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

3 Ding Li^a, Ming Gao^b, Wenxuan Hou^c, Malin Song^d, Jiandong Chen^{b*}

4 ^aInstitute of Development Studies, Southwestern University of Finance and
5 Economics, Chengdu, China

6 ^bSchool of Public Administration, Southwestern University of Finance and Economics,
7 Chengdu, China

8 ^cUniversity of Edinburgh Business School, University of Edinburgh, 29 Buccleuch
9 Place, Edinburgh

10 ^dSchool of Statistics and Applied Mathematics, Anhui University of Finance and
11 Economics, Bengbu, China

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

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

14

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

31

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

34 **1. Introduction**

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

46 The energy rebound effect was first proposed by Khazzoom (1980) and Brookes
47 (1990a, 1990b), and was described as a phenomenon whereby technological
48 development not only leads to energy conservation but also leads to a decrease in the
49 real cost of energy consumption and thus offset a part of potential energy savings.
50 Moreover, since carbon emissions are strongly and positively related to energy
51 consumption, the energy rebound effect can also impact carbon emissions and thus
52 lead to carbon rebound effects (Brännlund, 2007; Druckman et al., 2011). In line with
53 Druckman et al. (2011) and Yang et al. (2017), the definition of carbon rebound is
54 similar to that of the energy rebound effect: a portion of the potential reduction in

55 emissions is not attained due to the reduced effective price and cost of energy use
56 caused by energy technological progress.

57 Although the increased energy price caused by energy technological progress can
58 offset both potential energy savings and carbon reductions, carbon rebound effects
59 cannot be equated with energy rebound effects, since the potential carbon reductions
60 include not only the energy-saving effects derived from energy technological progress
61 but also the impacts of emission intensity caused by different types of energy
62 technological progress (Brännlund et al., 2007; Zhang et al., 2013; Wang and Wei.,
63 2014; Li and Lin, 2016; Li et al., 2017a; Chen et al., 2019). Changes in emission
64 intensity include the optimization of the energy consumption structure associated with
65 energy technological progress (i.e., a decreasing proportion of high-emission energy
66 use) and reductions in the carbon emission efficiency of particular energy types (Yang
67 et al., 2017a). Therefore, a gap should be present between carbon and energy rebound
68 effects, which help implement effective policies to reduce greenhouse gas emissions,
69 and is also benefit the development of future studies in the field.

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

73

74 [Insert Table 1 here]

75

76 Based on a thorough literature review, we found that many studies have mainly

77 focused on characterizing energy rebound effects, whereas research on carbon
78 rebound effects is scarce. In turn, carbon rebound effect studies can be divided into
79 two categories based on the rebound effect mechanism. The first category mainly
80 focuses on estimating carbon rebound effects in particular areas from a
81 microeconomic standpoint. The second category focuses on economy-wide carbon
82 rebound effects on a macroeconomic level.

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

93 As for the second category, research on economy-wide carbon rebound effects is
94 very scarce. Yang et al. (2017) used an energy rebound effect framework to estimate
95 regional carbon rebound effects in China (which excluded the impacts of emission
96 intensity) and found that carbon rebound effects varied regionally, ranging from
97 10-60%. Based on a framework provided by Zhang et al. (2017), Wu et al. (2019) also
98 calculated the regional carbon rebound effects in China by employing a combination

99 of the data envelopment analysis (DEA) production model and sequential
100 Malmquist-Luenberger index. The conclusions provided by Wu et al. (2019) also
101 confirmed the existence of carbon rebound effects in China, and the results were
102 similar to those of Zhang et al. (2017). Similarly, based on an integration of the
103 logarithmic mean Divisia index (LMDI) and production-theoretical decomposition
104 analysis (PDA), Yang et al. (2019) analyzed the driving forces of carbon emissions in
105 China and estimated carbon rebound effects. However, their study also failed to
106 account for the notable effects of emission intensity associated with technological
107 progress.

108 In line with existing studies, we found that the current methods for carbon
109 rebound effect calculation mainly derive from energy rebound effect estimation
110 frameworks. The traditional methods for calculating energy rebound effects can
111 successfully estimate potential and offset energy savings; however, they cannot reflect
112 the impacts of either the energy consumption structure or carbon emission efficiency,
113 which have been reported by several studies (Zwaan et al., 2002; Brännlund et al.,
114 2007; Ma et al., 2008; Chen et al., 2020a). Given that carbon rebound effects include
115 not only the energy-saving effects caused by technological progress but also the
116 optimization of the energy consumption structure and reductions in carbon emission
117 coefficients, the carbon rebound effects assessed by the traditional method may be
118 largely similar to energy rebound effects, thus leading to inaccurate conclusions.
119 Additionally, although several studies have calculated carbon rebound effects, few
120 studies have analyzed the underlying mechanisms that lead to different regional

121 results.

