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A modified and improved method to measure economy-wide carbon rebound effects based on the PDA-MMI approach

Ding Li[a], Ming Gao[b], Wenxuan Hou[c], Malin Song[d], Jiandong Chen[b*]

[a]Institute of Development Studies, Southwestern University of Finance and Economics, Chengdu, China

[b]School of Public Administration, Southwestern University of Finance and Economics, Chengdu, China

[c]University of Edinburgh Business School, University of Edinburgh, 29 Buccleuch Place, Edinburgh

[d]School of Statistics and Applied Mathematics, Anhui University of Finance and Economics, Bengbu, China

* Corresponding author. Email: jchen@swufe.edu.cn; Tel.: +86 13438025346

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Abstract: Although energy technological progress has been regarded as an important driver for reducing carbon emissions, the existence of carbon rebound effect prevents a portion of the potential carbon reductions to be realized. Compared with the energy rebound effect, research on the carbon rebound effect is scarce because it is always equated with the energy rebound effect. However, the carbon rebound effect is more complex. Given that the traditional method for carbon rebound effect assessment only reflects energy rebound effects, our study proposed an improved production-theoretical decomposition analysis (PDA)-Meta-frontier Malmquist index (MMI)-based method and explored carbon rebound effects in China from 2006 – 2015. Our results show that (1) the eastern and western regions faced fewer carbon rebound effect risks compared with those of the central region due to decreasing emission intensity associated with energy technological progress; (2) the reductions in emission intensity in the eastern region relied both on coal and non-coal technology, whereas the western region only relied on coal technology; and (3) the non-coal technology in the eastern region was at the meta-frontier, whereas the non-coal technology of other regions exhibited catch-up effects.

Keywords: carbon rebound; economic growth; technological progress; production-theoretical decomposition analysis

1. Introduction

With the rapid development of urbanization and industrialization around the world, several countries are facing a paradox between economic growth and carbon emission reductions (Liu et al., 2017; Cheng et al., 2018; Chen et al., 2019; Dubey et al., 2019). Given that many economic driving forces are also sources of carbon emissions, a focus on technology has become central to the research efforts of many countries, particularly as technological progress in energy has been widely regarded as an important factor in the reduction of carbon emissions worldwide (Liu et al., 2015; Zhang et al., 2016a; 2016b; Li et al., 2017a; Chen et al., 2019). However, many scholars have also pointed out that energy technological progress can also lead to increased carbon emissions due to the energy rebound effect (Yang et al., 2017a; Wu et al., 2018; Jin et al., 2019).

The energy rebound effect was first proposed by Khazzoom (1980) and Brookes (1990a, 1990b), and was described as a phenomenon whereby technological development not only leads to energy conservation but also leads to a decrease in the real cost of energy consumption and thus offset a part of potential energy savings. Moreover, since carbon emissions are strongly and positively related to energy consumption, the energy rebound effect can also impact carbon emissions and thus lead to carbon rebound effects (Brännlund, 2007; Druckman et al., 2011). In line with Druckman et al. (2011) and Yang et al. (2017), the definition of carbon rebound is similar to that of the energy rebound effect: a portion of the potential reduction in emissions is not attained due to the reduced effective price and cost of energy use caused by energy technological progress.

Although the increased energy price caused by energy technological progress can offset both potential energy savings and carbon reductions, carbon rebound effects cannot be equated with energy rebound effects, since the potential carbon reductions include not only the energy-saving effects derived from energy technological progress but also the impacts of emission intensity caused by different types of energy technological progress (Brännlund et al., 2007; Zhang et al., 2013; Wang and Wei., 2014; Li and Lin, 2016; Li et al., 2017a; Chen et al., 2019). Changes in emission intensity include the optimization of the energy consumption structure associated with energy technological progress (i.e., a decreasing proportion of high-emission energy use) and reductions in the carbon emission efficiency of particular energy types (Yang et al., 2017a). Therefore, a gap should be present between carbon and energy rebound effects, which help implement effective policies to reduce greenhouse gas emissions, and is also benefit the development of future studies in the field.

With regard to the existing literature, several studies have focused on assessing rebound effects from the time that this phenomenon was first described. Table 1 summarizes recent representative studies on carbon and energy rebound effects.

[Insert Table 1 here]

Based on a thorough literature review, we found that many studies have mainly focused on characterizing energy rebound effects, whereas research on carbon rebound effects is scarce. In turn, carbon rebound effect studies can be divided into two categories based on the rebound effect mechanism. The first category mainly focuses on estimating carbon rebound effects in particular areas from a microeconomic standpoint. The second category focuses on economy-wide carbon rebound effects on a macroeconomic level.

Regarding the first category, Brännlund et al. (2007) pointed out that Swedish household energy rebound effects significantly impacted carbon rebound effects. Further, they found that a 20% increase in household energy efficiency translated to an approximate 5% increase in carbon emissions. Similarly, Druckman et al. (2011) analyzed the carbon emissions and reductions of UK residents and confirmed the existence of carbon rebound effects, which amounted to approximately 34%. Zhang et al. (2017) implemented a two-stage almost ideal demand system (AIDS) model to estimate direct and indirect carbon rebound effects caused by provincial private vehicles in China from 2001 to 2012. They found that the direct carbon rebound effect dominated the total carbon rebound effect in most provinces.

As for the second category, research on economy-wide carbon rebound effects is very scarce. Yang et al. (2017) used an energy rebound effect framework to estimate regional carbon rebound effects in China (which excluded the impacts of emission intensity) and found that carbon rebound effects varied regionally, ranging from 10-60%. Based on a framework provided by Zhang et al. (2017), Wu et al. (2019) also calculated the regional carbon rebound effects in China by employing a combination of the data envelopment analysis (DEA) production model and sequential Malmquist-Luenberger index. The conclusions provided by Wu et al. (2019) also confirmed the existence of carbon rebound effects in China, and the results were similar to those of Zhang et al. (2017). Similarly, based on an integration of the logarithmic mean Divisia index (LMDI) and production-theoretical decomposition analysis (PDA), Yang et al. (2019) analyzed the driving forces of carbon emissions in China and estimated carbon rebound effects. However, their study also failed to account for the notable effects of emission intensity associated with technological progress.

In line with existing studies, we found that the current methods for carbon rebound effect calculation mainly derive from energy rebound effect estimation frameworks. The traditional methods for calculating energy rebound effects can successfully estimate potential and offset energy savings; however, they cannot reflect the impacts of either the energy consumption structure or carbon emission efficiency, which have been reported by several studies (Zwaan et al., 2002; Brännlund et al., 2007; Ma et al., 2008; Chen et al., 2020a). Given that carbon rebound effects include not only the energy-saving effects caused by technological progress but also the optimization of the energy consumption structure and reductions in carbon emission coefficients, the carbon rebound effects assessed by the traditional method may be largely similar to energy rebound effects, thus leading to inaccurate conclusions. Additionally, although several studies have calculated carbon rebound effects, few studies have analyzed the underlying mechanisms that lead to different regional results.

Therefore, this study proposes a modified and improved PDA-Meta-frontier Malmquist index (MMI)-based approach to assess economy-wide carbon rebound effects, which accounts for the effects of energy technological progress on emission intensity. Upon comparing carbon and energy rebound effects, we estimated the impacts of energy technological progress on emission intensity (i.e., the ratio of total carbon emissions to total energy consumption), which included the impacts of energy technological progress on the energy use structure and carbon emission efficiency. To further analyze the underlying mechanisms of energy technological progress on regional emission intensity, we divided total energy use into coal and non-coal technologies and combined the LMDI and PDA-MMI approaches to decompose the changes in emission intensity, after which we obtained the impacts of coal and non-coal technology on emission intensity and carbon rebound effects. Moreover, we further analyzed the regional catch-up effects of the coal and non-coal technological gaps on emission intensity and carbon rebound effects based on the group and global frontiers provided by the MMI method. Simultaneously, we focused on China as the research objective given that this nation is one of the largest carbon emitters worldwide (Dong et al., 2016; Chen et al, 2019; Cheng et al., 2018; Chen et al., 2020b). The results of this analysis may provide useful information and references for other countries with high carbon emissions.

Specifically, our study makes the following contributions: (1) We proposed a modified and improved PDA-MMI-based method to more accurately assess economy-wide carbon rebound effects, which overcomes the shortcomings of the traditional method and identifies the gap between energy and carbon rebound effects. (2) We further analyzed the mechanisms underlying how regional energy technological progress influences emission intensity and carbon rebound effects instead of only calculating carbon rebound effects. (3) Based on national and regional data from 2005-2015, we found that the eastern and western regions of China faced fewer risks of carbon rebound effects compared with those of the central region due to reduced emission intensity derived from technological development. (4) The reductions in emission intensity in the eastern region relied both on coal and non-coal technology, whereas those of the western region only relied on coal technology.

