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Decomposing the changes of energy-related carbon emissions in China: evidence from the PDA approach

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Abstract

In order to investigate the main drivers of CO₂ emissions changes in China during the 11th Five-Year Plan period (2006-2010) and seek the main ways to reduce CO₂ emissions, we decompose the changes of energy-related CO₂ emissions using the production-theoretical decomposition analysis (PDA) approach. The results indicate that, first, economic growth and energy consumption are the two main drivers of CO₂ emissions increase during the sample period; particularly in the northern coastal, northwest and central regions, where tremendous coal resources are consumed, the driving effect of their energy consumption on CO₂ emissions appears fairly evident. Second, the improvement of carbon abatement technology and the reduction of energy intensity play significant roles in curbing carbon emissions, and comparatively the effect of carbon abatement technology and carbon abatement technical efficiency have only slight influence on CO₂ emissions overall. In the end, we put forward some policy recommendations for China's government to reduce CO₂ emissions intensity in the future.

Keywords: CO₂ emissions; PDA; distance functions; environmental DEA

1. Introduction

China has become the world's largest energy consumer since 2009. With energy use per capita much lower than developed countries, the fast growing China, already the largest CO2 emitter, is set to put out even more greenhouse gases (GHG) in a scale, at a pace, unseen in history. China's GHG emissions and its contribution to climate change have, therefore,

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received increasing attention worldwide in recent years. To be a more "responsible" global stakeholder, the Chinese government has put forward rigid quantitative targets to reduce the growth rates of energy consumption and carbon emissions. In 2006, China announced the 20% target to reduce energy consumption per unit of gross domestic product (GDP) (i.e., energy intensity) during the 11th Five-Year Plan period (2006-2010); and in the end, 19.1% energy intensity reduction was achieved. In 2012, China's central government announced again that China's energy consumption and CO₂ emissions per unit of GDP (i.e., CO₂ emissions intensity) should be reduced 16% and 17% respectively during the 12th Five-Year Plan period (2011-2015), while the proportion of non-fossil fuels in primary energy consumption should rise to 11.4% from 8% in 2011. These quantitative targets set a responsible and pragmatic image for China in the international community.

Besides, according to China's mid- and long-term development plan, China aims to realize the well-off society (i.e., moderately prosperous society) by the end of 2020, therefore, the 12th Five-Year Plan period (2011-2015) is one of the most important stages for this goal. During such a period, China's CO₂ emissions may inevitably increase due to a number of driving factors, including the growing population, expanding economy, emerging high-level consumption pattern, transforming towards high-industrialized economy, advancing urbanization *et al.*

Under this circumstance, we have to find some effective ways to decouple the CO₂ emissions, energy consumption and economic growth. Therefore, we employ the recently proposed production-theoretical decomposition analysis (PDA) approach to decompose China's energy-related CO₂ emissions changes during 2006-2010 and try to assess the driving factors of CO2 emissions as well as the most effective ways to curb CO₂ emissions, and then some insightful policy recommendations are provided for the decision-making by China's government.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodologies and data. Section 4 sets out the empirical results. And Section 5 concludes the paper.

2. Literature review

With the growing attention on global warming issues, the literature pertaining to greenhouse gas emissions emerges these years. It has been universally acknowledged that CO₂ emissions have made the largest contribution to the greenhouse effect (Paul and Bhattacharya 2004), and there exists a great deal of literature discussing the decomposition of the changes of CO₂ emissions and their impacting factors in recent decades. As for the results, previous literature has commonly addressed that the factors affecting CO₂ emissions mainly cover economic growth, energy intensity, energy consumption structure, industrial structure, population and so on (Ang 1997, 1999; Wang et al. 2005; Zhang et al. 2009; Freitas and Kaneko 2011). And these studies almost show that economic growth is considered to be the main contributor to CO₂ emissions increase, while the decline in energy intensity and the use of clean energy and renewable energy are often the major inhibiting factors.

