Resources Policy 60 (2019) 203–214

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Resource abundance, industrial structure, and regional carbon emissions efficiency in China

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ARTICLE INFO

Keywords:
Resource abundance
Resource dependence
Industrial structure
Emissions efficiency
Abatement potential

ABSTRACT

With increasing concerns over climate change and the global consensus regarding low carbon growth, the transition of resource-based regions has become urgent and challenging. We employ a Slacks-Based Measure with windows analysis approach to estimate the carbon emissions efficiency and abatement potential of China's provinces over the period of 2003–2016. A panel Tobit model is further employed to analyze the direct and indirect effects of natural resource abundance on emissions efficiency. We find that: (1) There exists a negative correlation between resource abundance and carbon emissions efficiency. The more abundant the resources, the lower the emissions efficiency. (2) Although emissions efficiency and abatement potential are generally negatively correlated, abatement potential also depends on the scale of the economy. (3) Resource dependence is unfavourable for the rationalization and advancement of the industrial structure, which indirectly affects the carbon emissions efficiency. These findings imply that resource-based regions should make the improvement of emissions efficiency and the exploration of abatement potential as their top priority of actions for a low-carbon transition, and promote the transformation of industrial structure in order to obtain a double dividend in sustainable development and carbon emissions efficiency.

1. Introduction

Low carbon growth is widely regarded as the key way to resolve the contradictory demands for economic growth and carbon emissions mitigation. Finding ways to use resources including energy, more efficiently, is a key requirement for low carbon growth. China, as the world's largest carbon emitter, has urgency to increase emissions efficiency, reduce carbon emissions and realize low-carbon economic development. While China has formally promised the world in the Intended Nationally Determined Contributions (INDC) to peak its carbon emissions around 2030, it is actually trying to peak the emissions earlier than this deadline. China has integrated policies pertaining to the control of greenhouse gas emissions into the national economic and social development strategy, such as to increase the share of non-fossil fuels in primary energy consumption to around 20% (Xian et al., 2018). In 2017, non-fossil fuels accounts for 13.6% of China's total primary energy consumption (BP, 2018). In December 2016, the National Energy Administration issued the "Revolutionary Strategy for Energy Production and Consumption (2016–2030)" which states that non-fossil energy will account for more than half of primary energy in 2050 (NDRC, 2016). The national unified carbon market that was officially launched in December 2017, could increase the abatement costs of enterprises and reduce the demand for fossil fuels (Wang et al., 2018).

Although resource-based regions have played a major role in promoting the initial stages of industrialization, implementing low-carbon transition is a severe challenge for resource-based regions whose economic growth is often dominated by resource-intensive industries.

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https://doi.org/10.1016/j.resourpol.2019.01.001
Received 12 September 2018; Received in revised form 29 December 2018; Accepted 2 January 2019
Available online 12 January 2019
0301-4207/

Depending on resource advantages, resource-based regions have developed compatible industrial structures, and these have greatly accelerated regional development (Shi, 2013). However, most of the industries in these regions are likely to be characterized by high energy and emissions intensities (Feng et al., 2017). The abundance of the natural resources leads to low prices of resources, which has led to high extensive and inefficient energy consumption patterns and low emissions efficiency (Adom and Adams, 2018; Yang et al., 2018). Furthermore, resource intensive industries tend to cluster in resource-based regions and form industry agglomeration, eventually become the pillar industries, which further leads to resource dependence. After agglomeration, non-resource intensive industries are closely attached to the resource-intensive ones, and as a result the further resource dependence worsens the carbon emissions efficiency in resource-based regions. As the major outputs of resource-based regions, it is unrealistic to abandon resource-intensive industries since a consequent growth plummet resulting in serious social and economic problems.

However, where natural resource endowment is rich, resource dependence is not necessarily high. Natural resource abundance includes two related cases: rich endowment and high dependence. The natural resources endowment refers to the quantity of natural resources that a country or region can use for social and economic development; the natural resources dependence refers to the role of resource-based industries in the development of regional economy (Sun and Ye, 2012; Wu et al., 2018).

Given the difficulties in improving emissions efficiency and reducing carbon emissions in resource-based regions, it is a timely and valuable exercise to investigate the relationship between resource abundance, industrial structure and carbon emissions efficiency so as to offer policy suggestions for low carbon transition in resource-based regions. As the world's largest producer of coal and the largest emitter of carbon, China provides an excellent case to study the topic and focusing on China is important for the global community. The developing country status and lagged economic development mean that China's lessons and experience can be useful for other developing countries that rely on natural resources.

In this paper, we apply the Slakes-Based Measure (SBM) with windows analysis approach to estimate carbon emissions efficiency and abatement potential of China's 30 provinces from 2003 to 2016, and analyze the direct and indirect impact of resource abundance on carbon emissions efficiency from two perspectives of resource dependence and endowment. Our analysis is a useful extension to the existing literature and can offer suggestions relating to low-carbon transition in China's resource-based regions. The contributions of this paper are twofold: 1) analysis of the impacts of natural resources abundance on carbon emissions efficiency; and 2) analysis of the influence of natural resource abundance on industrial structures, and then examination of the indirect effects on carbon emissions efficiency.

The paper proceeds as follow: Section 2 reviews the literature, Section 3 discusses the influence mechanism of resource abundance on emissions efficiency, Section 4 elaborates on the methodology and data, and Section 5 presents the empirical results and discussion. The concluding section provides policy recommendations and suggestions for further research.

2. Literature review

This paper is closely related to three research strands in the literature. The first strand is “resource curse”, which is a popular topic in resource economics. The second strand is carbon emissions efficiency and abatement potential. The last strand is industrial structure which connects closely with the first two strands. Therefore, the literature review here deals with these three aspects.

