement		
Scenario B1	Both industries: improve efficiency by 1%	
Scenario B2	Both industries: improve efficiency to the best-practice of group-frontier technology (PEI_i^G)	
Scenario B3	Both industries: improve efficiency to the best-practice of meta-frontier technology (PEI_i^M)	
Combination of economic structure adjustment and CO_2 emission efficiency improvement		
Scenario C1	Both industries: a combination of scenarios A1 and B1	
Scenario C2	Both industries: a combination of scenarios A2 and B2	
Scenario C3	Both industries: a combination of scenarios A2 and B3	

economic structure is assumed to be unchanged, that is $AIS_i = PIS_i$. Scenario B1 is designed to describe the marginal change (1%) of CO_2 emission efficiency. The best-practice of group-frontier technology mentioned in scenario B2 indicates the theoretical largest CO_2 emission efficiency improvement within a group (PEI_i^G) (Li and Lin, 2015). After reaching the group frontier, the DMU can further move towards the best practice of the meta-frontier, that is scenario B3. To be noticed, the largest CO_2 emission efficiency improvement is based on the most advanced production technology currently available in China. It is not permanently fixed, and future technology innovation can create further improvement.

Scenarios C1-C3 are presented to examine their combined effects. Scenario C3 is the most challenging integrated strategy, indicating a significant increase in the tertiary industry share to high-income economics' level and adoption of the most advanced technology. In these eight scenarios, the amount of CO_2 emissions produced in the primary industry is assumed to be unchanged. One reason is that this study mainly focuses on the economic structure adjustment shifting from the secondary industry to the tertiary industry and their emission efficiency improvement. Another reason is that the emissions from primary industry are very small, representing only 1.10 % of total CO_2 emissions in 2017 (Shan et al., 2020). GDP in 2017 is used as the reference year, as shown in the baseline described in Table 1, indicating that the designed scenarios measure the reduction potential of CO_2 emissions by producing the same amount of GDP ($PGDP = AGDP$).