122 Therefore, this study proposes a modified and improved PDA-Meta-frontier
123 Malmquist index (MMI)-based approach to assess economy-wide carbon rebound
124 effects, which accounts for the effects of energy technological progress on emission
125 intensity. Upon comparing carbon and energy rebound effects, we estimated the
126 impacts of energy technological progress on emission intensity (i.e., the ratio of total
127 carbon emissions to total energy consumption), which included the impacts of energy
128 technological progress on the energy use structure and carbon emission efficiency. To
129 further analyze the underlying mechanisms of energy technological progress on
130 regional emission intensity, we divided total energy use into coal and non-coal
131 technologies and combined the LMDI and PDA-MMI approaches to decompose the
132 changes in emission intensity, after which we obtained the impacts of coal and
133 non-coal technology on emission intensity and carbon rebound effects. Moreover, we
134 further analyzed the regional catch-up effects of the coal and non-coal technological
135 gaps on emission intensity and carbon rebound effects based on the group and global
136 frontiers provided by the MMI method. Simultaneously, we focused on China as the
137 research objective given that this nation is one of the largest carbon emitters
138 worldwide (Dong et al., 2016; Chen et al, 2019; Cheng et al., 2018; Chen et al.,
139 2020b). The results of this analysis may provide useful information and references for
140 other countries with high carbon emissions.

141 Specifically, our study makes the following contributions: (1) We proposed a
142 modified and improved PDA-MMI-based method to more accurately assess

143 economy-wide carbon rebound effects, which overcomes the shortcomings of the
144 traditional method and identifies the gap between energy and carbon rebound effects.
145 (2) We further analyzed the mechanisms underlying how regional energy
146 technological progress influences emission intensity and carbon rebound effects
147 instead of only calculating carbon rebound effects. (3) Based on national and regional
148 data from 2005-2015, we found that the eastern and western regions of China faced
149 fewer risks of carbon rebound effects compared with those of the central region due to
150 reduced emission intensity derived from technological development. (4) The
151 reductions in emission intensity in the eastern region relied both on coal and non-coal
152 technology, whereas those of the western region only relied on coal technology.

153

154 **2. Methodology**

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

161 *2.1. Traditional methods for economy-wide carbon rebound effect calculation*

162 It is crucial to first introduce the traditional method for rebound effect
163 measurement, including its origin and derivations. In line with the existing literature,

164 the framework to calculate the economy-wide carbon rebound effect is derived from
165 the method for energy rebound effect assessment (Yang et al., 2017a; Wu et al., 2018;
166 Chen et al., 2019; Chen et al., 2020a, 2020b). The traditional formula to estimate
167 economy-wide energy rebound effects is the following:

$$168 \quad \text{Re}^{t+1} = \frac{A^{t+1} \times (Y^{t+1} - Y^t) \times EI^{t+1}}{B^{t+1} \times (EI^t - EI^{t+1}) \times Y^t} \quad (1)$$

169 where Re^{t+1} represents the economy-wide energy rebound effects during period $t+1$;
170 Y^{t+1} represents the economic output during period $t+1$; EI^{t+1} represents the energy
171 intensity during period $t+1$; A^{t+1} represents the contribution rate of technological
172 progress to economic output, which is always represented by the ratio of
173 technological change rate to the output change rate (Lin et al., 2012; Li et al., 2016;
174 Yang et al., 2017; Chen et al., 2020a); B^{t+1} represents the contribution rate of
175 technological progress to potential energy savings caused by energy intensity, which
176 is represented by the contribution of industrial energy intensity to energy intensity¹.
177 The numerator and denominator of Eq. (1) represent the increase in energy
178 consumption through the technological progress output channels and the potential
179 energy consumption savings associated with technological progress, respectively.

180 The traditional economy-wide approach to estimate the energy rebound effect has
181 been widely accepted by several studies (Lin et al., 2012; Li et al., 2017b; Lin et al.,
182 2017; Jin et al., 2019; Chen et al., 2020a), and some scholars further assessed carbon
183 rebound effects based on the traditional method (Yang et al., 2017a; Wu et al., 2018;
184 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.

185 is as follows:

$$186 \quad CRe^{t+1} = \frac{A^{t+1} \times (Y^{t+1} - Y^t) \times CI^{t+1}}{C^{t+1} \times (CI^t - CI^{t+1}) \times Y^t} \quad (2)$$

187 where CRe^{t+1} represents the economy-wide carbon rebound effects during period
188 $t+1$; Y^{t+1} represents the economic output during period $t+1$; CI^{t+1} represents the
189 energy intensity during period $t+1$; C^{t+1} represents the contribution rate of
190 technological progress to the potential carbon reductions caused by carbon use
191 intensity, which is represented by the contribution of the industrial energy intensity to
192 carbon intensity².

193 This approach is not fundamentally different from the previous method for energy
194 rebound effect assessment, except that energy intensity is replaced by carbon intensity.
195 In fact, we consider this to be the major flaw of this carbon rebound effect calculation
196 method. The denominator in Equation (2) reflects the direct effects of technological
197 progress on energy savings and carbon reductions, which can be easily understood
198 with Eq. (A1.3-4) provided in Appendix A1. However, technological progress can
199 also have significant impacts on emission intensity (i.e., C/E ; not to be confused
200 with carbon intensity). Consistent with previous studies, technological progress
201 reduces the proportion of fossil fuel (e.g., coal) consumption (Cheng et al., 2017;
202 Chen et al., 2020a). Notably, the $C^{t+1} \times (CI^t - CI^{t+1}) \times Y^t$ calculation has the same
203 meaning as the $B^{t+1} \times (EI^t - EI^{t+1}) \times Y^t$ calculation, since they both only consider the
204 direct impacts of technological progress on energy. Therefore, based on the traditional
205 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.