For most countries and regions, having abundant resources hinder long-run economic growth rather than promote it. The “resource curse” has become a popular academic topic and has been discussed from different perspectives using various theories and methods. Many studies have empirically demonstrated that a large number of regions with abundant natural resources, especially coal, oil and gas, are trapped in the “resources curse” (Ahmed et al., 2016; Badeeb et al., 2017; Brunnschweiler, 2008; Friedrichs and Inderwildi, 2013; Gerelmaa and Kotani, 2016; Shao and Yang, 2014; Song et al., 2018)

Various approaches have been applied to evaluate the carbon emissions efficiency and carbon abatement potentials. By applying a data envelopment analysis (DEA) method, recent studies (Wang et al., 2013; Xian et al., 2018; Zha et al., 2016) found that even if all electricity-generating units in each region were able to adopt the best practices, the nationwide 18% intensity reduction target was not feasible through improving technical efficiency in a short or medium term. Owing to the diversity among the development patterns and natural resource endowments in China's various regions, there is significant difference in the carbon emissions performances at the provincial levels (Chang et al., 2017; Yao et al., 2015). The remarkable imbalances in economic development, technology gaps, policies, industrial structures and energy consumption structures may explain the regional differences in carbon emissions efficiency (Lin and Du, 2015; Wang et al., 2016; Yao et al., 2015).

Some researchers argued that rational industrial structure adjustment could improve resource utilization efficiency (Zhang and Deng, 2010) and mitigate carbon emissions (Li et al., 2017; Shao et al., 2016). There are many studies discussing how to adjust the industrial structure so as to reduce carbon emissions, such as increasing the proportion of tertiary industry in GDP (Zhang et al., 2014). Tian et al. (2014) pointed out that different solutions should be used to control CO_2 emissions in regions which are at different stages in the process of industrial structural change.

The role of industrial structure in carbon emissions control may be more important in resource-based regions than in other regions. Long-term resource development has made industrial structures in resource-based regions dominated by natural resource development and primary processing (Sun and Ye, 2012). Such industrial structures will likely lead to high emissions intensity in the resource-based regions. Furthermore, low level industrial structures in the resource-based regions have “lock-in effect” and “crowd-out effect”, which hinder the adjustment and evolution of regional industrial structures (Li et al., 2019; Morris et al., 2012). Such features make it difficult for resource-based regions to achieve sustainable development in a low carbon world. However, a few researches show potential of overcoming negative resource abundance effects. Balsalobre-Lorente et al. (2018) found that countries with natural resources reduced their imports of dirty energy resources, which had a positive effect on CO_2 emissions reduction.

In summary, the existing related research provides a little study of carbon emissions efficiency and abatement potential while considering the natural resources abundance and industrial structure. In this paper, by introducing two indicators which denote industrial structure and employing the panel Tobit model, we analyze the direct and indirect effects of resource abundance on emissions efficiency from the perspectives of resource dependence and endowment.

3. Influence mechanism of regional carbon emissions efficiency

This paper will analyze the impact of natural resources abundance on carbon emissions efficiency from both direct and indirect channels. On the one hand, abundant natural resources loosen the resource constraints of enterprises, leading to the use of resources in a more extensive and inefficient manner, which directly affects the carbon emissions efficiency of resource-based regions. On the other hand, abundant natural resources will also distort the industrial structure of resource-based regions, making high emissions industries as pillar industries, which indirectly affects the carbon emissions efficiency of resource-based regions.

3.1. Direct influence

The natural resources abundance causes relatively low resource prices and thus make companies' behavior in resource-based regions different from those in other regions. Due to the convenience, availability and lower prices, companies located in resource-based regions face a lower risks as well as a lower costs for resource reserves. Low resource prices lead to a lower willingness to invest in resource-saving technologies and equipment (Shi, 2014). Furthermore, resource-intensive companies have to keep certain quantities of resource reserves to guard against possible operational risks caused by resource shortages, which places an extra pressure on companies' financial status. Overall, the extensive use of resources will inevitably lead to a decline in carbon emissions efficiency.

3.2. Indirect influence

Abundance of natural resources not only leads to a rigid industrial structures, but also reduces the emissions reductions derived from the industrial structure dividend (Sun and Ye, 2012), which in turn affects the carbon emissions efficiency. The industrial structures dominated by a single resource sector, that is resource dependence, have squeezed the development space of modern manufacturing. Thus resources-based regions often fall into a rigid specialization trap. The tendency of "de-industrialization" has caused the industrial structure of resource-based regions to be in a state of distortion for a long time, thus they cannot gain the "structural dividend" resulting from the optimization and upgrading of industrial structures. However, the industrial structure is shaped by market selection under the constraints of natural resources, technologies, economic development stages and other factors within the economic system. Each of these factors offer spontaneity, endogeneity and rationality to some degree. Fig. 1 summarizes the direct and indirect effects of natural resource abundance on carbon emissions efficiency.

4. Methodology and data

Two distinctive methods are employed in this study. The Slacks-based Measure (SBM) with window analysis approach estimates the carbon emissions efficiency and abatement potential, while the panel Tobit model investigates the influencing factors of carbon emissions efficiency.

4.1. The SBM with window analysis approach

4.1.1. The Slacks-Based Measure

The SBM with window analysis approach is employed to estimate the carbon emissions efficiency of China's 30 provinces (except for Tibet) from 2003 to 2016. Under the framework of DEA, the non-radial and non-oriented Slacks-Based Measure (SBM) can utilize input and output slacks directly in producing an efficiency, it has been widely applied to evaluate carbon emissions efficiency and abatement potential (Cecchini et al., 2018; Choi et al., 2012; Guo et al., 2017; Song et al., 2013; Zhang et al., 2017, 2015; Zhang and Choi, 2013; Zhou et al., 2006, 2013).