As for the approaches to decompose CO_2 emissions changes, there are mainly two categories, i.e., structural decomposition analysis (SDA) and index decomposition analysis (IDA). The SDA approach is based on the input-output model in quantitative economics to decompose CO₂ emissions changes for specific years only when the input-output tables are available, and the data requirement is relatively higher (Zhou and Ang 2008; Chang et al. 2008). Compared to SDA, the application of IDA proves more extensive. The early IDA forms mainly include Laspeyres and Divisia index approaches. And comparatively, the Laspeyres index approach is easier to understand but has large residual terms in decomposition results. As for this respect, Sun (1998) proposes an approach which is a refinement of the Laspeyres index approach without residual terms and is called the complete decomposition model, but its decomposition formulae appear very complicated when the number of factors exceeds three (Ang and Zhang 2000). Moreover, the Divisia index approach mainly includes arithmetic mean Divisia index (AMDI) and log mean Divisia index (LMDI), and they use the arithmetic mean weight function and log mean weight function respectively (Hatzigeorgiou et al. 2008). Meanwhile, the AMDI approach fails the factor-reversal test and may produce a large residual term in several situations, while the LMDI does not have such problems corresponding with perfect decomposition approaches proposed by Ang (2004). Overall, the IDA approach proves superior to the SDA in terms of CO₂ emissions decomposition.

In addition to the IDA and SDA approaches, the production theory is also increasingly applied to energy and environment studies in recent years, combined with the distance functions and environmental Data Envelopment Analysis (DEA) technique, so as to decompose CO₂ emissions changes. For instance, Zhou and Ang (2008) decompose the changes of aggregate CO₂ emissions into seven factors using the Shephard input distance function and environmental DEA technique based on the production theory. Their results indicate that economic growth proves the most important contributor to CO₂ emissions increase while the improvement of carbon abatement technology and energy saving technology has the most important effect on CO₂ emissions reduction. And they call the proposed approach as the production- theoretical decomposition analysis (PDA) approach. Afterwards, Zhang et al. (2012) use the PDA approach to decompose the CO₂ emissions changes of 20 developing counties into nine drivers, and the results also reveal that economic growth is the main contributor to CO₂ emissions increase and good output technical change is the most important component to CO₂ emissions reduction. Besides, Li (2010) employs the DEA technique to decompose China's provincial CO₂ emissions changes into seven factors based on the Shephard output distance function, and finds that the GDP scale effect proves the main factor of CO₂ emissions increase, but the emissions index associated with capital proves a dominant contributor to CO_2 emissions reduction; additionally, the effect of technical change in production and change in GDP composition by sector play positive roles in curbing CO₂ emissions. Overall, the PDA approach has significant characteristics compared with the IDA and SDA approaches, and one of its key characteristics is that it uses the production theory combined with distance functions and environmental DEA technique to decompose CO₂ emissions changes and a number of drivers are obtained including economy, energy, technology and technical efficiency et al. Besides, as mentioned in Zhou and Ang (2008), the PDA approach has low data requirement and completely satisfies the three index properties which are possessed in perfect decomposition approaches proposed by Ang (2004).

Moreover, some literature has considered the regional differences in the main impacting factors of CO₂ emissions in China. For example, Li et al. (2012) divide 30 provinces of China into five regions based on the level of CO₂ emissions per capita during 1990-2010, and then use the STIRPAT model to discuss the regional differences in impacting factors of CO₂ emissions. The results indicate that in most regions, GDP per capital and urbanization have bigger effect on CO₂ emissions than other factors, and although the improvement of technology exerts relatively weaker effect on CO₂ emissions reduction, it is still a major way for CO₂ emissions reduction in China. It should be noted that the factors they consider are different from those with PDA approach. In addition, Meng et al. (2011) develop a panel data model with fixed effect to analyze the relationship among CO₂ emissions, economic growth and energy intensity during 1997-2009 at the regional level in China. The results show that the contribution of economic growth to CO₂ emissions increase appears more concentrated in the central region, while more polarized in eastern and western regions; meanwhile, the influence of energy intensity on CO₂ emissions reduction differs from regions. It should be pointed out that Meng et al. (2011) only consider the disparity among eastern, central and western regions and the regional elasticity of GDP per capita and energy intensity on CO₂ emissions, therefore, some further and specific work can be conducted, such as more regions, more factors. Furthermore, currently little literature has explored the main drivers of CO₂ emissions changes during the 11th Five-Year Plan period as well as the main ways to curb CO₂ emissions increase; however, this kind of exploration should be of great importance for decision makers.

Under this circumstance, this paper makes full use of the PDA approach and to decompose China's CO₂ emissions changes into seven impacting factors according to the context in both 30 provinces and 8 regions during the 11th Five-Year Plan period.