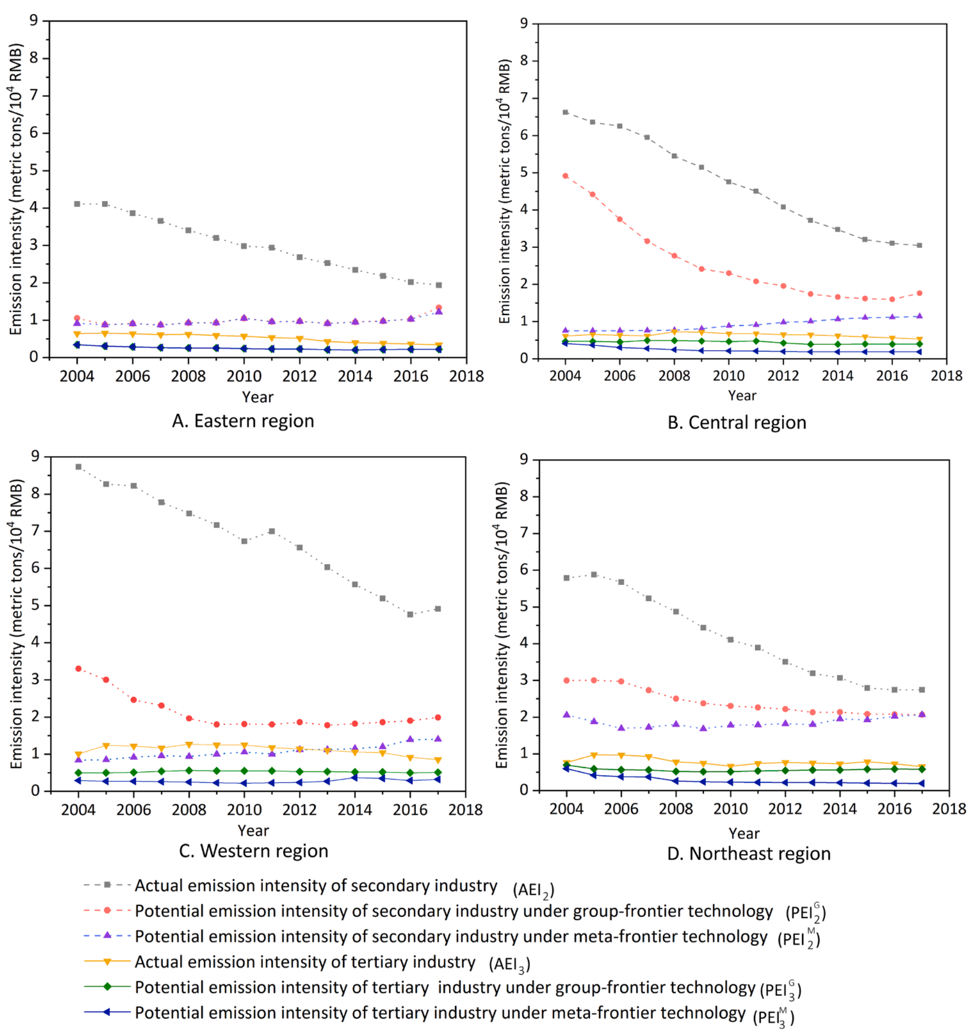

Fig. 2. The emission efficiency of secondary and tertiary industries of four regions in China, 2004-2017.

4. Results

4.1. CO_2 emission efficiency of secondary and tertiary industries

Fig.2. compares *AEI* with PEI^G and PEI^M of secondary and tertiary industries of China's four regions during 2004-2017. Compared with the secondary industry, the tertiary industry's *AEI* of all four regions were lower than that of the secondary industry, indicating the tertiary industry was more efficient and low-carbon friendly, which is consistent with Xiao et al. (2019) and Feng et al. (2017). It was also proved that shifting the industry from the secondary industry to the tertiary industry helps to reduce CO_2 emissions. Also, there was a large difference in emission intensity between secondary and tertiary industries, which further proved that it is more rational to consider that these two industries have their own meta-frontier technology, as shown in **Fig. A1**.

For the situation of secondary industry, AEI_2 was the largest one among the three indexes. AEI_2 can be reduced to the level of PEI_2^G were it to adopt the best practices within the group. PEI_2^M was the smallest because all group-frontier technologies are enveloped by meta-frontier technology. For AEI_2, the eastern region had the lowest level and saw a significant decrease from 4.10 tonnes /10^4 RMB in 2004 to a mere 1.94 tonnes /10^4 RMB in 2017 (**Fig.2**). It is noticeable that the overlap of the red dotted line and the purple dotted line indicates the level of PEI_2^G was almost the same as PEI_2^M for the eastern region (**Fig.2**). This overlap suggests that the production technology of secondary industry within the eastern region was at the forefront of such practices in China. By contrast, the western region saw the highest AEI_2 in 2017, at 4.91 tonnes /10^4 RMB (**Fig.2**). For the tertiary industry, the eastern region's AEI_3 was the most efficient in CO_2 emissions over the study period, showing a decrease from 0.64 tonnes /10^4 RMB in 2004 to 0.34 tonnes /10^4 RMB in 2017 (**Fig.2**). It is noticeable that the level of PEI_3^G was almost the same as PEI_3^M for the eastern region, suggesting that the technology of the tertiary industry in the eastern region can almost represent the meta-frontier technology.

4.2. Reduction potential of emission intensity and CO_2 emissions

The central government seeks to reduce the national CO_2 emission intensity by 60 to 65% by 2030 compared with the 2005 level (The Chinese Government, 2015). **Table 2** illustrates the reduction potential of the emission intensity under eight scenarios that explore possible intensity mitigation situations. By 2017, China had reduced its emission intensity by around 39.44% compared with the levels of 2005 (**Table 2**). This reduction shows the positive effects of the government's reforms and environmental regulations on CO_2 emission abatement. However, more efforts should still be taken to further reduce the emission intensity to achieve the mitigation target.