Taking China's 30 provinces as DMU_j (j = 1,2…30), the SBM can be written as follows:

$$\rho^* = min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)} \tag{1}$$

$$\text{s.t.}\quad \begin{aligned} x_0 &= X\lambda + s^-;\\ y_0^g &= Y^g\lambda - s^g;\\ y_0^b &= Y^b\lambda + s^b;\end{aligned}$$
$$\lambda \geq 0,\ s^- \geq 0,\quad s^g \geq 0,\quad s^b \geq 0 \tag{2}$$

where the vectors $x \in R^m$, $y^g \in R^{s_1}$ and $y^b \in R^{s_2}$ represent inputs, desirable outputs and undesirable outputs respectively. The vectors $s^- \in R^n$ and $s^b \in R^{s_2}$ correspond to excesses in inputs and undesirable outputs respectively, while $s^g \in R^{s_1}$ expresses shortages in desirable outputs. The objective value satisfies $0 < \rho^* \leq 1$. Let an optimal solution of the above program be $(\lambda^*, s^{-*}, s^{g*}, s^{b*})$. Then, the DMU_j is efficient in the presence of undesirable outputs if and only if $\rho^* = 1$, i.e., $s^{-*} = 0$, $s^{g*} = 0$, and $s^{b*} = 0$. If the DMU_j is inefficient, i.e., $\rho^*<1$, it can be improved and become efficient by deleting the excesses in inputs and undesirable outputs, and augmenting the shortfalls in desirable outputs by the following SBM-projection:

$$\begin{aligned} \hat{x}_0 &\leftarrow x_0 - s^{-*}\\ \hat{y}_0^g &\leftarrow y_0^g + s^{g*}\\ \hat{y}_0^b &\leftarrow y_0^b - s^{b*}\end{aligned} \tag{3}$$

In this paper, the excess in undesirable outputs means the carbon abatement potential and is denoted as s^{b*}, which is the quantity of potential emissions reduction of DMU_j when ρ^* is improved to 1.

Clearly, abatement potential measures the absolute reductions of carbon emissions. It depends both on the emissions efficiency and the scale of the economy. Some regions with high emissions efficiency, due

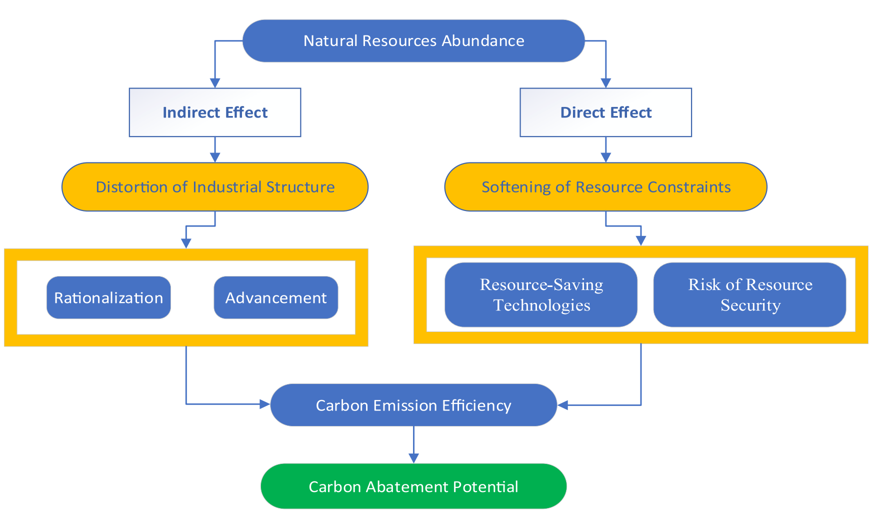

Fig. 1. Influence mechanism.

to the large scale of the economy, may still have larger absolute quantity of emissions reductions. Some regions with low emissions efficiencies, due to the smaller scale of the economy, may have smaller absolute quantity of emissions reductions. Thus, SBM provides a scalar measure ranging from 0 to 1 that encompasses all of the inefficiencies that the model can identify.

In estimating carbon emissions efficiency based on SBM, we employ labor, capital and energy to represent the inputs, GDP as a desirable output, and the total amount of CO_2 emissions as an undesirable output. Specifically, labor is denoted by the number of employed persons, capital is estimated using the perpetual inventory method:

$$K_{it} = (1 - \delta_{it})K_{it-1} + I_{it} \tag{4}$$

energy is represented by the total energy consumption of each province, and CO_2 emissions are calculated with the energy emissions factors and energy consumption.

4.1.2. The window analysis approach

Due to the advantages of analyzing a frontier shift between different periods under a possible occurrence of a frontier crossover and in handling panel data, the window analysis approach is used to evaluate carbon emissions efficiencies over time and across different regions, sectors and subjects (Al-Refaie et al., 2018; Cuccia et al., 2017; Lin and Tan, 2017; Shawtari et al., 2015; Sueyoshi et al., 2013; Vlontzos and Pardalos, 2017; Wang et al., 2013).

A window with $n \times w$ observations is denoted starting at time t ($1 \le t \le T$) with window width w ($1 \le w \le T - t$), $n = 30$ for China's 30 provinces and the $T = 14$ for the 2003–2016 period. The selection of the width of the window w is a key point in the window analysis approach. As is most commonly done in the literature, we set $w = 3$ (Halkos and Tzeremes, 2009; Vlontzos and Pardalos, 2017).