2. Methodology

This section of our study introduces the derivations of the traditional method to calculate economy-wide carbon rebound effects and points out the flaws of the traditional method, with the aim to provide more accurate policies for curbing carbon rebound effects. Next, this study proposes a modified and improved method to estimate carbon rebound effects, which overcomes the disadvantages of the traditional methods.

2.1. Traditional methods for economy-wide carbon rebound effect calculation

It is crucial to first introduce the traditional method for rebound effect measurement, including its origin and derivations. In line with the existing literature, the framework to calculate the economy-wide carbon rebound effect is derived from the method for energy rebound effect assessment (Yang et al., 2017a; Wu et al., 2018; Chen et al., 2019; Chen et al., 2020a, 2020b). The traditional formula to estimate economy-wide energy rebound effects is the following:

$$\mathrm{Re}^{t+1} = \frac{A^{t+1} \times (Y^{t+1} - Y^{t}) \times EI^{t+1}}{B^{t+1} \times (EI^{t} - EI^{t+1}) \times Y^{t}} \tag{1}$$

where Re^{t+1} represents the economy-wide energy rebound effects during period $t+1$; Y^{t+1} represents the economic output during period $t+1$; EI^{t+1} represents the energy intensity during period $t+1$; A^{t+1} represents the contribution rate of technological progress to economic output, which is always represented by the ratio of technological change rate to the output change rate (Lin et al., 2012; Li et al., 2016; Yang et al., 2017; Chen et al., 2020a); B^{t+1} represents the contribution rate of technological progress to potential energy savings caused by energy intensity, which is represented by the contribution of industrial energy intensity to energy intensity[1]. The numerator and denominator of Eq. (1) represent the increase in energy consumption through the technological progress output channels and the potential energy consumption savings associated with technological progress, respectively.

The traditional economy-wide approach to estimate the energy rebound effect has been widely accepted by several studies (Lin et al., 2012; Li et al., 2017b; Lin et al., 2017; Jin et al., 2019; Chen et al., 2020a), and some scholars further assessed carbon rebound effects based on the traditional method (Yang et al., 2017a; Wu et al., 2018; Cheng et al., 2018). The formula for economy-wide carbon rebound effect estimation

[1] Scholars always use the LMDI method to decompose the changes in energy intensity into the effects of industrial structure and industrial energy intensity and used the contribution of industrial energy intensity to represents B^{t+1}. The detailed formula can be found in Appendix A1.

is as follows:

$$C\mathrm{Re}^{t+1} = \frac{A^{t+1} \times (Y^{t+1} - Y^{t}) \times CI^{t+1}}{C^{t+1} \times (CI^{t} - CI^{t+1}) \times Y^{t}} \tag{2}$$

where $C\mathrm{Re}^{t+1}$ represents the economy-wide carbon rebound effects during period $t+1$; Y^{t+1} represents the economic output during period $t+1$; CI^{t+1} represents the energy intensity during period $t+1$; C^{t+1} represents the contribution rate of technological progress to the potential carbon reductions caused by carbon use intensity, which is represented by the contribution of the industrial energy intensity to carbon intensity[2].

This approach is not fundamentally different from the previous method for energy rebound effect assessment, except that energy intensity is replaced by carbon intensity. In fact, we consider this to be the major flaw of this carbon rebound effect calculation method. The denominator in Equation (2) reflects the direct effects of technological progress on energy savings and carbon reductions, which can be easily understood with Eq. (A1.3-4) provided in Appendix A1. However, technological progress can also have significant impacts on emission intensity (i.e., C/E; not to be confused with carbon intensity). Consistent with previous studies, technological progress reduces the proportion of fossil fuel (e.g., coal) consumption (Cheng et al., 2017; Chen et al., 2020a). Notably, the $C^{t+1} \times (CI^{t} - CI^{t+1}) \times Y^{t}$ calculation has the same meaning as the $B^{t+1} \times (EI^{t} - EI^{t+1}) \times Y^{t}$ calculation, since they both only consider the direct impacts of technological progress on energy. Therefore, based on the traditional method, the energy and carbon rebound effect results would be largely equal,

[2] Similar to the calculation of the contributions of technological progress to potential energy savings, the LMDI method is used to decompose the carbon intensity and obtain C^{t+1}. The detailed formula can be found in Appendix A1.

rendering the carbon rebound effect calculations questionable.

2.2. Revised and improved PDA-based method

According to the definition proposed by previous studies (Saunders, 2008; 2013; Jin et al., 2019), the energy rebound effect is derived from the elasticity of the energy service to energy efficiency, and can be calculated as follows:

$$\mathrm{Re} = \frac{\partial S \times h}{\partial h \times S} = \frac{\partial (hE) \times h}{\partial (hE) \times e} = \frac{\partial E \times h}{\partial h \times E} + 1 \tag{3}$$

where S represents the energy service; E represents the actual energy consumption under the effect of technological progress or energy efficiency; h represents the technological level or energy efficiency. Based on the definition of carbon rebound effects (Brännlund et al., 2007; Druckman et al., 2011), the formula to estimate carbon rebound effect can be obtained as follows:

$$C\,\mathrm{Re} = \frac{\partial C \times h}{\partial h \times C} + 1 \tag{4}$$

where c represents the actual carbon emission under the impacts of technological progress or energy efficiency.

Based on the principles of the economy-wide method for energy rebound effect calculation, deformations to Eq. (4) were made to obtain Eq. (5):

$$\begin{aligned} C\,\mathrm{Re}^{t+1} &= \frac{dc \times h}{dh \times c} + 1 = \frac{\Delta c^{t,t+1} \times h^{t}}{\Delta h^{t,t+1} \times C^{t}} + 1 = \frac{(AC^{t+1} - C^{t}) \times h^{t}}{(h^{t} - h^{t+1}) \times C^{t}} + 1 \\ &= \frac{AC^{t+1} \times h^{t} - C^{t} \times h^{t+1}}{(h^{t} - h^{t+1}) \times C^{t}} = \frac{\left(\frac{AC^{t+1}}{h^{t+1}} - \frac{C^{t}}{h^{t}}\right) \times h^{t+1}}{(h^{t} - h^{t+1}) \times \frac{C^{t}}{h^{t}}} \end{aligned} \tag{5}$$

where AC^{t} represents the actual and eventual carbon emissions after the reduction and rebound impacts of technological progress or energy efficiency. Here, a decrease in h reflects technological progress, which is similar to energy intensity and carbon intensity. Given that C^t represents carbon emissions under the impacts of technological progress, $\frac{AC^t}{h^t}$ reflects the potential carbon emissions in an economic context with regard to technological progress, whereas $\frac{C^t}{h^t}$ reflects the potential carbon emissions under a specific economic context without technological progress. It is worth mentioning that such principles originated from previous studies, which used the production-theoretical decomposition analysis (PDA) method to decompose the changes in carbon emissions (Wang et al., 2015; Wang et al., 2018).

Thus, $(\frac{AC^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$ represents the increased carbon emissions (or unrealized carbon reductions) caused by economic growth which was stimulated by technological progress. Moreover, $(h^t - h^{t+1}) \times \frac{C^t}{h^t}$ represents the potential carbon reductions caused by technological progress, which help overcome the shortcomings of the traditional method and reveal the gap between energy and carbon rebound effects, given that they reflect three key aspects in potential carbon reductions associated with technological development: (1) the energy-saving effects caused by energy technological progress; (2) energy consumption structure optimization caused by different types of energy technological progress; and (3) reductions in carbon emission coefficients. Given that the carbon emission estimation is mostly based on the method proposed by the Intergovernmental Panel on Climate Change (IPCC), yearly carbon emission coefficients remain unchanged. Therefore, the potential carbon reductions only include energy-saving effects and optimization of energy consumption structure optimization (i.e., the decreasing proportion of high-emission energy in total energy use).