3. Methodologies and data definitions

3.1 The decomposition approach

According to Zhou and Ang (2008), in production theory, the production technology can be described as Eq. (1), which is assumed to be a closed and bounded set; put another way, finite input can only produce finite outputs. Here, energy consumption (*E*) to be the only input, while GDP (Y) and CO₂ emissions (*C*) are considered to be desirable and undesirable outputs respectively. It should be noted that *S* is also referred to as the environmental DEA technology exhibiting constant returns to scale (CRS) since it is formulated in the DEA framework.

$$S = \{ (E, Y, C) \colon E \text{ can produce } (Y, C) \}$$
(1)

Then we define the Shephard distance functions for the input(E) and undesirable

output(C) as Eqs. (2) and (3) respectively, which denote the ratios between the actual value and theoretical value of *E* and *C* respectively.

$$D_e(E,Y,C) = \sup\{\lambda : (E / \lambda, Y, C) \in S\}$$
(2)

$$D_{c}(E,Y,C) = \sup\{\theta : (E,Y,C/\theta) \in S\}$$
(3)

Specifically, Eq. (2) means decreasing energy consumption as much as possible given the GDP, CO₂ emissions and production technology. Since this distance function is the ratio of actual value and theoretical value, the consequence must be equal to or greater than unity. And the unity indicates the optimal production process, while greater than unity suggests that the production process is not optimal.

Similar to Eq. (2), Eq. (3) means reducing CO₂ emissions as much as possible given the energy consumption, GDP and production technology. And in the results, the unity means the optimal production process, otherwise non-optimal.

Now here there are 30 emitting entities, and the CO₂ emissions of certain entity *k* (*k*=1, 2, 3, ..., 30) change from C_k^0 in period 0 (i.e., the base period or the year of 2006) to C_k^T in period *T* (i.e., the year of 2010). We can decompose the changes of CO2 emissions as follows:

$$D_{k} = \frac{C_{k}^{T}}{C_{k}^{0}} = \left(\frac{C_{k}^{T} / E_{k}^{T}}{C_{k}^{0} / E_{k}^{0}}\right) \cdot \left(\frac{E_{k}^{T} / Y_{k}^{T}}{E_{k}^{0} / Y_{k}^{0}}\right) \cdot \left(\frac{Y_{k}^{T}}{Y_{k}^{0}}\right)$$
(4)

Based on this decomposition form, we introduce the two distance functions above into Eq. (4) by using the production technology of the base period as follows.

$$D_{k} = \left(\frac{\left[C_{k}^{T} / D_{c}^{0}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)\right] / E_{k}^{T}}{\left[C_{k}^{0} / D_{c}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)\right] / E_{k}^{0}}\right) \times \left(\frac{\left[E_{k}^{T} / D_{e}^{0}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)\right] / Y_{k}^{T}}{\left[E_{k}^{0} / D_{e}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)\right] / Y_{k}^{0}}\right)} \times \left(\frac{\left(\frac{Y_{k}^{T}}{Y_{k}^{0}}\right) \times \left(\frac{D_{c}^{0}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)}{D_{c}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)}\right) \times \left(\frac{D_{e}^{0}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)}{D_{e}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)}\right) \right)$$
(5)

In Eq. (5), the first part in the right side represents the ratio of CO2 emissions per energy consumption between period T and period 0, which indicates the potential energy emissions intensity changes ($PEECH_k^0$); the second part represents the ratio of energy consumption per unit of GDP between period T and period 0, which indicates the changes of potential energy intensity ($PEICH_k^0$); the third part represents the ratio of desirable output GDP

between period *T* and period 0, which means the influence of economic growth on CO_2 emissions ($GDPCH_k^0$); and the last two parts are both Malmquist index numbers taking the production technology in period 0 as references, which mean the changes of CO_2 emissions performance ($CEPCH_k^0$) and energy use performance ($EUPCH_k^0$) respectively. The Malmquist productivity index was first developed by Caves et al. (1982) and Färe et al. (1994) extended it by considering technical inefficiency in productivity measurement and calculating the Malmquist productivity index within a non-parametric framework. It should be noted that, according to Zhou et al. (2012), the Malmquist index numbers here may be considered as extensions to the Malmquist productivity index that is a popular approach to compute total factor performance index; on the other hand, the Malmquist index numbers in this paper measure the relative performance from the viewpoint of production efficiency.