206 rendering the carbon rebound effect calculations questionable.

207

208 2.2. Revised and improved PDA-based method

209 According to the definition proposed by previous studies (Saunders, 2008; 2013;

210 Jin et al., 2019), the energy rebound effect is derived from the elasticity of the energy

211 service to energy efficiency, and can be calculated as follows:

$$212 \quad \text{Re} = \frac{\partial S \times h}{\partial h \times S} = \frac{\partial(hE) \times h}{\partial(hE) \times e} = \frac{\partial E \times h}{\partial h \times E} + 1 \quad (3)$$

213 where S represents the energy service; E represents the actual energy consumption

214 under the effect of technological progress or energy efficiency; h represents the

215 technological level or energy efficiency. Based on the definition of carbon rebound

216 effects (Brännlund et al., 2007; Druckman et al., 2011), the formula to estimate carbon

217 rebound effect can be obtained as follows:

$$218 \quad C \text{ Re} = \frac{\partial C \times h}{\partial h \times C} + 1 \quad (4)$$

219 where c represents the actual carbon emission under the impacts of technological

220 progress or energy efficiency.

221 Based on the principles of the economy-wide method for energy rebound effect

222 calculation, deformations to Eq. (4) were made to obtain Eq. (5):

$$223 \quad \begin{aligned} C \text{ Re}^{t+1} &= \frac{dc \times h}{dh \times c} + 1 = \frac{\Delta c^{t,t+1} \times h^t}{\Delta h^{t,t+1} \times C^t} + 1 = \frac{(AC^{t+1} - C^t) \times h^t}{(h^t - h^{t+1}) \times C^t} + 1 \\ &= \frac{AC^{t+1} \times h^t - C^t \times h^{t+1}}{(h^t - h^{t+1}) \times C^t} = \frac{\left(\frac{AC^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}\right) \times h^{t+1}}{(h^t - h^{t+1}) \times \frac{C^t}{h^t}} \end{aligned} \quad (5)$$

224 where AC^t represents the actual and eventual carbon emissions after the reduction

225 and rebound impacts of technological progress or energy efficiency. Here, a decrease

226 in h reflects technological progress, which is similar to energy intensity and carbon
227 intensity. Given that C^t represents carbon emissions under the impacts of
228 technological progress, $\frac{AC^t}{h^t}$ reflects the potential carbon emissions in an economic
229 context with regard to technological progress, whereas $\frac{C^t}{h^t}$ reflects the potential
230 carbon emissions under a specific economic context without technological progress. It
231 is worth mentioning that such principles originated from previous studies, which used
232 the production-theoretical decomposition analysis (PDA) method to decompose the
233 changes in carbon emissions (Wang et al., 2015; Wang et al., 2018).

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

248 energy in total energy use).

249 Additionally, now that $\frac{AC^t}{h^t}$ accounted for both economic context and

250 technological progress, $(\frac{AC^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$ can be replaced by $A^{t+1} \times (\frac{C^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$.

251 Where A^{t+1} also represents the contribution rate of technological progress to

252 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

253 different economic situations (i.e., carbon emissions at different production fronts).

254 Hence, $A^{t+1} \times (\frac{C^{t+1}}{h^{t+1}} - \frac{C^t}{h^t}) \times h^{t+1}$ can also reflect the increased carbon emissions (or

255 unrealized carbon reductions) caused by economic growth that was stimulated by

256 technological progress. Moreover, we adopted the distance function to reflect the

257 technological level, which has been implemented in many studies (Fan et al., 2015;

258 Wang et al., 2015; 2018; Zhao et al., 2019). Therefore, the following equations for

259 carbon and energy rebound effect assessment were obtained:

$$260 \quad CRe^{t+1} = \frac{A^{t+1} \times (\frac{C^{t+1}}{D_C^{t+1}} - \frac{C^t}{D_C^t}) \times D_C^{t+1}}{(D_C^t - D_C^{t+1}) \times \frac{C^t}{D_C^t}} \quad Re^{t+1} = \frac{A^{t+1} \times (\frac{E^{t+1}}{D_E^{t+1}} - \frac{E^t}{D_E^t}) \times D_E^{t+1}}{(D_E^t - D_E^{t+1}) \times \frac{E^t}{D_E^t}} \quad (6-7)$$

261 where D_C^t and D_E^t respectively represent the Shephard undesirable output and

262 energy input distance functions, which were first adopted by Zhou and Ang (2008)

263 and are now widely accepted.