Additionally, now that $\frac{AC^t}{h^t}$ accounted for both economic context and technological progress, $(\frac{AC^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$ can be replaced by $A^{t+1} \times (\frac{C^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$. Where A^{t+1} also represents the contribution rate of technological progress to economic output. $(\frac{C^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$ reflects the changes in carbon emission under different economic situations (i.e., carbon emissions at different production fronts). Hence, $A^{t+1} \times (\frac{C^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$ can also reflects the increased carbon emissions (or unrealized carbon reductions) caused by economic growth that was stimulated by technological progress. Moreover, we adopted the distance function to reflect the technological level, which has been implemented in many studies (Fan et al., 2015; Wang et al., 2015; 2018; Zhao et al., 2019). Therefore, the following equations for carbon and energy rebound effect assessment were obtained:

$$C\,\mathrm{Re}^{t+1} = \frac{A^{t+1} \times (\frac{C^{t+1}}{D_C^{t+1}} - \frac{C^t}{D_C^t}) \times D_C^{t+1}}{(D_C^t - D_C^{t+1}) \times \frac{C^t}{D_C^t}} \qquad \mathrm{Re}^{t+1} = \frac{A^{t+1} \times (\frac{E^{t+1}}{D_E^{t+1}} - \frac{E^t}{D_E^t}) \times D_E^{t+1}}{(D_E^t - D_E^{t+1}) \times \frac{E^t}{D_E^t}} \tag{6-7}$$

where D_C^t and D_E^t respectively represent the Shephard undesirable output and energy input distance functions, which were first adopted by Zhou and Ang (2008) and are now widely accepted.

Moreover, as the economy-wide carbon and energy rebound effects can be estimated by our improved approach, we can further obtain the elasticity of emission intensity with regard to energy technological progress, which is similar to the approach used by Chen et al (2020a). The calculation model is as follows:

$$
\begin{aligned}
k_{CE} &= C\mathrm{Re} - \mathrm{Re} = \frac{\partial (CE \times E) \times h}{\partial h \times (CE \times E)} - \frac{\partial E \times h}{\partial h \times E} \\
&= \frac{\partial CE \times h}{\partial h \times CE} + \frac{\partial E \times h}{\partial h \times E} - \frac{\partial E \times h}{\partial h \times E} \\
&= \frac{A^{t+1} \times \left(\frac{C^{t+1}}{D_C^{t+1}} - \frac{C^t}{D_C^t}\right) \times D_C^{t+1}}{(D_C^t - D_C^{t+1}) \times \frac{C^t}{D_C^t}} - \frac{A^{t+1} \times \left(\frac{E^{t+1}}{D_E^{t+1}} - \frac{E^t}{D_E^t}\right) \times D_E^{t+1}}{(D_E^t - D_E^{t+1}) \times \frac{E^t}{D_E^t}}
\end{aligned}
\tag{8}
$$

2.3. Effects of different types of technological development on emission intensity

Similar to the elasticity of emission intensity to technological progress, we can obtain the difference between carbon and energy rebound effects, which is caused by the impacts of different types of energy technological development on emission intensity. However, the underlying mechanism is not clear by calculating the elasticity of emission intensity to technological progress. Therefore, we further analyzed the impacts of different types of energy technological development on targeted regional emission intensities by combining the LMDI and PDA approaches. The index identity can be constructed as follows:

$$
\begin{aligned}
\frac{C^t}{E^t} &= \sum_{i=1}^{i} \frac{C_i^t}{E_i^t} \times \frac{E_i^t}{E^t} \\
&= \sum_{i=1}^{i} \frac{C_i^t}{E_i^t} \times \frac{E_i^t / D_{E_i^t}^{G,t}\left(K, L, E, Y, C\right)}{E^t} \times D_{E_i^t}^{G,t}\left(K, L, E, Y, C\right) \\
&= \sum_{i=1}^{i} ce_i^t \times PES_i^t \times TE_i^t
\end{aligned}
\tag{9}
$$

where i represents the i^{th} type of energy consumption; ce_i represent the carbon emission coefficient of the i^{th} type of energy consumption; PES_i represents the potential energy consumption structure, excluding the impacts of technological progress (Zhang et al., 2013; Wang et al., 2015, 2018); TE_i represents the i^{th} type of energy technological progress calculated with the PDA approach (Oh et al., 2010;

Wang et al., 2018).

Based on the LMDI provided by Ang et al. (2005), the emission intensity changes caused by the carbon emission coefficient, potential energy consumption structure, and energy technology from a start time to the reported time can be decomposed with Equation (10), as presented in Table 2. Additionally, since the carbon emission coefficient was obtained from the IPCC and remains constant each year, the impact of the carbon emission coefficient would be zero and thus was not considered in downstream calculations.

$$\begin{aligned}\Delta CE^{b,t} &= \Delta CE_{ce}^{b,t} + \Delta CE_{PES}^{b,t} + \Delta CE_{TE}^{b,t} \\ &= \Delta CE_{PES}^{b,t} + \Delta CE_{TE}^{b,t} \\ &= \sum_{i=1}^{i} \Delta CE_{PES_i}^{b,t} + \sum_{i=1}^{i} \Delta CE_{TE_i}^{b,t}\end{aligned} \tag{10}$$

[Insert Table. 2 here.]

2.4. Environmental production technology based on meta-frontier

In accordance with section 2.2, we proposed an improved approach to calculate economy-wide carbon and energy rebound effects based on the PDA approach. Moreover, we adopted the meta-frontier PDA approach to estimate the Shephard undesirable output and energy input distance functions instead of using the traditional PDA approach. The meta-frontier PDA approach was adopted mainly for two reasons, as explained below.

First, although the traditional PDA approach helps estimate the Malmquist index, which reflects technological changes, it can only obtain relative technological progress rates based on a contemporaneous benchmark technology set and fails to analyze the time-series technological changes based on an intertemporal benchmark technology set (Li et al., 2016). Second, considering that interregional technology differences may cause changes in carbon emissions (Du et al., 2014, 2017; Zhang et al., 2015; 2016a; Zha et al., 2019; Liu et al., 2019; Chen et al., 2020a), especially between the eastern, central, and western regions of China[3], it is important to divide the technology set into three groups and estimate the technological progress based on interregional differences.

Therefore, we treated each province as a decision-making unit (DMU) in the production process and divided their production technology into three groups based on region (i.e., eastern, central, and western).

Furthermore, contemporaneous, intertemporal, and global production technology is defined as follows:

$$P_{groupi}^{t} = \left\{(K,L,E,Y,C):(K,L,E)\,produce(Y,C); i=1,2,3\right\} \tag{11}$$

$$P_{groupi}^{T} = \left\{(K,L,E,Y,C):(K,L,E)\,produce(Y,C); i=1,2,3; T=1,2,...,t\right\} \tag{12}$$

$$P_{global}^{T} = conv\left\{P_{group1}^{T} \cup P_{group2}^{T} \cup P_{group3}^{T}\right\} \tag{13}$$

where E represents energy consumption; K represents capital; L represents labor force; Y represents economic output and desirable output; C represents carbon emissions and undesirable output; P_{groupi}^{t} represents the i^{th} group's production

[3] The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Shanxi; the western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

technology at time point t; P^{T}_{groupi} represents the i^{th} group's production technology during period T ($T=\{1,2,3,...,t\}$).

Based on the PDA approach proposed by Zhou and Ang (2008), we first calculated each group's energy input and undesirable output distance for the contemporaneous benchmark technology set as follows:

$$D_E^S = \sup\left\{\lambda_1 : (K, L, E/\lambda_1, Y, C); P^t_{groupi}\right\} \tag{14}$$

$$D_C^S = \sup\left\{\theta_1 : (K, L, E, Y, C/\theta_1; P^t_{groupi})\right\} \tag{15}$$

Next, following the meta-frontier concepts proposed by Oh et al. (2010), global meta-frontier's and each group's energy input and undesirable output distance for a given intertemporal benchmark technology set were estimated as follows:

$$D_E^G == D_E^S \times D_E^I(E/D_E^S) \times D_E^G(E/D_{Ei}^I) = D_E^S \times D_E^{IS} \times D_E^{GI} \tag{16}$$

$$D_C^G = D_C^S \times D_C^I(C/D_C^S) \times D_C^G(C/D_C^I) = D_C^S \times D_C^{IS} \times D_C^{GI} \tag{17}$$

Therefore, we can obtain the global meta-frontier energy input and undesirable output distance by solving the corresponding linear equations, and they are detailed in Appendix A2.

2.5 Data

Due to data availability and consistency constraints, the scope of our study was limited to carbon emissions produced by energy sources in 30 provinces of China (except for the Tibet, Hong Kong, Macao, and Taiwan regions due to a lack of data) from 2005 to 2015[4]. Additionally, as the fixed capital stock of Chongqing and

[4] In the China Energy Statistical Yearbook, the total energy consumption comprises raw coal, cleaned coal, briquettes, other washed coal, coke, gasoline, diesel oil,

Sichuan were merged during the early periods, Chongqing and Sichuan were evaluated as a single province.