From the perspective of economic structure adjustment, if China's economic structure shifts from the secondary to the tertiary industry by 1%, China's emission intensity can be reduced by 1.56% (**Table 2; Scenario A1**). If China's economic structure is adjusted to the level of high-income economies, the emission intensity will be reduced by 0.695 tonnes/10^4 RMB (40.10%) compared with 2017 levels, which is 63.74% lower compared with the 2005 level (**Table 2; Scenario A2**). In regard to CO_2 emission efficiency improvement, a 1% increase in CO_2 emission efficiency of secondary and tertiary industries can bring about a 0.017 (0.98%) decrease in national emission intensity compared with 2017 levels (**Table 2; Scenario B1**). If China only relies on CO_2 emission efficiency improvement to the best-practice level of group-frontier, national emission intensity can be reduced to a relatively low level, at 1.154 tonnes/10^4 RMB (**Table 2; Scenario B2**). The emission intensity under meta-frontier technology is 0.895 tonnes/10^4 RMB, indicating that China could further improve emission intensity by 0.259 tonnes/10^4 RMB were it to replace the group-frontier technology with the meta-frontier technology (**Table 2; Scenario B2; Scenario B3**).

Under scenario C2, emission intensity can be reduced by approximately 75.15% compared with the 2005 level (**Table 2**). To realize the blueprint of scenario C2, the Chinese government should not only significantly promote the development of the service industry to the level of high-income economies but enable all provinces to catch up with the best performer within their corresponding regions. Under scenario C3, emission intensity can be 81.39% lower than that in 2005 (**Table 2**). In this case, China's economic structure should be adjusted to the level of high-income economies and the most advanced technology should be adopted by all provinces.

Fig. 3 shows the national reduction potential in CO_2 emissions under the eight scenarios. The results are presented relative to a baseline of current emissions from China's secondary industry (7815.27 Mt) and tertiary industry (975.75 Mt) in 2017, at 8893.55 Mt in total (including primary industry) (**Fig.3**). The reduced emissions under scenario A1 can reach 140.17 Mt (**Fig.3**). This indicates that a 1% increase in the share of the value added of the tertiary industry from the secondary industry results in around 1.58% decrease in CO_2 emissions in China (**Fig.3; Scenario A1**). Carbon neutrality indicates net-zero CO_2 emissions which can be achieved by generating fewer emissions or removed emissions from the atmosphere with numerous technologies, such as carbon capture, utilisation, and storage (CCUS) technologies. Economic structure change and emission efficiency can both contribute to generating fewer CO_2 emissions, which can help to reduce the burden through carbon offsetting. China's CO_2 emissions can be reduced by 3567.97 Mt (40.12%) in total if China's economic structure is the same as that of high-income economies (**Fig. 3; Scenario A2**), indicating that the remaining 5325.58 Mt of emissions should be balanced out. For scenario B2, the reduction potential of CO_2 emissions is on average 99.02 Mt for each province (30 provinces are included in this study), and 2970.64 Mt

Table 2
Reduction Potential of emission intensity under eight scenarios of China.

Category	Scenario	Emission intensity (tonnes/10^4 RMB)	The reduction compared with the emission intensity in 2005 (%)
Actual emission intensity in 2005		2.861	
Baseline		1.733	-39.44
Economic structure adjustment	A1	1.706	-40.40
	A2	1.038	-63.74
CO_2 emission efficiency improvement	B1	1.716	-40.04
	B2	1.154	-59.67
	B3	0.895	-68.73
Combination of both	C1	1.689	-40.99
	C2	0.711	-75.15
	C3	0.532	-81.39

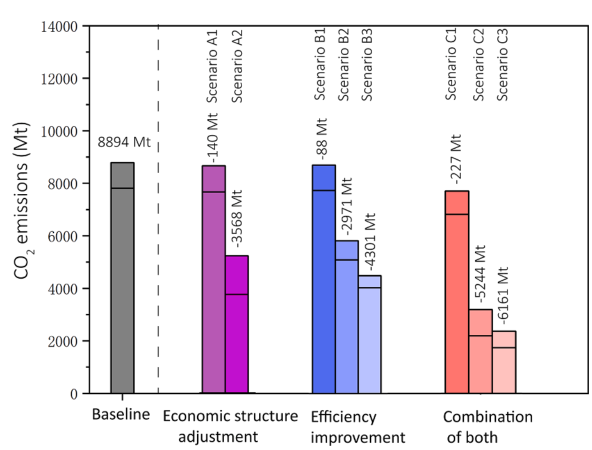

Fig. 3. Reduction potential of CO_2 emissions under eight scenarios of China. The bottom part of the stacked bar indicates CO_2 emissions emitted from the secondary industry, while the top of the stacked bar means emissions produced from the tertiary industry.

for the whole country (**Fig.3**). For scenario B3, CO_2 emissions can be reduced by 143.38 Mt for each province, and 4301.38 Mt for the whole country (**Fig.3**).