264 Moreover, as the economy-wide carbon and energy rebound effects can be

265 estimated by our improved approach, we can further obtain the elasticity of emission

266 intensity with regard to energy technological progress, which is similar to the

267 approach used by Chen et al (2020a). The calculation model is as follows:

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

269

270 2.3. Effects of different types of technological development on emission intensity

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

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

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

285 Wang et al., 2018).

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

$$\begin{aligned} \Delta CE^{b,t} &= \Delta CE_{ce}^{b,t} + \Delta CE_{PES}^{b,t} + \Delta CE_{TE}^{b,t} \\ 293 \quad &= \Delta CE_{PES}^{b,t} + \Delta CE_{TE}^{b,t} \\ &= \sum_{i=1}^i \Delta CE_{PES_i}^{b,t} + \sum_{i=1}^i \Delta CE_{TE_i}^{b,t} \end{aligned} \quad (10)$$

294

295 [Insert Table. 2 here.]

296

297 2.4. Environmental production technology based on meta-frontier

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

304 First, although the traditional PDA approach helps estimate the Malmquist index,
305 which reflects technological changes, it can only obtain relative technological

306 progress rates based on a contemporaneous benchmark technology set and fails to
 307 analyze the time-series technological changes based on an intertemporal benchmark
 308 technology set (Li et al., 2016). Second, considering that interregional technology
 309 differences may cause changes in carbon emissions (Du et al., 2014, 2017; Zhang et
 310 al., 2015; 2016a; Zha et al., 2019; Liu et al., 2019; Chen et al., 2020a), especially
 311 between the eastern, central, and western regions of China³, it is important to divide
 312 the technology set into three groups and estimate the technological progress based on
 313 interregional differences.

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

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

$$319 \quad P_{groupi}^t = \{(K, L, E, Y, C) : (K, L, E) produce(Y, C); i = 1, 2, 3\} \quad (11)$$

$$320 \quad P_{groupi}^T = \{(K, L, E, Y, C) : (K, L, E) produce(Y, C); i = 1, 2, 3; T = 1, 2, \dots, t\} \quad (12)$$

$$321 \quad P_{global}^T = conv\{P_{group1}^T \cup P_{group2}^T \cup P_{group3}^T\} \quad (13)$$

322 where E represents energy consumption; K represents capital; L represents labor
 323 force; Y represents economic output and desirable output; C represents carbon
 324 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.

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

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

$$330 \quad D_E^S = \sup \left\{ \lambda_1 : (K, L, E / \lambda_1, Y, C); P_{groupi}^t \right\} \quad (14)$$

$$331 \quad D_C^S = \sup \left\{ \theta_1 : (K, L, E, Y, C / \theta_1); P_{groupi}^t \right\} \quad (15)$$

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

$$335 \quad D_E^G = D_E^S \times D_E^I (E / D_E^S) \times D_E^G (E / D_{Ei}^I) = D_E^S \times D_E^{IS} \times D_E^{GI} \quad (16)$$

$$336 \quad D_C^G = D_C^S \times D_C^I (C / D_C^S) \times D_C^G (C / D_C^I) = D_C^S \times D_C^{IS} \times D_C^{GI} \quad (17)$$

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

340

341 2.5 Data

342 Due to data availability and consistency constraints, the scope of our study was
 343 limited to carbon emissions produced by energy sources in 30 provinces of China
 344 (except for the Tibet, Hong Kong, Macao, and Taiwan regions due to a lack of data)
 345 from 2005 to 2015⁴. 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,

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

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

357 Regarding input variables, we considered capital stock (100 million yuan), human
358 capital stock (10,000 people per year), and energy consumption (10,000 tons of
359 standard coal equivalent, TCE). The perpetual inventory method was used to calculate
360 fixed capital stock, as described in previous studies (Liu et al., 2019; Chen et al.,
361 2020a; 2020b), after which it was converted to its real value in 1978 to eliminate the
362 impact of prices and inflation. The “education years law” method was used to
363 estimate human capital, as described by many previous studies (Yang et al., 2017b;
364 Chen et al., 2020a). The data for industrial and residential energy consumption was
365 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

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

367 **3. Results and Discussion**

368 *3.1 Comparison of the results calculated by the traditional and improved methods*

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

374

375 [Insert Table. 3 here.]

376

377 Among said results, CRe and Re represent the carbon and energy rebound
378 effects, respectively. Notably, the economy-wide carbon and energy rebound effects
379 calculated with the traditional approach were not significantly different, indicating
380 that carbon rebound effects estimated by the traditional method are equivalent to the
381 energy rebound effect, which is a questionable conclusion. Figure 1 compares the
382 results of the two methods more intuitively:

383

384 [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.

385

386 where CRe_0 , Re_0 , CRe_1 , and Re_1 represent carbon and energy rebound effects
387 calculated by the traditional and improved methods, respectively. Importantly, the
388 results estimated by the traditional method are consistent with our predictions and
389 opinions that were proposed in Section 2.1 regarding its flaws as it ignores the
390 impacts of technological progress on the energy consumption structure, which has
391 been confirmed by previous studies (Chen et al., 2020a). Therefore, the traditional
392 framework and method may be unsuitable to estimate the carbon rebound effect, even
393 if it can be applied to assess energy rebound effects.

394 On the other hand, our improved method evidently overcomes the disadvantages
395 of traditional methods, and the results estimated by our improved method reveal the
396 significant impacts of technological progress on emission intensity. At the same time,
397 the energy rebound effects estimated by our method are close to those estimated by
398 the traditional method, suggesting that our method is robust and trustworthy (Lin et al.,
399 2012; Li et al., 2017b; Wu et al., 2018).