The variables examined in this study can be classified as output and input variables. Output variables include regional economic output (100 million yuan) and carbon emissions (million tons), which represent desirable and undesirable output, respectively. In order to eliminate the impact of prices on economic output, we converted the nominal GDP to its true GDP value in 1978. The data was obtained from the China Statistical Yearbook (2006–2016). Regional carbon emissions were calculated following the methods described by the IPCC, which have been widely adopted in several studies (Yang et al., 2017a; Wang et al., 2018; Chen et al., 2019; Zha et al., 2019).

Regarding input variables, we considered capital stock (100 million yuan), human capital stock (10,000 people per year), and energy consumption (10,000 tons of standard coal equivalent, TCE). The perpetual inventory method was used to calculate fixed capital stock, as described in previous studies (Liu et al., 2019; Chen et al., 2020a; 2020b), after which it was converted to its real value in 1978 to eliminate the impact of prices and inflation. The "education years law" method was used to estimate human capital, as described by many previous studies (Yang et al., 2017b; Chen et al., 2020a). The data for industrial and residential energy consumption was obtained from the China Energy Statistical Yearbook (2006–2016)[5] following widely

lubricants, fuel oil, naphtha, lubricants, paraffin waxes, white spirit, bitumen asphalt, petroleum, coke, LPG, refinery gas, other petroleum products, natural gas, LNG, heat, electricity, and other energy sources.

[5] The total energy consumption in the China Energy Statistical Yearbook comprises

accepted procedures (Wang et al., 2014; Ji et al., 2018).

3. Results and Discussion

3.1 Comparison of the results calculated by the traditional and improved methods

As described in Section 2, we calculated the economy-wide carbon and energy rebound effects with the improved methods. Furthermore, we also calculated the carbon and energy rebound effect with the traditional method in order to compare results and reveal the shortcomings of the traditional method. These results are summarized in Table 3.

[Insert Table. 3 here.]

Among said results, $C\mathrm{Re}$ and Re represent the carbon and energy rebound effects, respectively. Notably, the economy-wide carbon and energy rebound effects calculated with the traditional approach were not significantly different, indicating that carbon rebound effects estimated by the traditional method are equivalent to the energy rebound effect, which is a questionable conclusion. Figure 1 compares the results of the two methods more intuitively:

[Insert Figure. 1 here.]

---

raw coal, cleaned coal, briquettes, other washed coal, coke, gasoline, diesel oil, lubricants, fuel oil, naphtha, lubricants, paraffin waxes, white spirit, bitumen asphalt, petroleum, coke, LPG, refinery gas, other petroleum products, natural gas, LNG, heat, electricity, and other energy sources.

where $CRe0$, $Re0$, $CRe1$, and $Re1$ represent carbon and energy rebound effects calculated by the traditional and improved methods, respectively. Importantly, the results estimated by the traditional method are consistent with our predictions and opinions that were proposed in Section 2.1 regarding its flaws as it ignores the impacts of technological progress on the energy consumption structure, which has been confirmed by previous studies (Chen et al., 2020a). Therefore, the traditional framework and method may be unsuitable to estimate the carbon rebound effect, even if it can be applied to assess energy rebound effects.

On the other hand, our improved method evidently overcomes the disadvantages of traditional methods, and the results estimated by our improved method reveal the significant impacts of technological progress on emission intensity. At the same time, the energy rebound effects estimated by our method are close to those estimated by the traditional method, suggesting that our method is robust and trustworthy (Lin et al., 2012; Li et al., 2017b; Wu et al., 2018).

At the same time, it was evident that there was a gap between the carbon and energy rebound effects estimated by the traditional method, indicating that the traditional method can only be applied when estimating energy rebound effects and not carbon rebound effects, while our improved method can be applied to estimate both energy and carbon rebound effects.

As for the empirical results calculated by our approach, we found that the national, eastern, central, and western average carbon rebound effects were 36%, 38%, 41%, and 30% during 2006-2015, suggesting that the carbon rebound impact in the western region was relatively low, whereas the risk of carbon rebound in the eastern and central regions was relatively high. The average national carbon rebound effects based on our methods were similar to those of Wu et al. (2018) at 32.5% and Yang et al. (2016) at 35%. Furthermore, although there were some fluctuations in the national, eastern, central, and western rebound effects during 2006-2015, the trends of carbon and energy rebound effects ultimately decreased overall, which is consistent with what has been found in previous studies (Lin et al., 2017; Chen et al., 2019; Chen et al., 2020a). Additionally, the carbon rebound effect turning point approximately occurred between 2010-2011, which is consistent with the results provided by Wu et al. (2018).

However, the regional differences in the carbon rebound effect based on our approach are not consistent with those of previous studies. We found that the risk of carbon rebound effects in the western region was lower than that in the eastern and central regions. However, previous studies by Yang et al. (2016), Wu et al. (2019), and Chen et al. (2019) determined that the risk of carbon rebound effects in the central region was lower than in either the eastern or western regions, and the western region presented a high carbon rebound effect risk.

These evident differences may be due to the shortcomings of the traditional approach that ignore the impacts of emission intensity. To test the reliability of the conclusions from past research, we also used the traditional method to estimate the regional carbon rebound effects, and they are presented in Table 3. Clearly, the results we estimated in Table 3 can also be used to draw a similar conclusion. Therefore, we can reasonably speculate that the conclusions drawn by previous studies regarding regional carbon rebound effects may be wrong due to the limitations of the traditional method. In fact, the western region had the lowest risk of carbon rebound effects, but presented a relatively high risk of energy rebound effects.

3.2 Impacts of regional technological progress on emission intensity

Based on the empirical results provided in Section 3.1, we confirmed that our improved approach overcame the shortcomings of the traditional method for calculating carbon rebound effects by accounting for changes in energy consumption structure. Thus, it is important to further analyze the impacts of energy technological progress on emission intensity as well as to explore the reasons for the differences in regional carbon rebound effects.

Based on the method provided in Section 2.3, the regional elasticity of energy technological progress to emission intensity was obtained, as illustrated in Figure 2.

[Insert Figure. 2 here.]

As can be seen in Figure 2, it is evident that national technological progress played an important role in reducing emission intensity in most years, which helped to reduce the proportion of high-emission energy use, as has been reported in previous studies (Chang et al., 2010; Cheng et al., 2018; Chen et al., 2020a). Regionally, we found that eastern and western energy technological progress had a strong effect on reducing emission intensity, whereas central regional technological progress had no visible effects. The different impacts of regional technological progress may explain why the risk of carbon rebound effects in the western region was lower than that in either the western or central regions. Furthermore, western technological progress played a more significant role in decreasing emission intensity compared to that of the eastern region, indicating that the proportion of high-emission energy use declined faster in the west.

The decreasing emission intensity observed in our study may have derived from the decreasing proportion of high-emission energy use with regard to total energy consumption. Further, the decreasing proportion of high-emission energy use may have been caused by two factors. Firstly, novel energy technological progress may have ultimately led to the widespread use of low-emission energy to substitute high-emission energy use and optimize the energy use structure. Secondly, energy technological progress focused more on high-emission energy and therefore conserved more high-emission energy use.

Hence, on the one hand, given that the promotion of renewable and sustainable energy was mainly concentrated in the east (Gu et al., 2019; Chen et al., 2020a), we speculate that the decreasing ratio of high-emission energy use in the east may have been mainly due to the first factor. On the other hand, since "the optimized development of the energy and chemical industry" was regarded as a significant development goal of the western region, the western region paid more attention to the development of high-emission energy technology and had a greater reduction of emission intensity than either the eastern or central regions (Chen et al., 2010; Dong et al., 2016; Liu et al., 2019). Therefore, we speculate that the decreasing ratio of high-emission energy use in the west may have been mainly due to the second factor.

3.3 Effects of technological advance on coal and non-coal emission intensity

Based on the results presented in Sections 3.1 and 3.2, we found that the eastern and western regions presented a relatively low risk of carbon rebound effects, which may have been due to the impacts of different types of energy technological progress on emission intensity. Furthermore, the changes in emission intensity reflected the adjustment of the energy consumption structure, which we attributed to either the widespread use of low-emission energy or high-emission energy conservation. To further validate our conjecture and explore the underlying mechanisms, it was necessary to analyze the impacts of different types of energy technological development on emission intensity.