Under scenario C2, to achieve net-zero CO_2 emissions, 5243.76 Mt of CO_2 emissions can be less generated for the whole country and the remaining 3649.79 Mt of CO_2 emissions should be balanced out. For each province, the reduction potential of CO_2 emissions is on average 174.79 Mt, and 121.66 Mt of CO_2 emissions should be offset with negative emission technologies (Fig. 3**; Scenario C2**). According to the results under scenario C3, this study has a preliminary estimate that emission reduction potential can reach 6161.16 Mt if China's economic structure can be adjusted to the level of high-income economies, and all provinces are brought up to the best-practice level of meta-frontier (**Fig.3**). To achieve carbon neutrality, scenario C3 also shows that the remaining 2732.40 Mt of CO_2 emissions should be balanced out. These findings help quantify the deployment of CCUS technologies in China which are important measures for balancing out the human-driven emissions.

Under scenario C1, the reduction potential of CO_2 emissions can be 221.07 Mt. It was observed that the reduction potential of integrated scenario C1 (226.68 Mt) is smaller than the sum of individual effects from scenario A1 (140.17 Mt) and scenario B1 (87.91 Mt). Also, scenarios C2 and C3 show a similar situation, which can be interpreted that the CO_2 emission reduction caused by efficiency improvement can be offset partially by the economic structure shifting from secondary towards the tertiary industry. Taking an extreme example, if an economic entity, which only has the secondary industry, transfers all the value added of secondary industry to that of tertiary industry, the reduction potential of the secondary industry will be transformed into that of the tertiary industry. Since the reduction potential of the tertiary industry is generally smaller than that of the secondary industry, as shown in **Fig.3**, the reduction potential of this economy entity will become smaller. It also provides practical implications when predicting the reduction potential that simple summation of individual measures may lead to an inaccurate estimate of the reduction potential. In the case of scenario C3, the estimation gap between the actual effects (6161.16 Mt) and the summation effects (7869.35 Mt) reach 1708.19 Mt or 19.21% of total CO_2 emissions.

The comparisons of the mitigation effects of CO_2 emissions under different scenarios of the 30 provinces can be found in **Table 3**. The mitigation effects indicate the potential reduction level in CO_2 emissions compared to 2017 levels under a specific scenario. For better comparison, the mitigation effect has been standardized on a scale of 0 to 1 using the min-max normalization method (Jain et al., 2005). The stronger the mitigation effects are , the more effective a specific scenario is for this province. Since the economic structure change strategies of different provinces vary, in this part, only scenarios A1, B1, B2, B3, and C1 are applied to calculate provincial reduction potential (**Table 3**). The mitigation effects of economic structure change and CO_2 efficiency improvement differ significantly among provinces. For example, economic structure change is an effective strategy for Hebei, which is China's largest iron and steel producer, generating up to 23.67% of the national output of crude steel in 2017 . A 1% increase in the tertiary industry share of Hebei can cut down a substantial amount of CO_2 emissions, decreasing by 11.19 Mt, or 1.63% of total emissions, while the mitigation effect of economic structure change for Beijing, the capital of China, is very small (0.45 Mt or 0.66%). (**Table 3; Scenario A1**). For emission efficiency improvement strategies, Hebei and Beijing can mitigate a similar percentage of CO_2 emissions (around 28%) under scenario B3, while Beijing is much easier to achieve this reduction potential based on TFRE shown in **Fig. 4**. It can be summarized that manufacturing-based and less-developed regions rely more on economic structure change to reduce CO_2 emissions. More affluent regions should focus more on technological innovation to improve emission efficiency, and further provide technological support for the whole country. Another example to support this finding is the comparison between

Table 3
Comparisons of CO_2 emissions (Mt) and mitigation effects of 30 provinces under five scenarios.