In this way, we may rewrite Eq. (5) as follows:

$$D_{k} = PEECH_{k}^{0} \times PEICH_{k}^{0} \times GDPCH_{k}^{0} \times CEPCH_{k}^{0} \times EUPCH_{k}^{0}$$
(6)

The referenced production technology in the distance functions of Eq. (5) and Eq. (6) are both based on period 0. In order to avoid the possible arbitrariness existing in the decomposition results, we adopt the reference which is the geometric mean of those distance functions based on period 0 and period T as follows:

$$D_{k} = \left(\frac{\left\{ C_{k}^{T} / \left[D_{c}^{0} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right) D_{c}^{T} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right) \right]^{1/2} \right\} / E_{k}^{T}}{\left\{ C_{k}^{0} / \left[D_{c}^{0} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right) D_{c}^{T} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right) \right]^{1/2} \right\} / E_{k}^{0}} \right) \right. \\ \times \left(\frac{\left\{ E_{k}^{T} / \left[D_{e}^{0} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right) D_{e}^{T} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right) \right]^{1/2} \right\} / Y_{k}^{T}}{\left\{ E_{k}^{0} / \left[D_{e}^{0} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right) D_{e}^{T} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right) \right]^{1/2} \right\} / Y_{k}^{0}} \right) \right. \\ \times \left(\frac{Y_{k}^{T}}{Y_{k}^{0}} \right) \times \left(\left[\frac{D_{c}^{0} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right)}{D_{c}^{0} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right)} \cdot \frac{D_{c}^{T} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right)}{D_{c}^{T} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right)} \right]^{1/2} \right) \right. \\ \times \left(\left[\frac{D_{e}^{0} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right)}{D_{e}^{0} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right)} \cdot \frac{D_{e}^{T} \left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T} \right)}{D_{c}^{T} \left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0} \right)} \right]^{1/2} \right) \right.$$
(7)

For simplicity, Eq. (7) can be expressed as follows:

$$D_{k} = PEECH_{k} \times PEICH_{k} \times GDPCH_{k} \times CEPCH_{k} \times EUPCH_{k}$$
(8)

In Eq. (8), $CEPCH_k$ and $EUPCH_k$ are the two Malmquist index numbers, and we can reform them as Eqs. (9) and (10) respectively:

$$CEPCH_{k} = \left(\frac{D_{c}^{T}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)}{D_{c}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)}\right) \times \left(\left[\frac{D_{c}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)D_{c}^{0}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)}{D_{c}^{T}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)D_{c}^{T}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)}\right]^{1/2}\right)$$
(9)
$$EUPCK_{k} = \left(\frac{D_{e}^{T}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)}{D_{e}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)}\right) \times \left(\left[\frac{D_{e}^{0}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)D_{e}^{0}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)}{D_{e}^{T}\left(E_{k}^{T}, Y_{k}^{T}, C_{k}^{T}\right)D_{e}^{T}\left(E_{k}^{0}, Y_{k}^{0}, C_{k}^{0}\right)}\right]^{1/2}\right)$$
(10)

In Eq. (9), the first part in the right side shows carbon abatement technical efficiency changes ($CATECH_k$), while the second means carbon abatement technology changes ($CATCH_k$). And in the right side of Eq. (10), the first part indicates energy use technical efficiency changes ($EUTECH_k$), while the second denotes energy use technology changes ($EUTCH_k$). Then, we may rewrite Eq. (8) as:

$$D_{k} = PEECH_{k} \times PEICH_{k} \times GDPCH_{k} \times CATECH_{k} \times CATCH_{k}$$
$$\times EUTECH_{k} \times EUTCH_{k} \qquad (11)$$

In fact, each part in the right side of Eq. (11) denotes an impacting factor of CO₂ emissions changes, and is considered to be a positive role in CO₂ emissions increase if it is greater than unity and the greater value means the more positive effect. But if some part is less than unity, it tends to have restrictive effect on CO₂ emissions increase and the smaller value means the more restrictive effect. It should be noted that the last four parts relate to technology or technical efficiency, and their values larger than unity suggest the decline of technology or technical efficiency without positive role in reducing CO₂ emissions during specific periods, while their values less than unity imply the improvement of technology or technical efficiency needs than unity imply the improvement of technology or technical efficiency in reducing CO₂ emissions .

3.2 The distance functions

In the decomposition approach above, we introduce the distance functions based on input and undesirable output. Now we use the environmental DEA technique to solve these distance functions. The environmental DEA models are defined as Eqs. (12) and (13) and are referred to be constant returns to scale (CRS).