Considering that coal is the main source of high carbon emissions in China (Cheng et al., 2018; Chen et al., 2020b) and the proportion of coal use had a significant influence on energy consumption structure (Cheng et al., 2018), we classified energy use into coal and non-coal categories. Based on a combination of the PDA and LMDI approaches provided in Section 2.3, we obtained the regional average effects of the potential consumption structure, and coal and non-coal energy technological progress on emission intensity. The empirical results are presented in

Table 4. Additionally, the detailed PDA formulas to estimate coal and non-coal distances are presented in Appendix A3.

[Insert Table. 4 here.]

$\Delta CE_{PES}^{b,t}$, $\Delta CE_{TE}^{b,t}$, $\Delta CE_{TE1}^{b,t}$, and $\Delta CE_{TE2}^{b,t}$ respectively represent the average impacts of the potential energy consumption structure and energy technology, coal technology, and non-coal technology on emission intensity. Evidently, the potential energy consumption structure in the eastern and central regions favored a reduction in emission intensity from 2005-2015, indicating that optimization of the eastern and central industrial structure played a more important role in carbon reduction, which is consistent with what has been reported in previous studies (Dhakal, 2009; Wang and Wang, 2018; Gu et al., 2019; Chen et al., 2020b). Further, $\Delta CE_{TE}^{b,t}$ indicated that energy technological changes in the eastern and western regions strongly decreased the emission intensity, whereas the technological changes of the central region had no visible effect. In the eastern region, the reduction effects from energy technological progress on emission intensity may have been the result of the promotion of low-emission energy, especially renewable and sustainable energy, being mainly concentrated in the east, which is consistent with what has been reported in the literature and existing conditions (Gu et al., 2019; Chen et al., 2020a). Actually, many scholars have also pointed out that locations within the eastern region, such as Beijing, Shanghai, and Jiangsu, always have more renewable and cleaner energy technology than those of other areas and help to optimize the energy use structure (Wang and Wang, 2018; Lin et al., 2019).

At the same time, in the western region, we found that a reduction in the effects of energy technological changes on emission intensity was more accentuated than that of the eastern region, which is consistent with what has been reported previously (Dong et al., 2016; Liu et al., 2019). Further, this phenomenon may be due to the energy technological progress in the western region being focused more on high-emission energy thus conserving more high-emission energy use, which has been confirmed by previous studies (Chen et al., 2010; Dong et al., 2016). For example, given the goal of "the optimized development of the energy and chemical industry" in the west, the western regional power industry had lower carbon emission growth because of the use of advanced coal fired power generation technologies, such as supercritical flue gas desulfurization (FGD) systems ultra-supercritical FGD systems, and Integrated Gasification Combined Cycle Technology (IGCC; Chen et al., 2010).

Furthermore, in order to characterize energy technological progress by region, we analyzed the impacts of coal and non-coal technological changes on emission intensity, which is presented in Table 4. Notably, the average effects of coal technological changes on the emission intensity of the eastern and western regions were both negative from 2005-2015, whereas coal technology failed to reduce emission intensity altogether. At the same time, we found that coal technology in the western region reduced emission intensity more than in the eastern region, which may explain why the western region faced fewer carbon rebound effect risks. On the other hand, we found that non-coal technology in the eastern region played a role in decreasing emission intensity, whereas non-coal technology in the central and western regions rarely influenced emission intensity.

Moreover, based on the meta-frontier analysis method provided in Section 2.4, we determined the catch-up effects due to the gap between contemporary technology and global benchmark technology (Liu et al., 2019) and estimated their effects on emission intensity based on the LMDI method. The results were presented as $\Delta CE_{Gap1}^{b,t}$ and $\Delta CE_{Gap2}^{b,t}$. It is clear that the catch-up effect of coal technology played a positive role in reducing the emission intensity in the eastern and western regions, which is consistent with the results reported by Liu et al. (2019) and Zha et al. (2019). The catch-up effect of non-coal technology also played a positive role in reducing the emission intensity for the central and western regions, whereas the catch-up effect of non-coal technology in the eastern region was almost zero, suggesting that the renewable and cleaner technology in this region was optimal and at the meta-frontier, which is consistent with the findings of Gu et al. (2019) and Chen et al. (2020a).

In summary, we can draw some conclusions regarding the mechanisms behind the carbon rebound effect gap in various regions: (1) The eastern region may continue to focus on both coal and non-coal technology, which helped to decrease the emission intensity and translated to carbon rebound effects that were lower than the energy rebound effects (Gu et al., 2019; Chen et al., 2020a). (2) Energy technology in the central region failed to reduce emission intensity, leading to high carbon rebound effect risks. (3) Energy technology in the western region was focused on coal technology, which favored a decrease in emission intensity and carbon rebound effects (Chen et al., 2010). (4) The effects on emission intensity in the western region resulted in a greater reduction of the carbon rebound effects than in the eastern region, which may be because non-fossil energy is unable to substitute fossil energy in the short term (York, 2012; Chen et al., 2020a).

4. Conclusions and Policy Implications

Given that the traditional method for calculating rebound effects confuses carbon rebound and energy rebound effects, it is important to propose a modified method to accurately estimate the carbon rebound effect while identifying the difference between carbon and energy rebound effects, which is valuable for the development of future studies in the field. Therefore, this study has provided an improved method that was used to calculate the economy-wide carbon rebound effects in the national and regional economies of China from 2006-2015. Notably, the results estimated by our proposed method reveal the gap between carbon and energy rebound effects and draw conclusions that previous studies have failed to draw.

As for the carbon rebound effect, we found that the eastern and western regions faced fewer carbon rebound effect risks compared with those of the central region, which contrasts with the findings of previous studies (Yang et al., 2017; Wu et al., 2018). The differences derive from the impacts of technological progress on emission intensity. We found that the reduction in emission intensity caused by energy technological progress resulted in fewer carbon rebound effects in the eastern and western regions. Further, decreasing emission intensity in the eastern region may have been mainly due to the widespread use of low-emission energy (Wang and Wang, 2018; Gu et al., 2019; Chen et al., 2020a), whereas the decreasing emission intensity in the western region may have mainly come from greater technological progress in high-emission energy, such as coal use (Chen et al., 2010; Dong et al., 2016; Liu et al., 2019). Based on our empirical results, we suggest the following policy proposals to reduce carbon rebound effects.

First, China should undoubtedly continue to invest in developments in energy efficiency to achieve energy conservation, as energy rebound effects still dominated carbon rebound effects and technological progress has strong potential to reduce energy consumption. Therefore, governments should continue to encourage technological innovation in the field of energy use. In particular, government should increase R&D investments and set up R&D platforms for both high-emission and cleaner advanced energy technologies (Chen et al., 2010; Chen et al., 2020a). At the same time, more fiscal subsidies should be put toward research institutes and enterprises, strengthening their cooperation and integrating production, teaching, and research (Zhou, 2018).

Second, it is more useful to focus on improving high-emission energy efficiency to reduce carbon rebound effects, as emission intensity effects can lead to a greater reduction in carbon rebound effects. According to our empirical analysis, focusing on coal played a more significant role than any other factor in decreasing emission intensity and carbon rebound effects (Chen et al., 2010), which explains why the western region faced fewer carbon rebound effect risks than those of the other regions, even with relatively high energy rebound effects. Considering that renewable and cleaner energy cannot substitute fossil energy in the short term (Chen et al., 2020a), the eastern and central regions should prioritize the improvement of coal efficiency, after which cleaner energy sources should be developed.

Third, it is essential for governments to propose strict tax policy regulations to increase the effective price of energy consumption, especially for coal use and that of other fossil fuels. In accordance with the definition of energy and carbon rebound effects, it is the increase in the demand for energy services that leads to rebound effects. As a result, taxation policy regulations can help reduce energy rebound effects (Brännlund et al., 2007). Moreover, given that fossil energy consumption (especially coal use) is the main driver of carbon emissions around the world (Cheng et al., 2018), the tax policy regulations should focus more on the use of coal and other high-emission fossil fuels, which will not only reduce energy and carbon rebound effects but help renewable and cleaner energy alternatives substitute fossil fuels in the long term (Chen et al., 2020a), resulting in more potential carbon emission reductions.