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

405 As for the empirical results calculated by our approach, we found that the national,
406 eastern, central, and western average carbon rebound effects were 36%, 38%, 41%,

407 and 30% during 2006-2015, suggesting that the carbon rebound impact in the western
408 region was relatively low, whereas the risk of carbon rebound in the eastern and
409 central regions was relatively high. The average national carbon rebound effects based
410 on our methods were similar to those of Wu et al. (2018) at 32.5% and Yang et al.
411 (2016) at 35%. Furthermore, although there were some fluctuations in the national,
412 eastern, central, and western rebound effects during 2006-2015, the trends of carbon
413 and energy rebound effects ultimately decreased overall, which is consistent with
414 what has been found in previous studies (Lin et al., 2017; Chen et al., 2019; Chen et
415 al., 2020a). Additionally, the carbon rebound effect turning point approximately
416 occurred between 2010-2011, which is consistent with the results provided by Wu et
417 al. (2018).

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

425 These evident differences may be due to the shortcomings of the traditional
426 approach that ignore the impacts of emission intensity. To test the reliability of the
427 conclusions from past research, we also used the traditional method to estimate the
428 regional carbon rebound effects, and they are presented in Table 3. Clearly, the results

429 we estimated in Table 3 can also be used to draw a similar conclusion. Therefore, we
430 can reasonably speculate that the conclusions drawn by previous studies regarding
431 regional carbon rebound effects may be wrong due to the limitations of the traditional
432 method. In fact, the western region had the lowest risk of carbon rebound effects, but
433 presented a relatively high risk of energy rebound effects.

434

435 *3.2 Impacts of regional technological progress on emission intensity*

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

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

444

445 [Insert Figure. 2 here.]

446

447 As can be seen in Figure 2, it is evident that national technological progress
448 played an important role in reducing emission intensity in most years, which helped to
449 reduce the proportion of high-emission energy use, as has been reported in previous
450 studies (Chang et al., 2010; Cheng et al., 2018; Chen et al., 2020a). Regionally, we

451 found that eastern and western energy technological progress had a strong effect on
452 reducing emission intensity, whereas central regional technological progress had no
453 visible effects. The different impacts of regional technological progress may explain
454 why the risk of carbon rebound effects in the western region was lower than that in
455 either the western or central regions. Furthermore, western technological progress
456 played a more significant role in decreasing emission intensity compared to that of the
457 eastern region, indicating that the proportion of high-emission energy use declined
458 faster in the west.

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

467 Hence, on the one hand, given that the promotion of renewable and sustainable
468 energy was mainly concentrated in the east (Gu et al., 2019; Chen et al., 2020a), we
469 speculate that the decreasing ratio of high-emission energy use in the east may have
470 been mainly due to the first factor. On the other hand, since “the optimized
471 development of the energy and chemical industry” was regarded as a significant
472 development goal of the western region, the western region paid more attention to the

473 development of high-emission energy technology and had a greater reduction of
474 emission intensity than either the eastern or central regions (Chen et al., 2010; Dong
475 et al., 2016; Liu et al., 2019). Therefore, we speculate that the decreasing ratio of
476 high-emission energy use in the west may have been mainly due to the second factor.

477

478 *3.3 Effects of technological advance on coal and non-coal emission intensity*

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

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

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

497

498 [Insert Table. 4 here.]

499

500 $\Delta CE_{PES}^{b,t}$, $\Delta CE_{TE}^{b,t}$, $\Delta CE_{TE1}^{b,t}$, and $\Delta CE_{TE2}^{b,t}$ respectively represent the average impacts
501 of the potential energy consumption structure and energy technology, coal technology,
502 and non-coal technology on emission intensity. Evidently, the potential energy
503 consumption structure in the eastern and central regions favored a reduction in
504 emission intensity from 2005-2015, indicating that optimization of the eastern and
505 central industrial structure played a more important role in carbon reduction, which is
506 consistent with what has been reported in previous studies (Dhakal, 2009; Wang and
507 Wang, 2018; Gu et al., 2019; Chen et al., 2020b). Further, $\Delta CE_{TE}^{b,t}$ indicated that
508 energy technological changes in the eastern and western regions strongly decreased
509 the emission intensity, whereas the technological changes of the central region had no
510 visible effect. In the eastern region, the reduction effects from energy technological
511 progress on emission intensity may have been the result of the promotion of
512 low-emission energy, especially renewable and sustainable energy, being mainly
513 concentrated in the east, which is consistent with what has been reported in the
514 literature and existing conditions (Gu et al., 2019; Chen et al., 2020a). Actually, many
515 scholars have also pointed out that locations within the eastern region, such as Beijing,
516 Shanghai, and Jiangsu, always have more renewable and cleaner energy technology

517 than those of other areas and help to optimize the energy use structure (Wang and
518 Wang, 2018; Lin et al., 2019).

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

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

539 hand, we found that non-coal technology in the eastern region played a role in
540 decreasing emission intensity, whereas non-coal technology in the central and western
541 regions rarely influenced emission intensity.