Province	Baseline	Scenario A1		Scenario B1		Scenario B2		Scenario B3		Scenario C1	
	Emis.	Emis.	Miti. effect	Emis.	Miti. effect	Emis.	Miti. effect	Emis.	Miti. effect	Emis.	Miti. effect
Beijing	68.35	67.90	0.00	67.67	0.04	49.20	0.05	49.20	0.05	67.22	0.01
Tianjin	132.42	130.86	0.10	131.11	0.13	128.03	0.01	128.03	0.01	129.56	0.11
Hebei	685.96	674.77	1.00	679.17	0.88	677.81	0.02	490.58	0.49	668.09	1.00
Shanghai	177.42	175.88	0.10	175.66	0.19	177.42	0.00	177.42	0.00	174.13	0.14
Jiangsu	717.36	707.09	0.91	710.26	0.92	378.68	0.93	378.68	0.86	700.10	0.96
Zhejiang	364.41	358.90	0.47	360.85	0.44	189.34	0.48	189.34	0.44	355.39	0.48
Fujian	224.54	221.80	0.21	222.32	0.25	158.61	0.18	158.61	0.17	219.61	0.23
Shandong	774.94	765.04	0.88	767.27	1.00	503.70	0.74	503.70	0.69	757.47	0.98
Hainan	40.71	39.82	0.04	40.32	0.00	14.24	0.07	14.24	0.07	39.44	0.02
Guangdong	501.20	496.34	0.41	496.24	0.63	292.12	0.57	292.12	0.53	491.43	0.52
Henan	473.35	467.28	0.52	468.68	0.59	368.19	0.29	259.37	0.54	462.67	0.57
Anhui	355.54	351.12	0.37	352.03	0.43	354.35	0.00	160.79	0.49	347.65	0.41
Jiangxi	215.60	213.03	0.20	213.47	0.24	152.05	0.17	107.04	0.27	210.92	0.22
Hubei	305.45	302.65	0.22	302.47	0.36	298.53	0.02	199.57	0.27	299.69	0.28
Hunan	291.02	287.45	0.29	288.21	0.33	234.52	0.16	151.84	0.35	284.67	0.32
Shanxi	471.15	465.02	0.53	466.48	0.59	106.77	1.00	75.94	1.00	460.41	0.58
Sichuan	285.99	283.28	0.21	283.18	0.33	285.99	0.00	199.03	0.22	280.50	0.27
Chongqing	148.54	147.18	0.09	147.08	0.15	148.54	0.00	90.13	0.15	145.72	0.11
Guizhou	238.17	236.17	0.14	235.84	0.27	71.50	0.46	49.87	0.48	233.85	0.20
Yunnan	184.04	182.04	0.14	182.25	0.19	120.30	0.17	97.08	0.22	180.26	0.17
Shaanxi	250.43	247.06	0.27	247.94	0.29	129.72	0.33	91.51	0.40	244.61	0.29
Gansu	141.39	139.48	0.14	140.00	0.14	56.24	0.23	45.51	0.24	138.10	0.14
Qinghai	49.80	49.31	0.00	49.30	0.01	27.80	0.06	17.05	0.08	48.82	0.00
Ningxia	173.24	170.84	0.18	171.51	0.18	20.65	0.42	16.27	0.40	169.14	0.19
Xinjiang	389.48	383.20	0.54	385.66	0.47	79.21	0.85	56.58	0.84	379.44	0.54
Guangxi	214.76	211.94	0.22	212.64	0.24	168.07	0.13	97.17	0.30	209.84	0.23
Inner Mongolia	627.10	619.45	0.67	620.96	0.79	558.12	0.19	396.11	0.58	613.38	0.75
Liaoning	461.54	455.33	0.54	456.98	0.57	295.64	0.46	260.69	0.51	450.83	0.58
Jilin	197.88	195.41	0.19	195.94	0.21	159.24	0.11	144.20	0.14	193.49	0.20
Heilongjiang	259.15	257.04	0.15	256.68	0.28	245.73	0.04	221.88	0.09	254.59	0.21

Notes: 'Emis.' and 'miti. effect' indicate CO_2 emissions and mitigation effect, respectively.