$$\begin{bmatrix} D_{e}^{s} \left(E_{k}^{t}, Y_{k}^{t}, C_{k}^{t} \right) \end{bmatrix}^{-1} = \min \lambda$$

$$s.t. \sum_{k=1}^{30} z_{k} E_{k}^{s} \le \lambda E_{k}^{t}$$

$$\sum_{k=1}^{30} z_{k} Y_{k}^{s} \ge Y_{k}^{t}$$

$$\sum_{k=1}^{30} z_{k} C_{k}^{s} = C_{k}^{t}$$

$$z_{k} \ge 0, k = 1, ..., 30$$
where $s, t \in \{0, T\}$

$$\begin{bmatrix} D_{e}^{s} \left(E_{k}^{t}, Y_{k}^{t}, C_{k}^{t} \right) \end{bmatrix}^{-1} = \min \theta$$

$$s.t. \sum_{k=1}^{30} z_{k} E_{k}^{s} \le E_{k}^{t}$$

$$\sum_{k=1}^{30} z_{k} Y_{k}^{s} \ge Y_{k}^{t}$$

$$\sum_{k=1}^{30} z_{k} C_{k}^{s} = \theta C_{k}^{t}$$

$$z_{k} \ge 0, k = 1, ..., 30$$
where $s, t \in \{0, T\}$
(13)

It should be noted that $\{0,T\}$ denotes the set of base period (2006) and reference period (2010) as mentioned above. Meanwhile, Eq. (12) solves the distance function of input in period t and the reference is based on period s. And Eq. (13) attempts to solve the distance function of undesirable output in period t while the reference is based on period s.

3.3 Data definitions

This paper mainly considers the panel data of 30 provinces in Chinese mainland

2006-2010 to decompose CO₂ emissions changes.¹ In modeling, the energy consumption, gross domestic product (GDP) and CO₂ emissions of each province from 2006 to 2010 are used. The energy consumption data come from China Energy Statistical Yearbook (NBSC and NDRC 2011), and the GDP data are quoted in 2005 constant price and come from China Statistical Yearbook (NBSC 2011).

We apply the calculation method proposed in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006) to estimate CO₂ emissions related with the consumption of coal, oil, nature gas and no-fossil fuels in energy balance table of China Energy Statistical Yearbook as Eq. (14).

$$C_{k} = \sum_{i=1}^{4} E_{ik} \times F_{i} \times \frac{44}{12}$$
(14)

where C_k denotes the CO₂ emissions of province k, E_{ik} denotes the consumption of energy source i in province k and F_i means the carbon emission factor of energy source $i_{,}$ which is adopted from China Sustainable Energy and Carbon Emissions Scenario Analysis Comprehensive Report released by Energy Research Institute, National Development and Reform Commission (NDRC), China(ERI 2003). Specifically, the carbon emission factors of coal, oil, nature gas and no-fossil fuels are 0.7476, 0.5825, 0.4435 and 0 respectively and are quoted in ton carbon per ton coal equivalent. And 44/12 indicates the conversion coefficient from carbon to carbon dioxide.

4. Empirical results and analyses

4.1 Empirical results at the provincial level

The decomposition results of carbon dioxide emissions changes for each province are shown in Table 1. We can identify several findings as follows.

First, due to the ratios of CO₂ emissions from the year of 2006 to 2010 greater than unity in all provinces, we note that the CO₂ emissions have increased during the 11th Five-Year Plan period, although the increasing extent varies significantly from one province to another. For example, the CO₂ emissions in Inner Mongolia, Hainan, Chongqing and Ningxia increase nearly 70%, while the CO₂ emissions in Beijing and Shanxi only increase 7% and 8%

¹ Due to data availability, this paper does not cover the data of Tibet.

respectively, and all provinces on average experience around 36% increase of CO_2 emissions from 2006 to 2010.