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Declarations of interest

None

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Appendix A1

The LMDI method to calculate the contributions of technological progress to potential energy savings (or energy intensity) is as follows:

$$EI^t = \sum_i^3 \frac{E_i^t}{Y_i^t} \times \frac{Y_i^t}{Y^t} = \sum_i^3 ei_i^t \times IND_i^t \qquad \text{(A1.1)}$$

where ei_i^t represents industrial energy intensity, reflecting technological progress; IND_i^t represents industrial structure; i represents the different industries, including primary, secondary and tertiary industries. Furthermore, the contribution rate of technological progress to energy intensity can be estimated by using the LMDI method as follows:

$$B^{t+1} = \frac{\dfrac{\Delta EI^{t,t+11}}{\ln(EI^t / EI^{t+1})} \times \ln(ei_i^t / ei_i^{t+1})}{\Delta EI^{t,t+11}} \qquad \text{(A1.2)}$$

Similarly, the method to calculate contributions of technological progress to potential carbon reductions (or carbon intensity) is as follows:

$$CI^t = \sum_i^3 \frac{C_i^t}{E_i^t} \times \frac{E_i^t}{Y_i^t} \times \frac{Y_i^t}{Y^t} = \sum_i^3 CE_i^t \times ei_i^t \times IND_i^t \qquad \text{(A1.3)}$$

$$C^{t+1} = \frac{\dfrac{\Delta CI^{t,t+11}}{\ln(CI^t / CI^{t+1})} \times \ln(ei_i^t / ei_i^{t+1})}{\Delta CI^{t,t+11}} \qquad \text{(A1.4)}$$

Appendix A2

The each group's contemporaneous Shephard energy input distance functions and Shephard undesirable output distance functions can be computed by the DEA method as described in the following equations, and we assumed constant returns to scale based on previous literature (Färe et al., 1989; Zhou et al., 2008)

$$\begin{aligned}
&[D_E^S(K,L,E,Y,C)]^{-1} = \min \lambda_1 && [D_C^S(K,L,E,Y,C)]^{-1} = \min \theta_1 \\
&s.t. \sum_{k=1}^{K} z_k E_k^t \le \lambda_{1,k}^t E_k^t ; \sum_{k=1}^{K} z_k K_k^t \le K_k^t ; && s.t. \sum_{k=1}^{K} z_k E_k^t \le E_k^t ; \sum_{k=1}^{K} z_k K_k^t \le K_k^t ; \\
&\sum_{k=1}^{K} z_k L_k^t \le L_k^t ; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t ; && \sum_{k=1}^{K} z_k L_k^t \le L_k^t ; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t ; \\
&\sum_{k=1}^{K} z_k C_k^t = C_k^t ; z_k \ge 0; k = 1,...,K && \sum_{k=1}^{K} z_k C_k^t = \theta_{1,k}^t C_k^t ; z_k \ge 0; k = 1,...,K
\end{aligned} \tag{A2.1}$$

Moreover, each group's intertemporal and global meta-frontier's Shephard energy input distance functions and Shephard undesirable output distance functions can be estimated with the following equations:

$$\begin{aligned}
&[D_E^{IS}(K,L,E,Y,C)]^{-1} = \min \lambda_2 && [D_C^{IS}(K,L,E,Y,C)]^{-1} = \min \theta_2 \\
&s.t. \sum_{k=1}^{K} z_k E_k^t \le \lambda_{2,k}^t \lambda_{1,k}^t E_k^t ; \sum_{k=1}^{K} z_k K_k^t \le K_k^t ; && s.t. \sum_{k=1}^{K} z_k E_k^t \le E_k^t ; \sum_{k=1}^{K} z_k K_k^t \le K_k^t ; \\
&\sum_{k=1}^{K} z_k L_k^t \le L_k^t ; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t ; && \sum_{k=1}^{K} z_k L_k^t \le L_k^t ; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t ; \\
&\sum_{k=1}^{K} z_k C_k^t = C_k^t ; && \sum_{k=1}^{K} z_k C_k^t = \theta_{2,k}^t \theta_{1,k}^t C_k^t ; \\
&z_k \ge 0; k = 1,...,K; && z_k \ge 0; k = 1,...,K
\end{aligned} \tag{A2.2}$$

$$\begin{aligned}
&[D_E^{GI}(K,L,E,Y,C)]^{-1} = \min \lambda_3 && [D_C^{GI}(K,L,E,Y,C)]^{-1} = \min \theta_3 \\
&s.t. \sum_{k=1}^{K} z_k E_k^t \le \lambda_{3,k}^t \lambda_{2,k}^t E_k^t ; \sum_{k=1}^{K} z_k K_k^t \le K_k^t ; && s.t. \sum_{k=1}^{K} z_k E_k^t \le E_k^t ; \sum_{k=1}^{K} z_k K_k^t \le K_k^t ; \\
&\sum_{k=1}^{K} z_k L_k^t \le L_k^t ; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t ; && \sum_{k=1}^{K} z_k L_k^t \le L_k^t ; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t ; \\
&\sum_{k=1}^{K} z_k C_k^t = C_k^t ; && \sum_{k=1}^{K} z_k C_k^t = \theta_{3,k}^t \theta_{2,k}^t C_k^t ; \\
&z_k \ge 0; k = 1,...,K && z_k \ge 0; k = 1,...,K
\end{aligned} \tag{A2.3}$$

Based on the linear programming above, the meta-frontier energy input and undesirable output distance could be obtained:

$$D_E^{G,t} = D_E^{GI,t} \times D_E^{I,t} = D_E^{GI,t} \times D_E^{IS,t} \times D_E^{S,t} = Gap_E^t \times Techch_E^t \times Effch_E^t \tag{A2.4}$$

$$D_C^{G,t} = D_C^{GI,t} \times D_C^{I,t} = D_C^{GI,t} \times D_C^{IS,t} \times D_C^{S,t} = Gap_C^t \times Techch_C^t \times Effch_C^t \tag{A2.5}$$

where $D_E^{IS,t}$ and $D_C^{IS,t}$ represent the technical level; $D_E^{S,t}$ and $D_C^{S,t}$ represent the level of technical efficiency; $D_E^{GI,t}$ and $D_C^{GI,t}$ represent the technology gap (Oh et al., 2010; Zha et al., 2019). Next, we can apply these factors to the estimation of economy-wide carbon and energy rebound effects as follows:

$$C\,\mathrm{Re}^{t+1}=\frac{A^{t+1}\times\left(\frac{C^{t+1}}{D_C^{G,t+1}}-\frac{C^{t}}{D_C^{G,t}}\right)\times D_C^{G,t+1}}{(D_C^{G,t}-D_C^{G,t+1})\times\frac{C^{t}}{D_C^{G,t}}} \tag{24}$$

$$\mathrm{Re}^{t+1}=\frac{A^{t+1}\times\left(\frac{E^{t+1}}{D_E^{G,t+1}}-\frac{E^{t}}{D_E^{G,t}}\right)\times D_E^{G,t+1}}{(D_E^{G,t}-D_E^{G,t+1})\times\frac{E^{t}}{D_E^{G,t}}} \tag{25}$$

Appendix A3

The global meta-frontier's coal and non-coal input distance for the intertemporal benchmark technology set can be estimated as follows:

$$D_{coal}^{G}=D_{coal}^{S}\times D_{coal}^{IS}\times D_{coal}^{GI} \tag{A3.1}$$

$$D_{non-coal}^{G}=D_{non-coal}^{S}\times D_{non-coal}^{IS}\times D_{non-coal}^{GI} \tag{A3.2}$$

and the corresponding distance functions can be computed by the DEA method as follows:

$$\begin{array}{ll}
[D_{coal}^{S}(K,L,coal,non-coal,Y,C)]^{-1} & [D_{non-coal}^{S}(K,L,coal,non-coal,Y,C)]^{-1} \\
=\min\lambda_1 & =\min\theta_1 \\
s.t.\sum_{k=1}^{K}z_k coal_k^t\le\lambda_{1,k}^t coal_k^t; & s.t.\sum_{k=1}^{K}z_k non-coal_k^t\le non-coal_k^t; \\
\sum_{k=1}^{K}z_k non-coal_k^t\le non-coal_k^t; & \sum_{k=1}^{K}z_k coal_k^t\le coal_k^t; \\
\sum_{k=1}^{K}z_k K_k^t\le K_k^t; & \sum_{k=1}^{K}z_k K_k^t\le K_k^t; \\
\sum_{k=1}^{K}z_k L_k^t\le L_k^t;\sum_{k=1}^{K}z_k Y_k^s\ge Y_k^t; & \sum_{k=1}^{K}z_k L_k^t\le L_k^t;\sum_{k=1}^{K}z_k Y_k^s\ge Y_k^t; \\
\sum_{k=1}^{K}z_k C_k^t=C_k^t;z_k\ge 0;k=1,\ldots,K & \sum_{k=1}^{K}z_k C_k^t=C_k^t;z_k\ge 0;k=1,\ldots,K
\end{array} \tag{A3.3-4}$$