4.2. Panel Tobit model

Since the carbon emissions efficiency base on SBM is censored by 0 and 1, in this case, parameter estimates obtained by conventional regression methods (e.g. OLS) are biased. Consistent estimates can be obtained by Tobit model proposed by Tobin (1958), which is a special case of the more general censored regression model (Baltagi and Boozer, 1997; Maddala, 1987) and has been used in a very wide range of applications characterized by censored observations. These are recent examples (Bi et al., 2016; Brown et al., 2015; Kaya Samut and Cafrı, 2016). We apply a random panel Tobit model to estimate the possible determinants of carbon emissions efficiency. The model is written as:

$$\begin{aligned} \ln \mathit{efficiency}_{it} \;=\;& \alpha + \beta_1 \ln NRD_{it} + \beta_2 \ln \mathit{rational}_{it} + \beta_3 \ln \mathit{advanced}_{it} \\ &+ \beta_4 \ln NRD_{it} {}^{*} \ln \mathit{rational}_{it} + \beta_5 \ln NRD_{it} {}^{*} \ln \mathit{advanced}_{it} \\ &+ \beta_6 \ln PGDP_{it} + \beta_7 \ln NRD_{it} {}^{*} \ln PGDP_{it} + X'_{it}\delta + \lambda_i + \varepsilon_{it} \end{aligned} \tag{5}$$

where *efficiency* indicates carbon emissions efficiency of province i in year t calculated by the SBM with window analysis approach. *NRD* indicates natural resource dependence. The variables of *rational* and *advanced* are two indicators used to characterize the development of the industrial structure. *PGDP* represents the level of economic development and is denoted by the GDP per capita measured by the price in 2003.

Xs are the control variable vectors. Besides the resource dependence and industrial structure, government intervention, technology innovation, energy price, the urbanization level and regulation are regarded as the important factors that impact the carbon emissions efficiency in many studies.

Because of the externality of carbon emissions, government intervention plays an important role in improving carbon emissions efficiency, and the fiscal policy is a common form of government intervention through providing funds for improving of energy-saving and emissions-reduction technologies, encouraging enterprises to eliminate backward production capacity through incentives and subsidies, supporting the development of clean energy (Price et al., 2005). Government intervention (*GOV*) is denoted by the ratio of fiscal expenditure to fiscal revenue.

The technology innovation is playing more and more important role in improving carbon emissions efficiency and it is essential to meet long-term emissions reduction targets (Dechezleprêtre et al., 2016; Gallagher et al., 2006). The technology innovation (*R&D*) is expressed as the ratio of R&D employees in all employed people.

When energy prices continue to rise, the cost effect will stimulate energy conservation and emissions reduction (Fisher-Vanden et al., 2004; McCollum et al., 2016), while speeding up the diffusion of energy-saving technologies, reducing energy consumption and improving carbon emissions efficiency (Jacobsen, 2015). The change of energy price (*EPI*) can be signified by purchasing price indices for industrial producers of fuel and power.

In the process of urbanization, economic activities are centralized and the energy has been consumed massively. On the other hand, the scale effect and technique spill-over effect from the agglomeration of economic activities will reduce the intensity of energy consumption, improve energy consumption efficiency and carbon emissions efficiency (Wang and Zhang, 2016). The level of urbanization (*UR*) is represented by the proportion of urban resident population in each province.

As the climate change become more serious, governments will take stricter environmental regulations, which exert extra costs on enterprises and force them to adopt emissions-reduction technologies and clean energy. However, excessive cost may not be conducive to the operation of enterprises and result in the decrease of carbon emissions efficiency. We apply the energy-saving and emissions-reducing targets for each province in "Five-Year Plans" as the indicator of environmental regulation (*Regulation*).

4.3. Variable construction and data sources

Considering the regional economic landscape, resource abundance and geographic features (Zhou et al., 2014), we divided China's 30 provinces into eight economy-geographic regions, i.e., the northeast, north coast, east coast, south coast, the middle Yellow River, the middle Yangtze River, southwest and northwest regions.

The measurement indicators of natural resources abundance can be roughly divided into two categories: the resource dependence index and the resource endowment index. Considering that this paper calculates the carbon emissions efficiency from energy consumption, we choose the output value proportion of the coal mining industry and the oil and gas extraction industry in total industrial output value to represent the degree of natural resource dependence (*NRD*). The larger the value, the higher the degree of dependence. At the same time, in order to carry out robustness tests, this paper also calculates other variables that can represent the natural resource dependence: the natural resource dependence in employment (*NRDL*), which is represented by the employment proportion of the coal mining industry and the oil and gas exploration industry in total industrial employment. Considering that this paper mainly measures the efficiency and potential of carbon emissions, we use fossil energy endowment (*FEE*) to represent resources endowment index, which is represented by the ratio of production to consumption of fossil fuels. The larger the ratio, the higher the degree of fossil energy endowment.

We employ two indicators to characterize the improvement of industrial structure: rationalization and advancement, separately measuring the allocation efficiency of production factors among industries and the stages of industrial structures evolution (Sun and Ye, 2012). Rationalization means high allocation efficiency and coupling quality, in which economic development is enhanced and carbon emissions efficiency is improved. *Rational* means rationalization index of industrial structure (Gan et al., 2011), which is shown in Eq. (6):

$$Rational = \sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right)ln\left(\frac{Y_i}{L_i}/\frac{Y}{L}\right) \tag{6}$$

where i = 1, 2, 3 indicate the primary, secondary and tertiary industries respectively, and n = 3. Y and L indicate the industrial output and the industrial employment respectively. When the economy is in an equilibrium state, the production efficiency of each industry will converge ($Y_i/L_i = \frac{Y}{L}$ and $Rational = 0$). The smaller the value of *Rational*, the more reasonable the industrial structure. *Advancement* is represented by the ratio of gross value of the tertiary industrial sector to that of the secondary industrial sector, and higher value means more advanced industrial structure. The development of tertiary industry plays an important role in emissions reduction and improvement in carbon emissions efficiency.

The annual data that was used to estimate the carbon emissions efficiency all come from the *China Statistical Yearbooks* of 2004–2017. Other data are collected from the *China Statistical Yearbook*, *China Industrial Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Population and Employment Statistics Yearbook*, *China Labor Statistics Yearbook*, and *China Science and Technology Statistical Yearbook*.