The decomposition	on of CO_2	emission	s change	es in each	province c	iuring 200	6-2010		
Province	C ^T /C ⁰	PEECH	PEICH	GDPCH	CATECH	CATCH	EUTECH	EUTCH	
Beijing	1.065	1.135	0.784	1.518	1.000	0.796	1.000	0.990	
Tianjin	1.392	1.215	0.873	1.840	1.078	0.701	1.042	0.905	
Hebei	1.294	1.213	0.890	1.533	1.204	0.701	0.974	0.951	
Shanxi	1.080	1.266	0.737	1.510	1.019	0.701	1.000	1.071	
Inner Mongolia	1.672	1.259	0.907	1.888	1.262	0.701	0.858	1.021	
Liaoning	1.269	1.205	0.827	1.684	1.074	0.701	1.067	0.940	
Jilin	1.237	1.240	0.791	1.741	1.013	0.701	1.075	0.949	
Heilongjiang	1.310	1.222	0.884	1.572	1.188	0.701	0.982	0.942	
Shanghai	1.195	1.165	0.903	1.508	1.130	0.720	1.032	0.898	
Jiangsu	1.252	1.200	0.881	1.640	1.088	0.708	1.037	0.902	
Zhejiang	1.259	1.180	0.913	1.539	1.166	0.717	1.008	0.900	
Anhui	1.498	1.213	0.934	1.665	1.282	0.701	0.954	0.925	
Fujian	1.319	1.159	0.904	1.665	1.129	0.701	1.064	0.897	
Jiangxi	1.358	1.212	0.905	1.652	1.172	0.701	1.004	0.908	
Shandong	1.304	1.239	0.878	1.612	1.154	0.701	0.994	0.925	
Henan	1.260	1.214	0.852	1.603	1.120	0.701	1.033	0.936	
Hubei	1.381	1.236	0.884	1.693	1.163	0.701	0.992	0.923	
Hunan	1.214	1.214	0.831	1.707	1.014	0.701	1.086	0.913	
Guangdong	1.301	1.093	0.907	1.564	1.186	0.745	1.038	0.915	
Guangxi	1.460	1.150	0.929	1.689	1.232	0.701	1.032	0.908	
Hainan	1.689	1.121	1.010	1.655	1.455	0.701	0.978	0.903	
Chongqing	1.669	1.220	0.965	1.786	1.333	0.701	0.932	0.911	
Sichuan	1.436	1.216	0.920	1.675	1.222	0.701	0.980	0.912	
Guizhou	1.124	1.212	0.744	1.606	0.998	0.701	1.074	1.032	
Yunnan	1.292	1.192	0.876	1.562	1.179	0.701	1.001	0.957	
Shanxi	1.600	1.211	0.938	1.755	1.300	0.701	0.926	0.950	
Gansu	1.348	1.221	0.916	1.525	1.260	0.701	0.927	0.965	
Qinghai	1.359	1.212	0.879	1.635	1.185	0.701	0.983	0.954	
Ningxia	1.638	1.239	1.015	1.612	1.449	0.701	0.730	1.089	
Xinjiang	1.523	1.086	1.017	1.489	1.458	0.701	0.925	0.979	
Mean	1.360	1.199	0.890	1.637	1.184	0.707	0.991	0.946	

Table 1The decomposition of CO2 emissions changes in each province during 2006-2010

Note: PEECH represents change of energy emissions intensity; PEICH represents change of energy intensity; GDPCH represents change of GDP; CATECH represents change of carbon abatement technical efficiency; CATCH represents change of carbon abatement technical efficiency; and EUTCH represents change of energy use technical efficiency; and EUTCH represents change of energy use technical efficiency.

Second, economic growth and energy consumption prove the main drivers of CO₂ emissions, which corroborate the results in an amount of previous literature (Zhang et al. 2009; Wang 2005; Zhou and Ang 2008; Ang et al. 2003; Li 2010). Comparatively, economic

growth has more significant effect on CO₂ emissions than that of energy consumption; specifically, the value of GDPCH reaches 1.637 on average and even gets to 1.888 in Inner Mongolia. Meanwhile, the contribution of energy consumption to CO₂ emissions cannot be ignored with the average of PEECH 1.199 and appears particularly significant in those huge coal-consuming provinces like Shanxi and Inner Mongolia with PEECH 1.266 and 1.259 respectively; however, the values of PEECH in some developed eastern coastal regions with relatively less coal consumption are below the average. These results are different from those proposed by Li (2010), who argues that carbon factor (i.e., the ratio of CO₂ emissions to energy consumption) is a less useful indicator in the study of climate change. In our opinions, these results may be attributed to the differences of energy consumption structure and energy use efficiency in these two kinds of regions. Therefore, in order to achieve the goals to reduce CO₂ emissions intensity by 17% and 16% in Shanxi and Inner Mongolia respectively during the 12th Five-Year Plan period, they have to adjust the pattern of economic growth and transform energy consumption structure towards lower carbon.

Third, both the improvement of carbon abatement technology and the reduction of energy intensity have significant effect to curb CO₂ emissions. As for the effect of energy intensity on CO₂ emissions changes, except Hainan, Ningxia and Xinjiang, the values of PEICH in other 27 provinces are less than unity, which indicates that energy intensity in most provinces has exerted significant effect to curb CO₂ emissions. In particular, Shanxi, Guizhou and Beijing have the least values of PEICH, 0.737, 0.744 and 0.784 respectively among 30 provinces, implying the most significant effect of energy intensity on CO₂ emissions during the 11th Five-Year Plan period. Additionally, primarily because the growing concerns on CO₂ emissions and mandatory pressure from China's central government towards low-carbon development these years, the CATCH values in all provinces are less than unity and around 0.7, which imply that carbon abatement technology improvement has played significant role in CO₂ emissions reduction. And comparatively, the curbing effect of carbon abatement technology improvement on CO₂ emissions on average appears more significant than that of energy intensity reduction, with the average values of CATCH and PEICH 0.707 versus 0.890 respectively.