Zhejiang and Guizhou, which can reduce a similar amount of CO_2 emissions, at 175.08 Mt and 188.30 Mt, respectively (Table 3**; Scenario A3)**. However, Zhejiang is much easier to achieve because the TFRE of Guizhou is 0.11 higher than that of Zhejiang (Fig. 4).

4.3. Technical feasibility of achieving reduction potential

Even with the knowledge of the reduction potential under a variety of scenarios, as shown in section 4.2, the technical feasibility of reducing the same amount of CO_2 emissions can vary significantly among provinces. **Fig. 4** shows the components of CO_2 emissions and TFRE of China and its 30 provinces. Since the dynamic changes of economic structure vary among 30 provinces, this study calculates TRP and TFRE based on equations (14) and (16) using the actual economic structure in 2017. The stacked bar indicates the components of CO_2 emissions. At the national level, 1059.40 Mt of the reduction potential of the secondary industry comes from TRP in 2017, while the figure for the tertiary industry was 271.35 Mt in (**Fig. 4**). To sum the TRP of secondary and service industries up, 1330.75 Mt of CO_2 emissions are caused by a regional technology gap, representing 14.96% of China's total emissions in 2017 (**Fig. 4**).

The scatter chart of **Fig.4** shows the TFRE of 30 provinces and China, which is represented by the triangle. Some provinces can reduce similar amounts of CO_2 emissions, but the technical feasibility of achieving the reduction potential is different. For example, Zhejiang and Anhui can reduce the CO_2 emissions by 175.08 Mt and 194.75 Mt, respectively, whereas for Anhui that is more difficult to achieve since the TFRE is equal to 0.99, while the figure for Zhejiang is 0.00. This difference indicates that mitigation targets should also consider the existence of TRP and more development space should be granted, and more efforts should be taken by the provinces, such as Anhui, with higher TFRE. The top five provinces where the TFRE is high are Sichuan (1.00), Chongqing (1.00), Anhui (0.99), Hebei (0.96), and Hubei (0.93). There are some provinces whose TFRE is zero, such as Shandong, Jiangsu, and Zhejiang, indicating these provinces can decrease the emissions without overcoming the technology gaps. This is because the group-frontier technology of these provinces is the same as the meta-frontier technology that covers all groups. In other words, they can achieve the reduction potential by just catching up with the best performer within the corresponding group. At the national level, the TFRE is 0.3094, which indicates that 30.94% of reduction potential are TRP. Some 69.06% of the reduction potential are relatively easier to achieve, however, if China wants to further cut down the 30.94% of the reduction potential, it needs to promote technology diffusion and narrow the technology gaps.

5. Conclusions

This study proposes a scenario analysis framework considering economic structure change and emission efficiency improvement simultaneously to calculate the CO_2 emission reduction potential and the technical feasibility of achieving the reduction potential. The CO_2 emission reduction capacities and achievement feasibility of China and the 30 provinces were then estimated under a range of scenarios.

The study finds that to achieve carbon neutrality, 6161.16 Mt of CO_2 emissions of China can be less generated compared to 2017 levels by significantly increasing the tertiary industry share to the levels of high-income economies and improving the emission efficiency to the best-practice level (Scenario C3); the remaining 2732.40 Mt of CO_2 emissions should be balanced out through carbon offsetting. Regarding emission intensity, 81.39% can be reduced compared with the 2005 level (Scenario C3). In regional heterogeneity analysis, economic structure change is a more effective measure for less-developed and manufacturing-based regions (e.g., Hebei) to reduce CO_2 emissions. More affluent regions (e.g., Beijing) should put more emphasis on technological innovation to improve emission efficiency, and further provide technological support for the whole country.

In addition, the technical feasibility of achieving the emission reduction potential varied significantly among the regions because of the large regional diversities in the levels of low-carbon technology. The top five provinces which have large technical barriers and require more effort in mitigating CO_2 emissions are Sichuan, Chongqing, Anhui, Hebei, and Hubei. China's TFRE was 0.3094, indicating 69.06% of the reduction potential was relatively straightforward to achieve. However, if China wants to further cut down the 30.94% of reduction potential, it needs to promote technology diffusion to narrow the technology gap among the regions.