The values of *Regulation* for 2006–2010 are calculated based on the energy consumption reduction target for each province during the 11th Five-Year Plan period, that for 2011–2016 are from “Work Plan for Controlling Greenhouse Gas Emissions in the 12th (and 13th) Five-Year Plan”, and the values for 2003–2005 are set to 0 indicating no environmental regulation policies on carbon emissions in that period. Except for environmental regulations, the values of the variables in the model are all logarithms.

5. Empirical results

5.1. Carbon emissions efficiency and abatement potential

Based on the SBM with window analysis approach mentioned above, we estimated the carbon emissions efficiency and abatement potential for China's 30 provinces.

Table 1 shows the results for selected years. Firstly, the carbon emissions efficiencies in almost all provinces improved from 2003–2016 but there were significant gaps among provinces. In 2016, the carbon emissions efficiency in 10 provinces (Shandong, Beijing, Tianjin, Ningxia, Qinghai, Hunan, Shanghai, Jiangsu, Guangdong and Hainan) achieved efficient production activities (the value of carbon emissions efficiency is 1), while the eight provinces of Xinjiang, Shanxi, Inner Mongolia, Henan, Hebei, Gansu, Liaoning and Shaanxi had very lower emissions efficiency (below 0.6). Secondly, there was regional clustering in carbon emissions efficiency. The efficiency of carbon emissions in the coastal regions was generally higher than that of the central and western regions. Not surprisingly, the coal-rich Middle Yellow River region and the Northeast region had the lowest emissions efficiencies.

Table 1
Carbon emissions efficiency in China's 30 provinces (2004–2016).

Region	2004	2006	2008	2010	2012	2014	2016
Middle Yellow River Region	**0.479**	**0.520**	**0.580**	**0.589**	**0.590**	**0.581**	**0.525**
Shanxi	0.394	0.404	0.455	0.487	0.490	0.475	0.469
Inner Mongolia	0.466	0.530	0.575	0.579	0.542	0.674	0.496
Henan	0.536	0.582	0.661	0.652	0.671	0.574	0.543
Shaanxi	0.519	0.565	0.631	0.641	0.656	0.599	0.591
North Coast Region	**0.677**	**0.711**	**0.764**	**0.776**	**0.781**	**0.831**	**0.886**
Hebei	0.556	0.575	0.587	0.612	0.624	0.601	0.545
Shandong	0.689	0.646	0.637	0.615	0.615	0.766	1.000
Beijing	0.792	0.942	0.960	0.944	0.989	0.992	1.000
Tianjin	0.673	0.682	0.872	0.935	0.896	0.967	1.000
Northeast Region	**0.497**	**0.553**	**0.607**	**0.621**	**0.663**	**0.669**	**0.643**
Liaoning	0.478	0.538	0.587	0.631	0.671	0.619	0.571
Heilongjiang	0.495	0.526	0.576	0.625	0.653	0.637	0.605
Jilin	0.518	0.594	0.656	0.607	0.664	0.749	0.753
Northwest Region	**0.679**	**0.642**	**0.681**	**0.675**	**0.698**	**0.671**	**0.756**
Xinjiang	0.495	0.525	0.554	0.541	0.518	0.493	0.464
Gansu	0.450	0.485	0.546	0.585	0.595	0.567	0.560
Ningxia	0.769	0.559	0.624	0.611	0.754	0.624	1.000
Qinghai	1.000	1.000	1.000	0.964	0.928	1.000	1.000
Southwest Region	**0.625**	**0.655**	**0.710**	**0.728**	**0.680**	**0.679**	**0.728**
Guizhou	0.415	0.442	0.527	0.559	0.575	0.600	0.614
Guangxi	0.694	0.763	0.861	0.808	0.668	0.694	0.661
Sichuan	0.631	0.691	0.714	0.778	0.701	0.607	0.685
Yunnan	0.554	0.568	0.624	0.635	0.676	0.694	0.740
Chongqing	0.832	0.810	0.823	0.862	0.781	0.800	0.939
Middle Yangtze River Region	**0.640**	**0.674**	**0.757**	**0.767**	**0.757**	**0.751**	**0.783**
Anhui	0.597	0.651	0.692	0.717	0.722	0.689	0.673
Jiangxi	0.669	0.763	0.868	0.816	0.803	0.714	0.718
Hubei	0.613	0.618	0.722	0.757	0.701	0.681	0.743
Hunan	0.681	0.662	0.746	0.778	0.803	0.922	1.000
East Coast Region	**0.796**	**0.844**	**0.876**	**0.930**	**0.878**	**0.818**	**0.975**
Zhejiang	0.850	0.794	0.809	0.789	0.794	0.782	0.925
Shanghai	0.765	0.918	0.917	1.000	0.839	0.884	1.000
Jiangsu	0.774	0.819	0.902	1.000	1.000	0.787	1.000
South Coast Region	**0.940**	**0.911**	**0.933**	**0.926**	**0.883**	**0.882**	**0.929**
Fujian	0.833	0.829	0.855	0.779	0.699	0.694	0.786
Guangdong	1.000	0.953	1.000	1.000	1.000	0.993	1.000
Hainan	0.988	0.951	0.944	1.000	0.948	0.960	1.000
Average	**0.658**	**0.680**	**0.731**	**0.744**	**0.733**	**0.728**	**0.769**

The abatement potential is the excess in carbon emissions when the DMU_i is inefficient and needs to be deleted as the carbon efficiency is improved and the DMU_i becomes efficient. Fig. 2 shows the aggregate abatement potential over time in 30 provinces. We can see that, firstly, there are distinct differences in the abatement potential among the provinces. Over the 11th Five-Year Plan, 12th Five-Year Plan and in 2016, the provinces with the largest abatement potential were Shandong, Shanxi and Inner Mongolia, and the average annual abatement potential was 595 mt, 677 mt and 822 mt separately, while the smallest abatement potential was only 1.28 mt, 1.17 mt and 0.[1] Secondly, although the carbon emissions for most of the provinces were improving, the abatement potentials were increasing, especially in the high emissions regions of Inner Mongolia, Shanxi, Hebei, Xinjiang, Liaoning, Henan, Shaanxi. The emissions reduction resulting from efficiency improvements cannot offset increases in emissions caused by the expansion of production activities (Choi et al., 2012; Zhang et al., 2016). This is the key for China in achieving the target of carbon emissions peak.