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

554 In summary, we can draw some conclusions regarding the mechanisms behind the
555 carbon rebound effect gap in various regions: (1) The eastern region may continue to
556 focus on both coal and non-coal technology, which helped to decrease the emission
557 intensity and translated to carbon rebound effects that were lower than the energy
558 rebound effects (Gu et al., 2019; Chen et al., 2020a). (2) Energy technology in the
559 central region failed to reduce emission intensity, leading to high carbon rebound
560 effect risks. (3) Energy technology in the western region was focused on coal

561 technology, which favored a decrease in emission intensity and carbon rebound
562 effects (Chen et al., 2010). (4) The effects on emission intensity in the western region
563 resulted in a greater reduction of the carbon rebound effects than in the eastern region,
564 which may be because non-fossil energy is unable to substitute fossil energy in the
565 short term (York, 2012; Chen et al., 2020a).

566 **4. Conclusions and Policy Implications**

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

576 As for the carbon rebound effect, we found that the eastern and western regions
577 faced fewer carbon rebound effect risks compared with those of the central region,
578 which contrasts with the findings of previous studies (Yang et al., 2017; Wu et al.,
579 2018). The differences derive from the impacts of technological progress on emission
580 intensity. We found that the reduction in emission intensity caused by energy
581 technological progress resulted in fewer carbon rebound effects in the eastern and

582 western regions. Further, decreasing emission intensity in the eastern region may have
583 been mainly due to the widespread use of low-emission energy (Wang and Wang,
584 2018; Gu et al., 2019; Chen et al., 2020a), whereas the decreasing emission intensity
585 in the western region may have mainly come from greater technological progress in
586 high-emission energy, such as coal use (Chen et al., 2010; Dong et al., 2016; Liu et al.,
587 2019). Based on our empirical results, we suggest the following policy proposals to
588 reduce carbon rebound effects.

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

599 Second, it is more useful to focus on improving high-emission energy efficiency
600 to reduce carbon rebound effects, as emission intensity effects can lead to a greater
601 reduction in carbon rebound effects. According to our empirical analysis, focusing on
602 coal played a more significant role than any other factor in decreasing emission
603 intensity and carbon rebound effects (Chen et al., 2010), which explains why the

604 western region faced fewer carbon rebound effect risks than those of the other regions,
605 even with relatively high energy rebound effects. Considering that renewable and
606 cleaner energy cannot substitute fossil energy in the short term (Chen et al., 2020a),
607 the eastern and central regions should prioritize the improvement of coal efficiency,
608 after which cleaner energy sources should be developed.

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

620

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627

628 **Declarations of interest**

629 None

630

631 **References**

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787

788 **Appendix A1**

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

$$791 \quad EI^t = \sum_i^3 \frac{E_i^t}{Y_i^t} \times \frac{Y_i^t}{Y^t} = \sum_i^3 ei_i^t \times IND_i^t \quad (A1.1)$$

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

$$797 \quad B^{t+1} = \frac{\frac{\Delta EI^{t,t+1}}{\ln(EI^t / EI^{t+1})} \times \ln(ei_i^t / ei_i^{t+1})}{\Delta EI^{t,t+1}} \quad (A1.2)$$

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

$$800 \quad CI^t = \sum_i^3 \frac{C_i^t}{E_i^t} \times \frac{E_i^t}{Y_i^t} \times \frac{Y_i^t}{Y^t} = \sum_i^3 CE_i^t \times ei_i^t \times IND_i^t \quad (A1.3)$$

$$801 \quad C^{t+1} = \frac{\frac{\Delta CI^{t,t+1}}{\ln(CI^t / CI^{t+1})} \times \ln(ei_i^t / ei_i^{t+1})}{\Delta CI^{t,t+1}} \quad (A1.4)$$

802

803 **Appendix A2**

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

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

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

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

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

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

$$816 \quad D_E^{G,t} = D_E^{GI,t} \times D_E^{I,t} = D_E^{GI,t} \times D_E^{IS,t} \times D_E^{S,t} = Gap_E^t \times Techch_E^t \times Effch_E^t \tag{A2.4}$$

$$817 \quad D_C^{G,t} = D_C^{GI,t} \times D_C^{I,t} = D_C^{GI,t} \times D_C^{IS,t} \times D_C^{S,t} = Gap_C^t \times Techch_C^t \times Effch_C^t \tag{A2.5}$$

818 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
819 level of technical efficiency; $D_E^{GI,t}$ and $D_C^{GI,t}$ represent the technology gap (Oh et al.,
820 2010; Zha et al., 2019). Next, we can apply these factors to the estimation of
821 economy-wide carbon and energy rebound effects as follows:

$$822 \quad CRe^{t+1} = \frac{A^{t+1} \times \left(\frac{C^{t+1}}{D_C^{G,t+1}} - \frac{C^t}{D_C^{G,t}} \right) \times D_C^{G,t+1}}{(D_C^{G,t} - D_C^{G,t+1}) \times \frac{C^t}{D_C^{G,t}}} \quad (24)$$

$$823 \quad Re^{t+1} = \frac{A^{t+1} \times \left(\frac{E^{t+1}}{D_E^{G,t+1}} - \frac{E^t}{D_E^{G,t}} \right) \times D_E^{G,t+1}}{(D_E^{G,t} - D_E^{G,t+1}) \times \frac{E^t}{D_E^{G,t}}} \quad (25)$$