Fourth, carbon abatement technical efficiency becomes one of the factors which promote CO₂ emissions increase. Specifically, the values of CATECH, which denotes carbon

abatement technical efficiency, are greater than or equal to unity in most provinces except 0.998 in Guizhou. This implies that the carbon abatement technical efficiency in most provinces accelerates CO₂ emissions increase during the 11th Five-Year Plan period.

Finally, both the energy use technical efficiency and energy use technology have not made significant contribution to CO₂ emission changes. Specifically, the values of EUTECH, which denotes the energy use technical efficiency, are around unity in most provinces with the average 0.991, which suggests that the influence of energy use technical efficiency on CO₂ emissions changes appears trivial. Similarly, the values of EUTCH, which denotes energy use technology, are also around unity in most provinces with the average 0.946, which indicates that the energy use technology has not significantly influenced CO₂ emissions changes during 2006-2010.

4.2 Empirical results at the regional level

According to the criterion of region classification proposed by China's State Information Center (please see the **Appendix**), we divide China's 30 provinces considered into eight regions and obtain the CO₂ emissions change decomposition results at the regional level in Table 2, and it can be found from Figure 1 that on average, GDPCH and PEECH are significantly larger than unity, PEICH and CATCH are less than unity apparently, while CATECH, EUTECH and EUTCH are almost around unity. Under this circumstance, several findings are obtained as follows.



Fig. 1. The mean values of factors for CO_2 emissions changes during 2006-2010 across regions

First, economic growth proves the main contributor to CO₂ emission increase across all regions, and energy emissions intensity follows. Meanwhile, the impacting effect of economic growth appears relatively approximate among regions with the values of GDPCH around 1.6, while the impacting effect of energy emissions appears more significant in the northwest, northern coastal and central regions than those in other regions, with the values of PEECH 1.397, 1.388 and 1.369 respectively; however, the effect seems relatively weaker in those developed regions like Beijing-Tianjin and eastern coastal regions, with the values of PEECH 1.111 and 1.119 respectively. In our opinions, these results are mainly because economic growth in inland regions proves more dependent on natural resources and coal consumption plays important role in their fossil fuel consumption, while economic growth in Beijing-Tianjin and eastern coastal regions is driven by technological innovation to a great extent, due to relatively higher energy use technology level.

Second, the improvement of carbon abatement technology and the reduction of energy intensity have significant restrictive effect on CO₂ emissions increase during the 11th Five-Year Plan period, and comparatively, the restrictive effect of carbon abatement technology proves stronger, according to the values of CATCH and PEICH 0.735 and 0.833 respectively. Meanwhile, the restrictive effect of the improvement of carbon abatement technology on CO₂ emissions appears relatively more significant in northern coastal, central and northwest regions. In fact, although these three regions cover many large coal-consuming provinces, their carbon abatement technologies have experienced great advancement due to the national energy conservation and emissions reduction policy control during the 11th Five-Year Plan period, such as the use of Integrated Gasification Combined Cycle (IGCC) system in coal-fired power plants. Besides, the PEICH in northeast region (0.789) appears the least across regions, 5.3% less than the average of eight regions (0.833), which suggests the relatively most significant effect of energy intensity reduction on CO₂ emissions increase in this region. In our opinions, this result mainly comes from two aspects of reasons. One is that during the 11th Five-Year Plan period, China's central government has given the priority to northeast region to vitalize the old industrial bases, while the other is that the Primary Industry (i.e., agriculture) plays an important role in northeast region, which has relatively lower energy intensity. For example, the shares of Primary Industry reached 12.1% and 12.6% in Jilin and Heilongjiang respectively in 2010, while the national average share is 10.1%.