While emissions efficiency and abatement potential are generally negatively correlated, the eight regions are categorized into four distinct groups according to the relationship between emissions efficiency and abatement potential over the 12th Five-Year Plan (See Fig. 3 for details). The first group has low efficiency in emissions with high abatement potential (**LE-HP**), including 11 provinces: Xinjiang, Inner

[1] When the carbon emissions efficiency is 1, there is no abatement potential.

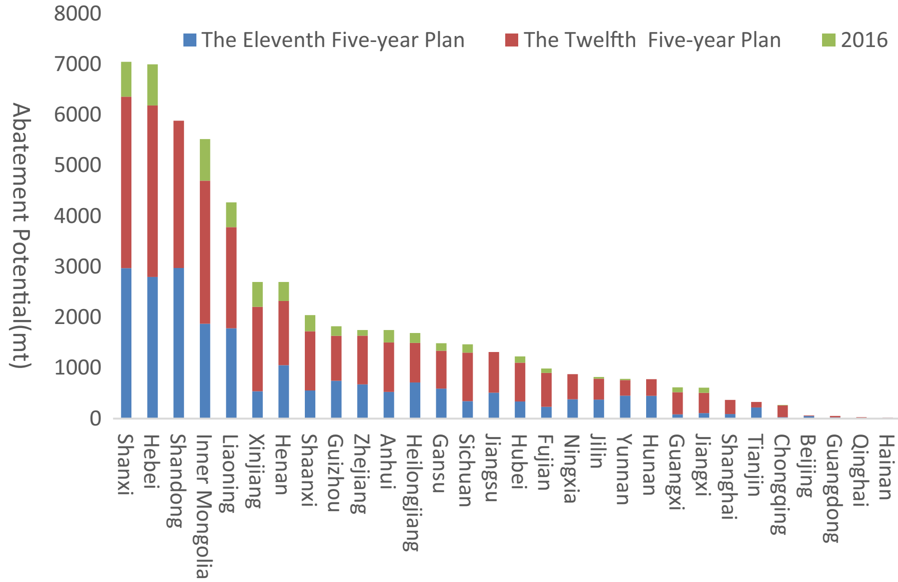

Fig. 2. The carbon abatement potential in China's provinces (mt CO_2).

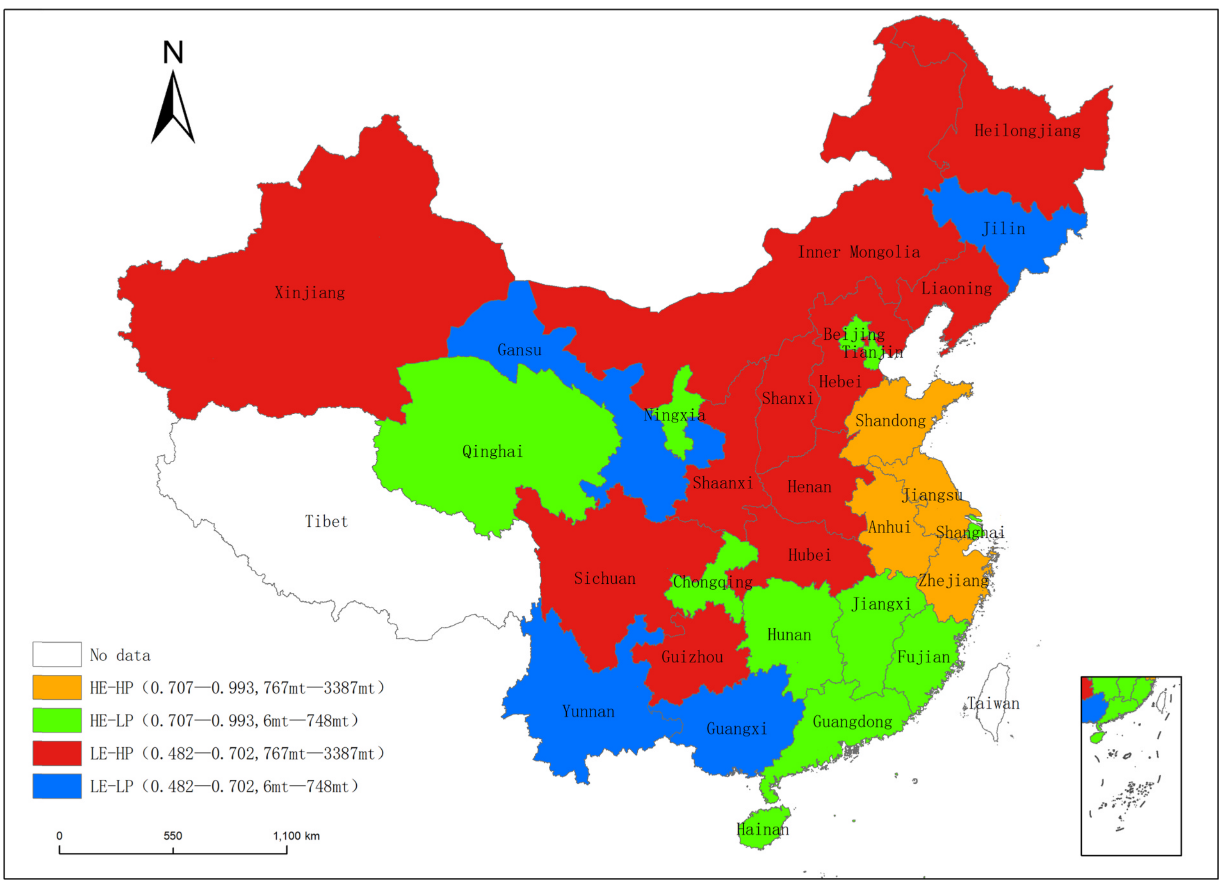

Fig. 3. The carbon emissions efficiency and potential of China's provinces in the 12th Five-Year Plan.