824

825

826 Appendix A3

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

$$829 \quad D_{coal}^G = D_{coal}^S \times D_{coal}^{IS} \times D_{coal}^{GI} \quad (A3.1)$$

$$830 \quad D_{non-coal}^G = D_{non-coal}^S \times D_{non-coal}^{IS} \times D_{non-coal}^{GI} \quad (A3.2)$$

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

$$833 \quad \begin{aligned} & [D_{coal}^S(K, L, coal, non-coal, Y, C)]^{-1} & [D_{non-coal}^S(K, L, coal, non-coal, Y, C)]^{-1} \\ & = \min \lambda_1 & = \min \theta_1 \\ & s.t. \sum_{k=1}^K z_k coal_k^t \leq \lambda_{1,k} coal_k^t; & s.t. \sum_{k=1}^K z_k non-coal_k^t \leq non-coal_k^t; \\ & \sum_{k=1}^K z_k non-coal_k^t \leq non-coal_k^t; & \sum_{k=1}^K z_k coal_k^t \leq coal_k^t; \\ & \sum_{k=1}^K z_k K_k^t \leq K_k^t; & \sum_{k=1}^K z_k K_k^t \leq K_k^t; \\ & \sum_{k=1}^K z_k L_k^t \leq L_k^t; \sum_{k=1}^K z_k Y_k^s \geq Y_k^t; & \sum_{k=1}^K z_k L_k^t \leq L_k^t; \sum_{k=1}^K z_k Y_k^s \geq Y_k^t; \\ & \sum_{k=1}^K z_k C_k^t = C_k^t; z_k \geq 0; k = 1, \dots, K & \sum_{k=1}^K z_k C_k^t = C_k^t; z_k \geq 0; k = 1, \dots, K \end{aligned} \quad (A3.3-4)$$

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

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

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

839

840 **Table Captions**

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

842 **Table 2.** Additive decomposition formula of driving factors.

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

844 **Table 4.** Effects of technological change on coal and non-coal emission intensity

845 (units: 10^{-4} t/cet).

846

847 **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
				Energy
Shao et	1991-2016	Shanghai	The state-space econometric	rebound
al. (2019)		(China)	method	effects

848

849

850 **Table 2.** Additive decomposition formula of driving factors.

Driving factors of carbon emissions

$\Delta CE_{ce}^{b,t}$	$\Delta CE_{ce}^{b,t} = \sum_{i=1}^i \frac{(CE^t - CE^b)}{\ln(CE^t / CE^b)} \times \ln(ce_i^t / ce_i^b)$
$\Delta CE_{PES}^{b,t}$	$\Delta CE_{PES}^{b,t} = \sum_{i=1}^i \frac{(CE^t - CE^b)}{\ln(CE^t / CE^b)} \times \ln(PES_i^t / PES_i^b)$
$\Delta CE_{TE}^{b,t}$	$\Delta CE_{TE}^{b,t} = \sum_{i=1}^i \frac{(CE^t - CE^b)}{\ln(CE^t / CE^b)} \times \ln(TE_i^t / TE_i^b)$

851

852

853 **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

854

855

856 **Table 4.** Effects of technological change on coal and non-coal emission intensity

857 (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
	East	-0.23	0.16	0.13	0.03	-0.02	0.04
2011-2012	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
	East	0.14	-0.26	-0.18	-0.08	-0.09	-0.09
2012-2013	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
	East	-0.01	0.00	0.03	-0.03	0.01	-0.02
2013-2014	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
	East	-0.02	-0.12	-0.07	-0.06	0.01	-0.07
2014-2015	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
	East	-0.05	-0.03	-0.02	-0.01	-0.02	0.00
2005-2015	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

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

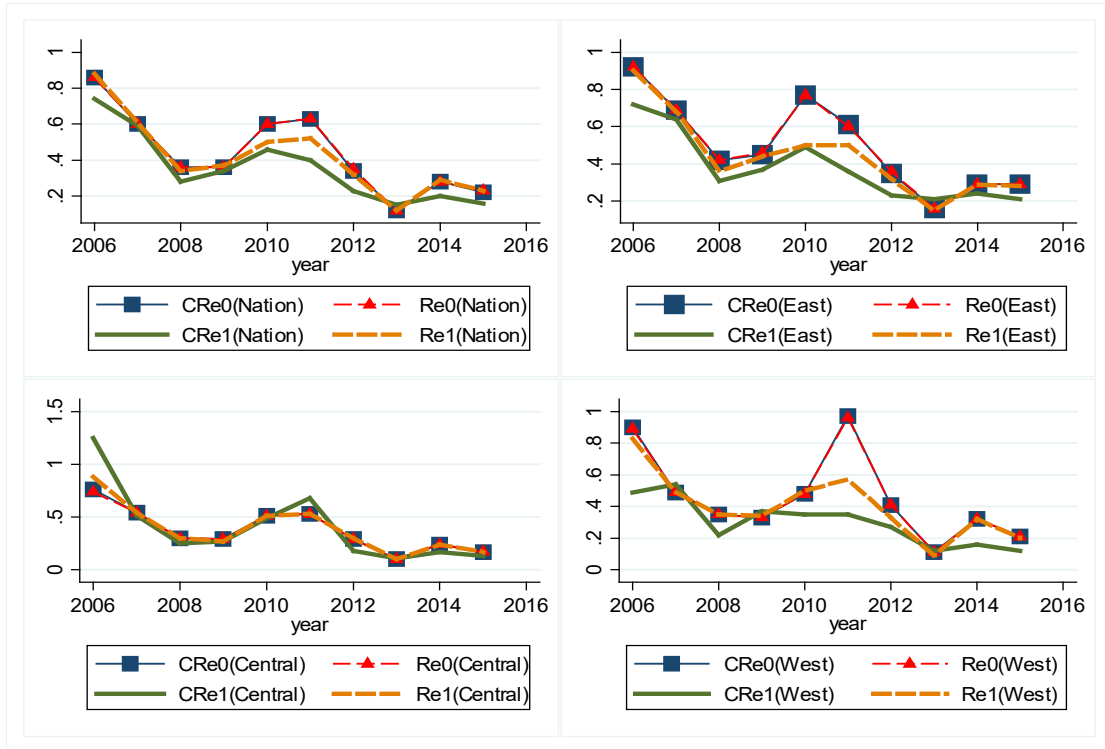
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862 **Figure Captions**