Moreover, each group's intertemporal and global meta-frontier's Shephard energy input distance functions and Shephard undesirable output distance functions can be estimated with the following equations:

$$
\begin{aligned}
&[D_{coal}^{IS}(K,L,coal,non-coal,Y,C)]^{-1} \\
&= \min \lambda_2 \\
&s.t.\sum_{k=1}^{K} z_k coal_k^t \le \lambda_{2,k}^t \lambda_{1,k}^t coal_k^t; \\
&\sum_{k=1}^{K} z_k non-coal_k^t \le non-coal_k^t; \\
&\sum_{k=1}^{K} z_k K_k^t \le K_k^t; \\
&\sum_{k=1}^{K} z_k L_k^t \le L_k^t; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t; \\
&\sum_{k=1}^{K} z_k C_k^t = C_k^t; \\
&z_k \ge 0; k = 1,...,K;
\end{aligned}
\qquad
\begin{aligned}
&[D_{non-coal}^{IS}(K,L,coal,non-coal,Y,C)]^{-1} \\
&= \min \theta_2 \\
&s.t.\sum_{k=1}^{K} z_k non-coal_k^t \le non-coal_k^t; \\
&\sum_{k=1}^{K} z_k coal_k^t \le coal_k^t; \\
&\sum_{k=1}^{K} z_k K_k^t \le K_k^t; \\
&\sum_{k=1}^{K} z_k L_k^t \le L_k^t; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t; \\
&\sum_{k=1}^{K} z_k C_k^t = C_k^t; \\
&z_k \ge 0; k = 1,...,K
\end{aligned}
\tag{A3.5-6}
$$

$$
\begin{aligned}
&[D_{coal}^{GI}(K,L,coal,non-coal,Y,C)]^{-1} \\
&= \min \lambda_3 \\
&s.t.\sum_{k=1}^{K} z_k coal_k^t \le \lambda_{3,k}^t \lambda_{2,k}^t coal_k^t; \\
&\sum_{k=1}^{K} z_k non-coal_k^t \le non-coal_k^t; \\
&\sum_{k=1}^{K} z_k K_k^t \le K_k^t; \\
&\sum_{k=1}^{K} z_k L_k^t \le L_k^t; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t; \\
&\sum_{k=1}^{K} z_k C_k^t = C_k^t; \\
&z_k \ge 0; k = 1,...,K
\end{aligned}
\qquad
\begin{aligned}
&[D_{non-coal}^{GI}(K,L,coal,non-coal,Y,C)]^{-1} \\
&= \min \theta_3 \\
&s.t.\sum_{k=1}^{K} z_k non-coal_k^t \le non-coal_k^t; \\
&\sum_{k=1}^{K} z_k coal_k^t \le coal_k^t; \\
&\sum_{k=1}^{K} z_k K_k^t \le K_k^t; \\
&\sum_{k=1}^{K} z_k L_k^t \le L_k^t; \sum_{k=1}^{K} z_k Y_k^s \ge Y_k^t; \\
&\sum_{k=1}^{K} z_k C_k^t = C_k^t; \\
&z_k \ge 0; k = 1,...,K
\end{aligned}
\tag{A3.6-7}
$$

Table Captions

Table 1. Representative literature on rebound effects from the past 10 years.

Table 2. Additive decomposition formula of driving factors.

Table 3. Comparison of the rebound effects estimated by the two methods.

Table 4. Effects of technological change on coal and non-coal emission intensity (units: 10^{-4} t/cet).

Table 1. Representative literature on rebound effects from the past 10 years.

Authors	Period	Regions	Methods	Research Objective
Lin et al. (2012)	1981–2009	China	The LMDI and econometric methods	Energy rebound effects
Broberg. (2015)	-	Swedish industry	Econometric method	Energy rebound effects
Yang et al. (2017)	1998-2010	Chinese provinces	The LMDI and PDA	Carbon rebound effects
Wang et al. (2017)	2000–2013	Chinese industry	Econometric method	Carbon emissions and carbon backfire effects
Zhou et al. (2018)	-	China	CGE method	Energy rebound effects
Jin et al. (2019)	1971-2011	Korean	DEA	Energy rebound

				effects
Shao et al. (2019)	1991-2016	Shanghai (China)	The state-space econometric method	Energy rebound effects

Table 2. Additive decomposition formula of driving factors.

Driving factors of carbon emissions	Additive decomposition formula
$\Delta CE_{ce}^{b,t}$	$\Delta CE_{ce}^{b,t} = \sum_{i=1}^{i} \frac{(CE^{t} - CE^{b})}{\ln(CE^{t} / CE^{b})} \times \ln(ce_{i}^{t} / ce_{i}^{b})$
$\Delta CE_{PES}^{b,t}$	$\Delta CE_{PES}^{b,t} = \sum_{i=1}^{i} \frac{(CE^{t} - CE^{b})}{\ln(CE^{t} / CE^{b})} \times \ln(PES_{i}^{t} / PES_{i}^{b})$
$\Delta CE_{TE}^{b,t}$	$\Delta CE_{TE}^{b,t} = \sum_{i=1}^{i} \frac{(CE^{t} - CE^{b})}{\ln(CE^{t} / CE^{b})} \times \ln(TE_{i}^{t} / TE_{i}^{b})$

Table 3. Comparison of the rebound effects estimated by the two methods.

Year	Region	Traditional method		Improved method	
		CRe	Re	CRe	Re
2006	Nation	0.86	0.86	0.74	0.88
	East	0.92	0.92	0.72	0.90
	Central	0.76	0.74	1.25	0.88
	West	0.90	0.89	0.49	0.83
2007	Nation	0.60	0.60	0.59	0.61
	East	0.69	0.69	0.64	0.68
	Central	0.54	0.54	0.51	0.54
	West	0.49	0.49	0.54	0.49
2008	Nation	0.36	0.36	0.28	0.34
	East	0.42	0.42	0.31	0.36
	Central	0.30	0.30	0.25	0.30
	West	0.35	0.35	0.22	0.35
2009	Nation	0.36	0.36	0.34	0.37
	East	0.45	0.46	0.37	0.44
	Central	0.29	0.29	0.27	0.27
	West	0.33	0.33	0.37	0.34
2010	Nation	0.60	0.60	0.46	0.50
	East	0.77	0.77	0.49	0.50

	Central	0.51	0.51	0.49	0.51
	West	0.48	0.48	0.35	0.50
2011	Nation	0.63	0.63	0.40	0.52
	East	0.61	0.60	0.36	0.50
	Central	0.53	0.53	0.68	0.53
	West	0.97	0.96	0.35	0.57
2012	Nation	0.34	0.35	0.23	0.32
	East	0.35	0.36	0.23	0.32
	Central	0.29	0.29	0.18	0.30
	West	0.41	0.41	0.27	0.33
2013	Nation	0.12	0.12	0.15	0.12
	East	0.16	0.16	0.21	0.15
	Central	0.10	0.10	0.11	0.10
	West	0.11	0.11	0.12	0.09
2014	Nation	0.28	0.28	0.20	0.29
	East	0.29	0.29	0.24	0.29
	Central	0.24	0.24	0.17	0.24
	West	0.32	0.32	0.16	0.32
2015	Nation	0.22	0.23	0.16	0.23
	East	0.29	0.29	0.21	0.28
	Central	0.17	0.17	0.13	0.17
	West	0.21	0.21	0.12	0.20

2006-2015(average)	Nation	0.44	0.44	0.36	0.42
	East	0.50	0.50	0.38	0.44
	Central	0.37	0.37	0.41	0.38
	West	0.46	0.45	0.30	0.40

Table 4. Effects of technological change on coal and non-coal emission intensity (units: 10^{-4} t/cet).