Mongolia, Heilongjiang, Liaoning, Hebei, Shanxi, Shaanxi, Henan, Hubei, Sichuan and Guizhou, accounting for 65% of the abatement potential in the 12th Five-Year Plan. All of the coal abundant areas are in this group. Reducing the carbon emissions from this group is crucial for achieving the emissions reduction targets. The second group is low efficiency but low potential regions (**LE-LP**): Gansu, Jilin, Yunnan, and Guangxi. These provinces have relatively underdeveloped economies and low carbon emissions efficiencies, but they have low fossil energy endowment and relatively clean energy consumption structures. This means that the total carbon emissions are low. Thus, there is little potential for further carbon reduction even if efficiencies are improved. The third group is high efficiency but with high potential (**HE-HP**): Shandong, Jiangsu, Anhui, and Zhejiang. The four provinces have large-scale economies and more sources of emissions, although the emissions efficiency is high, the quantity of potential emissions reduction will still be large. In 2016, the abatement potential in the four provinces was

Table 2
Analysis of influencing factors of carbon emissions efficiency.

Dependent variable	(1) lnefficiency	(2)	(3)	(4)	(5)	(6)
lnNRD	−0.041***	−0.029***	−0.042***	−0.117**	−0.249***	−0.277***
	(0.004)	(0.004)	(0.003)	(0.047)	(0.054)	(0.050)
lnrational		−0.032***		−0.027**		−0.029**
		(0.006)		(0.012)		(0.014)
lnadvanced			0.072***		0.058	0.094**
			(0.020)		(0.039)	(0.047)
*lnNRD*lnrational*				0.004*		−0.002
				(0.002)		(0.003)
*lnNRD*lnadvanced*					−0.011	−0.013
					(0.009)	(0.012)
lnPGDP				0.165***	0.185***	0.179***
				(0.020)	(0.021)	(0.027)
*lnNRD*lnPGDP*				0.013***	0.023***	0.027***
				(0.005)	(0.005)	(0.005)
lnGOV						0.107***
						(0.025)
lnR&D						0.039**
						(0.017)
lnEPI						0.143**
						(0.067)
lnUR						−0.028
						(0.040)
Regulation						0.985**
						(0.493)
_cons	−0.488***	−0.569***	−0.506***	−2.113***	−2.272***	−2.844***
	(0.015)	(0.017)	(0.015)	(0.196)	(0.210)	(0.493)
sigma_u	0.172***	0.147***	0.152***	0.162***	0.148***	0.170***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
sigma_e	0.120***	0.117***	0.118***	0.105***	0.107***	0.105***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
rho	0.672	0.613	0.625	0.705	0.655	0.723
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Prob > = chibar2	0.000	0.000	0.000	0.000	0.000	0.000
n	420	420	420	420	420	420

Note: Standard errors are shown in parentheses.
***, **, * denote the statistical significance at 1%, 5% and 10% separately.

dramatically reduced as a result of the improvements made in carbon efficiencies. The last group is high efficiency with low potential (**HE-LP**): Beijing, Shanghai, Tianjin, Chongqing, Guangdong, Fujian, Hunan, Jiangxi, Qinghai, Ningxia, and Hainan. These are all successful in terms of efficiency improvement and carbon reduction.

5.2. Influencing factors of carbon emissions efficiency

The panel Tobit regression results[2] are shown in Table 2. From column (1), it can be seen that the resource dependence (*NRD*) has a significant negative effect on the carbon emissions efficiency. For every 1% increase in resource dependence, the carbon emissions efficiency will decrease by about 0.04%. After the two industry structure indicators were added to columns (2)–(3), and cross-terms of industrial structure variables with resource dependence were added to columns (4)–(6) and all control variables were further included in column (6), the coefficients of resource dependence were still significantly negative. However, the values of the coefficients of resource abundance significantly increased in the regression models with cross-items, which is in line with previous theoretical analyses.

The results in columns (2)-(6) show that the increase in the rationalization and advancement of industrial structure will increase carbon emissions efficiency,[3] but the coefficient of advancement is no longer significant in column (5). The cross-terms show that in the regions with higher resource dependence, the advanced industrial structure fails to promote carbon emissions efficiency, and the rational industrial structure may not further reduce carbon emissions efficiency.

Economic development, however, can mitigate the negative effect of natural resource abundance on emissions efficiency. The cross-term coefficient of per capita GDP and its resource dependence is significantly positive in all regressions, indicating that higher levels of economic development can mitigate the negative impact of resource dependence on emissions efficiency.

5.3. Robustness test

In Table 3, we turn to using the *NRDL* to verify the reliability of the previous results. The regression results are basically the same as the previous findings. Specifically, in the absence of cross-terms and control variables, the emissions efficiency dropped by 0.03% for each 1% increase in resource dependence in columns (1)-(3). After adding the cross-terms and control variables, for each 1% increase in resource dependence in columns (4)-(6), the emissions efficiency will decrease by approximately 0.30%. The magnitude of the influence is similar to that of Table 2. The results of industrial structure variables and all cross terms are also basically the same, but the significance level of some coefficients declines.

[2] Before running the panel Tobit model, we conducted the correlation analysis for independent variables and the test result showed that there is no multicollinearity. We conducted fixed effect panel data model but did not find significant difference of results from the panel Tobit model. The results are available upon request. Since the literature shows that panel Tobit model is more efficiency than the fixed effect model for data used in this paper, we conducted our analysis based on the results of panel Tobit model.

[3] According to equation (7), the smaller the value of *Rational*, the more reasonable the industrial structure.