Our empirical results have certain policy implications. First, to achieve carbon neutrality by 2060, rapid and large emission reductions from production and consumption activities and a ramping up of measures to remove CO_2 emissions from the atmosphere are the two main combination strategies to go net-zero for China. The reduction potential analysis under various pathways in this study provides a quantitative estimation of the emissions that can be less generated and the deployment of zero carbon and negative carbon technologies. Second, more

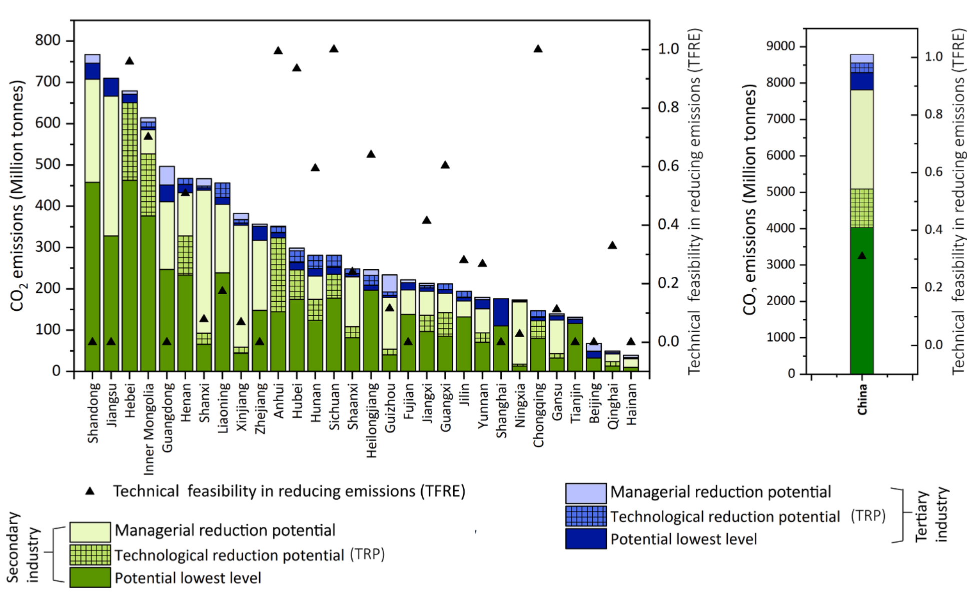

Fig. 4. Components of CO2 emissions and technical feasibility of reducing CO_2 emissions in 2017.

development space should be granted, and more efforts should be taken for the provinces with a higher level of TFRE to reduce CO_2 emissions, such as Sichuan, Chongqing, and Anhui. In addition, less-developed and manufacturing-based regions, such as Hebei, should put more emphasis on economic structure change. More affluent regions, such as Beijing, should focus more on technological innovation by strengthening scientific research and promoting the transformation of scientific and technological achievements. Lastly, it will be challenging for the provinces or the whole country to cut down CO_2 emissions with high TFRE, so narrowing the technology gaps among regions can be a solution to decrease TFRE. Advanced low-carbon technology should be adopted, not just locally but also in a wide spatial scope to cut down the technological reduction potential. There is an urgent need to establish an effective technology diffusion system to accelerate technology diffusion in a wider spatial scope.

This study has several limitations. Firstly, this study only includes secondary and tertiary industries for analysis. In future work, more socio-economic sectors can be included for an empirical study to detect the mitigation effect of economic structure adjustment and CO_2 emission efficiency improvement. Secondly, apart from industry structure adjustment and emission efficiency change, the business cycle can be a factor that affects CO_2 emissions, which can be included in future work.

CRediT authorship contribution statement

Huijuan Xiao: Conceptualization, Methodology, Data curation, Validation, Writing - original draft. **Ya Zhou:** Methodology, Validation, Writing - review & editing. **Ning Zhang:** Methodology. **Daoping Wang:** Methodology. **Yuli Shan:** Resources, Writing - review & editing. **Jingzheng Ren:** Writing - review & editing.

Declaration of Competing Interest

The authors declare no competing interests.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2021.105760.

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