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

865 **Fig. 2.** Impacts of technological progress on emission intensity in China from 2005 to
866 2015 (units: 10^{-2} t/cet).

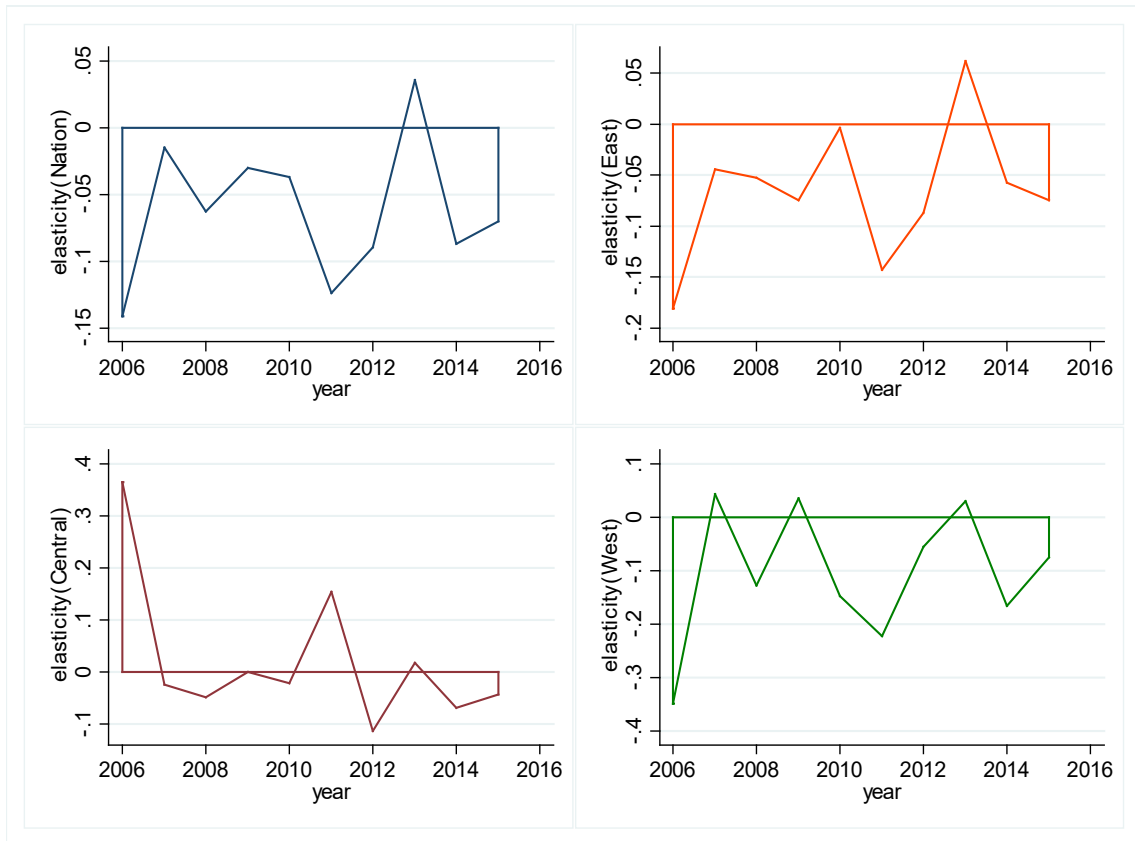
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869 **Fig. 1.** Temporal changes in carbon and energy rebound effects in China from 2005 to
 870 2015 based on the traditional and improved methods. CRe_0 , Re_0 , CRe_1 , and Re_1
 871 represent carbon and energy rebound effects calculated by the traditional and
 872 improved methods, respectively

873



874

875 **Fig. 2.** Impacts of technological progress on emission intensity in China from 2005 to

876 2015 (units: 10^{-2} t/cet).

877