The decomposition of CO ₂ emissions changes in each region during 2006-2010								
Region	C ^T /C ⁰	PEECH	PEICH	GDPCH	CATECH	CATCH	EUTECH	EUTCH
Northeast	1.274	1.216	0.789	1.661	1.025	0.748	1.000	1.042
Beijing-Tianjin	1.223	1.111	0.815	1.635	1.000	0.832	1.000	0.993
Northern coastal	1.294	1.388	0.824	1.613	1.072	0.656	0.993	1.004
Eastern coastal	1.242	1.119	0.868	1.578	1.052	0.806	1.000	0.956
Southern coastal	1.308	1.316	0.859	1.622	1.005	0.730	0.997	0.975
Central	1.292	1.369	0.820	1.628	1.061	0.664	1.000	1.003
Northwest	1.344	1.397	0.851	1.627	1.022	0.694	0.982	0.997
Southwest	1.362	1.206	0.837	1.670	1.090	0.748	0.979	1.012
Mean	1.292	1.265	0.833	1.629	1.041	0.735	0.994	0.998

Note: PEECH represents change of energy emissions intensity; PEICH represents change of energy intensity; GDPCH represents change of GDP; CATECH represents change of carbon abatement technical efficiency; CATCH represents change of carbon abatement technical efficiency; and EUTCH represents change of energy use technical efficiency; and EUTCH represents change of energy use technical efficiency.

Finally, the slight effect of carbon abatement technical efficiency, energy use technical efficiency and energy use technology on CO₂ emissions changes is identified during the 11th Five-Year Plan period, according to the CATECH, EUTECH and EUTCH values in all regions almost close to unity. This may provide much room for China's futures work directions to curb CO₂ emissions.

5. Conclusions and policy recommendations

Table 2

This paper employs the production-theoretical decomposition analysis (PDA) approach combined with environmental DEA technique and distance functions to decompose China's CO₂ emission changes at the provincial and regional levels during the 11th Five-Year Plan period. According to the decomposition results, we obtain several conclusions as follows.

(1) Economic growth and energy consumption are identified as the two main contributors to CO_2 emissions increase during the 11th Five-Year Plan period. And in the northern coastal, northwest and central regions, due to the huge coal consumption, the driving effect of energy consumption on CO_2 emissions increase appears fairly evident.

(2) The improvement of carbon abatement technology and the reduction of energy intensity play significant roles in restricting CO₂ emissions; and comparatively the effect of carbon abatement technology proves more significant.

(3) The effect of energy use technical efficiency, energy use technology and carbon abatement technical efficiency on CO₂ emissions changes proves still slight overall. Maybe this provides some outlets for China to reduce CO₂ emissions in the future.

Based on the decomposition results for CO₂ emission changes above, we also put forward several policy recommendations as follows to help achieve China's national goals to reduce CO₂ intensity by 2015 and 2020.

(1) The government should continue to transform the economic growth pattern and adjust the industrial structure towards low carbon. In particular, when the high technology is used to upgrade industries, many efforts should be made to significantly reduce the proportion of high energy consuming and high pollutant emissions industries in China's economy but enlarge low-carbon industries.

(2) The government is expected to persistently strictly implement energy conservation and CO₂ emissions reduction policies, legitimately control the total energy consumption and make use of coal resource in a cleaner way. In particular, the government should put forward some laws as soon as possible to restrain low-level, redundant infrastructure construction projects and avoid energy waste and meaningless CO₂ emissions. Besides, China should make persistent efforts to raise the proportion of non-fossil fuels in energy consumption structure in the future. To this end, the government is expected to formulate more encouraging policies towards clean energy development and exploitation.

(3) The government ought to propose relevant regulations to promote CO₂ emissions abatement technology development and make full use of technology advancement to curb CO₂ emissions. Meanwhile, much attention should be paid to the potential effect of the progress of carbon abatement technical efficiency, energy use technical efficiency and energy use technology on CO₂ emissions changes during the 12th Five-Year Plan period.

It should be pointed out that there is still a great deal of work to be done regarding the CO₂ emissions decomposition in the future. For instance, this paper follows Zhou and Ang (2008) to take energy as the single input. In fact, it can be easily adapted to the cases where other inputs like capital and labor are included. Additionally, although the PDA approach

here is based on the Shephard distance function, it is possible to extend it by using the more general directional distance function or the recently developed non-radial directional distance function (Zhou et al. 2012). This is also a possible valuable research direction in the future.

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Appendix

Region	Provinces			
Northeast	Heilongjiang, Jilin, Liaoning			
Beijing-Tianjin	Beijing, Tianjin			
Northern coastal	Hebei, Shandong			
Eastern coastal	Jiangsu, Shanghai, Zhejiang			
Southern coastal	Fujian, Guangdong, Hainan			
Central	Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi			
Northwest	Inner Mongolia and Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang			
Southwest	Sichuan, Chongqing, Guangxi, Yunnan, Guizhou			

Table A. The eight regions in China