Year	Region	$\Delta CE_{PES}^{b,t}$	$\Delta CE_{TE}^{b,t}$	$\Delta CE_{TE1}^{b,t}$	$\Delta CE_{TE2}^{b,t}$	$\Delta CE_{Gap1}^{b,t}$	$\Delta CE_{Gap2}^{b,t}$
2005-2006	East	0.00	-0.10	-0.07	-0.02	-0.04	-0.02
	Central	-0.09	0.08	0.07	0.00	0.04	-0.02
	West	-0.09	-0.02	-0.10	0.08	-0.13	-0.09
2006-2007	East	0.03	-0.10	-0.05	-0.05	-0.01	-0.02
	Central	-0.06	0.03	0.00	0.03	0.07	-0.01
	West	0.00	-0.16	-0.16	0.00	-0.08	0.03
2007-2008	East	-0.12	0.11	0.08	0.03	-0.03	0.02
	Central	-0.26	0.25	0.18	0.07	0.14	0.07
	West	0.02	0.03	0.02	0.01	-0.03	-0.03
2008-2009	East	0.02	-0.05	-0.04	-0.01	-0.02	0.01
	Central	-0.18	0.15	0.13	0.01	0.09	0.00
	West	-0.03	0.07	0.08	-0.01	-0.10	0.00
2009-2010	East	0.17	-0.25	-0.22	-0.03	-0.05	-0.05
	Central	0.41	-0.39	-0.31	-0.08	-0.11	-0.17
	West	0.08	-0.18	-0.15	-0.03	-0.03	0.03
2010-2011	East	-0.43	0.28	0.18	0.09	0.04	0.11
	Central	-0.51	0.45	0.37	0.08	0.22	0.14

	West	0.18	-0.25	-0.24	-0.01	0.00	0.00
2011-2012	East	-0.23	0.16	0.13	0.03	-0.02	0.04
	Central	-0.13	0.06	0.10	-0.04	0.25	-0.06
	West	-0.11	0.13	0.11	0.02	-0.01	-0.02
2012-2013	East	0.14	-0.26	-0.18	-0.08	-0.09	-0.09
	Central	-0.12	0.03	-0.01	0.04	0.00	-0.03
	West	0.23	-0.37	-0.27	-0.10	-0.06	-0.01
2013-2014	East	-0.01	0.00	0.03	-0.03	0.01	-0.02
	Central	0.09	-0.10	-0.05	-0.04	0.08	-0.04
	West	-0.16	0.13	0.13	0.00	-0.01	-0.01
2014-2015	East	-0.02	-0.12	-0.07	-0.06	0.01	-0.07
	Central	-0.07	0.03	0.06	-0.03	0.10	-0.04
	West	-0.14	0.19	0.17	0.02	0.01	0.02
2005-2015	East	-0.05	-0.03	-0.02	-0.01	-0.02	0.00
	Central	-0.09	0.06	0.05	0.00	0.09	-0.01
	West	0.00	-0.04	-0.04	0.00	-0.04	-0.01

Note: Given that emission intensity is a type of ratio indicator, we averaged the decomposition results of the provinces in each region to represent the impacts of the potential energy structure and technology on emission intensity.

Figure Captions

Fig. 1. Temporal changes in carbon and energy rebound effects in China based on the traditional and improved methods from 2005 to 2015.

Fig. 2. Impacts of technological progress on emission intensity in China from 2005 to 2015 (units: 10^{-2} t/cet).

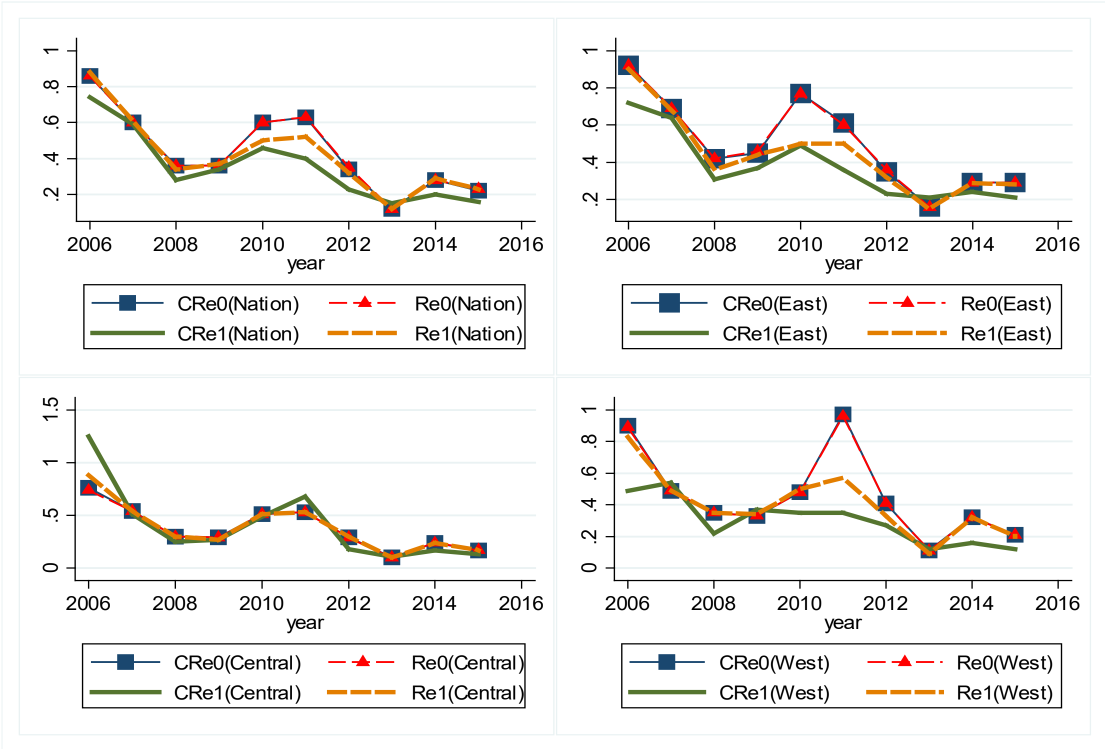

Fig. 1. Temporal changes in carbon and energy rebound effects in China from 2005 to 2015 based on the traditional and improved methods. $CRe0$, $Re0$, $CRe1$, and $Re1$ represent carbon and energy rebound effects calculated by the traditional and improved methods, respectively

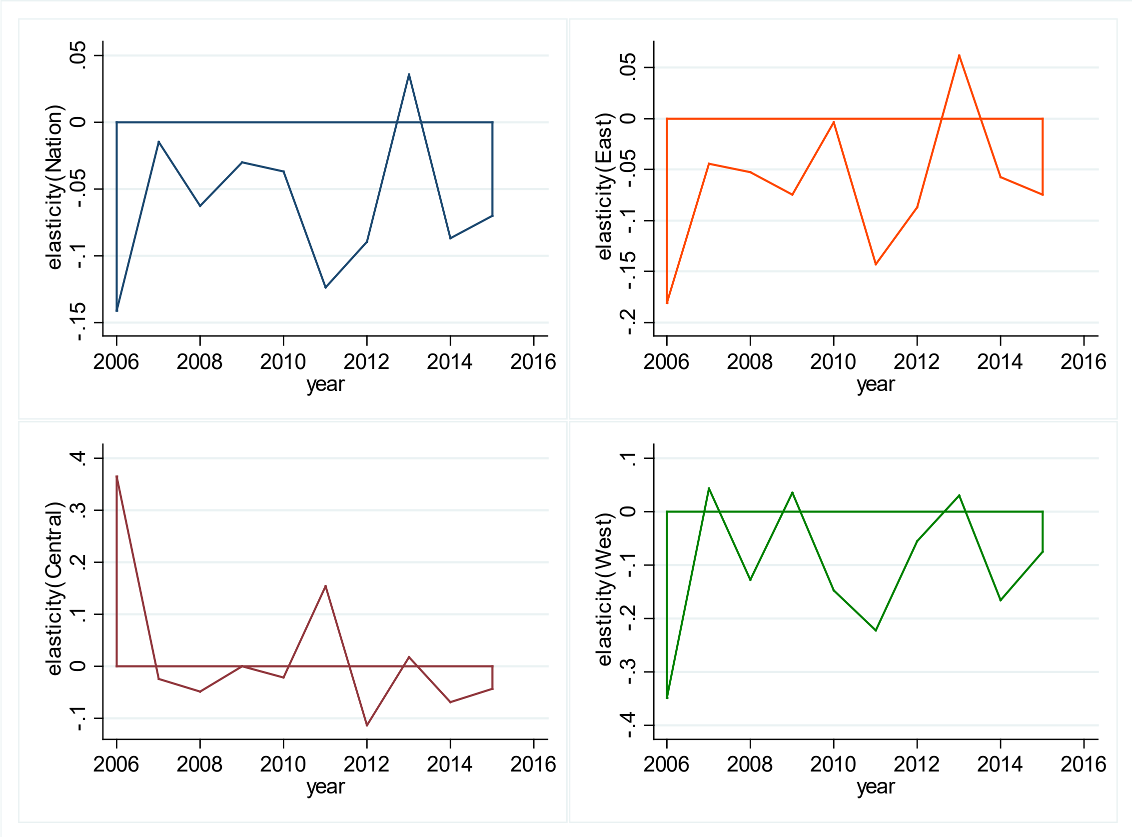

Fig. 2. Impacts of technological progress on emission intensity in China from 2005 to 2015 (units: 10^{-2} t/cet).