Table 3
Analysis of the effects of resource dependence and industrial structure on carbon emissions efficiency.

Dependent variable	(1) *lnefficiency*	(2)	(3)	(4)	(5)	(6)
lnNRDL	−0.029***	−0.026***	−0.025***	−0.256***	−0.266***	−0.330***
	(0.003)	(0.003)	(0.004)	(0.051)	(0.054)	(0.057)
lnrational		−0.052***		−0.004		−0.019
		(0.005)		(0.014)		(0.013)
lnadvanced			0.057***		0.005	−0.004
			(0.020)		(0.047)	(0.054)
*lnNRDL*lnrational*				0.006***		0.003
				(0.002)		(0.002)
*lnNRDL*lnadvanced*					−0.017**	−0.016
					(0.009)	(0.010)
lnPGDP				0.177***	0.200***	0.198***
				(0.024)	(0.022)	(0.029)
*lnNRDL*lnPGDP*				0.024***	0.024***	0.031***
				(0.005)	(0.005)	(0.005)
lnGOV						0.074***
						(0.025)
lnR&D						0.029
						(0.018)
lnEPI						0.075
						(0.069)
lnUR						−0.033
						(0.040)
Regulation						0.982***
						(0.381)
_cons	−0.505***	−0.587***	−0.482***	−2.259***	−2.429***	−2.804***
	(0.016)	(0.018)	(0.017)	(0.229)	(0.233)	(0.502)
sigma_u	0.178***	0.162***	0.177***	0.135***	0.140***	0.161***
	(0.008)	(0.011)	(0.007)	(0.006)	(0.006)	(0.008)
sigma_e	0.121***	0.118***	0.119***	0.106***	0.107***	0.105***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
rho	0.684	0.653	0.687	0.620	0.629	0.700
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Prob > = chibar2	0.000	0.000	0.000	0.000	0.000	0.000
n	420	420	420	420	420	420

Note: Standard errors are shown in parentheses.
***, **, * denote the statistical significance at 1%, 5% and 10% separately.

Natural resource abundance has a certain correlation with natural resource dependence. However, where natural resources are abundant, natural resource dependence is not necessarily high. The natural resources abundance refers to the quantity of natural resources that a country or region can use for social and economic development; the natural resources dependence refers to the role of resource-based industries in the development of regional economy (Sun and Ye, 2012; Wu et al., 2018). To distinguish the effect of resource endowment to that of the resource dependence, we use *FEE* (fossil energy endowment) as the main dependent variable, which is the ratio of production to consumption of fossil fuels to measure the level of resource endowment.

From the results in columns (1) to (3) in Table 4, it can be seen that resource endowment have a significant negative correlation with carbon emissions efficiency. For each 1% increase in resource endowment, the emissions efficiency will decrease by about 0.12%. In addition, similar to the previous results, the increase in the rationalization and advancement of the industrial structure will improve the carbon emissions efficiency. When adding the cross-terms of the industrial structure variable and resource endowment in columns (4)-(6), it can be seen that the distortion of resource endowment to industrial structure is not as serious as that of resource dependence.

5.4. Test of control variables effects

As shown in Tables 2–4, the coefficients of GOV are significantly positive since fiscal expenditure can finance the improvement of energy-saving and abatement technologies, and encouraging enterprises to eliminate backward production capacity. As in the literature, the role of R&D in improving carbon emissions efficiency is significant. The impact of energy prices on carbon emissions efficiency is significantly positive because the rise of energy prices will force enterprises to introduce energy-saving technologies or reduce energy consumption. The coefficient of urbanization is negative, but not significant in Tables 2 and 3, and weakly significant in Table 4. The reason could be that the economic activities are centralized and the energy has been consumed massively in the process of urbanization but the scale effect and technique spill-over effect cannot be reflected in short-term. The significant effect of environmental regulation on carbon emissions efficiency suggest that the energy-saving and emissions-reduction target is an effective tool for controlling emissions.

5.5. Medium-term and long-term effects

The effect of medium-run and long-run are indeed important to the analysis of the impact of natural resource abundance on carbon emissions efficiency. According to the method in the previous studies (Arin and Braunfels, 2018; Kneller et al., 1999; Wu et al., 2018), this study further carries out the panel Tobit model with 5-year moving average data to examine the medium-term effect of natural resource abundance and industrial structure on carbon emissions efficiency and carries out the Tobit model to analyze long-term effect with the cross-sectional data of 14-year (2013–2016) averages.

Table 4
Analysis of the effects of resource endowments and industrial structure on carbon emissions efficiency.

Dependent variable	(1) *lnefficiency*	(2)	(3)	(4)	(5)	(6)
LnFEE	−0.117***	−0.117***	−0.121***	−0.289**	−0.406***	−0.244**
	(0.013)	(0.012)	(0.014)	(0.115)	(0.139)	(0.120)
lnrational		−0.016***		−0.020**		−0.009
		(0.006)		(0.009)		(0.010)
lnadvanced			0.110***		0.064**	0.081***
			(0.019)		(0.028)	(0.031)
*lnFEE*lnrational*				0.009		0.025***
				(0.008)		(0.009)
*lnFEE*lnadvanced*					−0.035	0.035
					(0.023)	(0.029)
lnPGDP				0.115***	0.117***	0.118***
				(0.012)	(0.011)	(0.023)
*lnFEE *lnPGDP*				0.023**	0.035***	0.025**
				(0.012)	(0.014)	(0.012)
lnGOV						−0.002
						(0.024)
lnR&D						0.025
						(0.017)
lnEPI						0.092
						(0.068)
lnUR						−0.081**
						(0.040)
Regulation						0.850**
						(0.376)
_cons	−0.452***	−0.485***	−0.431***	−1.578***	−1.537***	−1.951**
	(0.012)	(0.017)	(0.010)	(0.113)	(0.112)	(0.490)
sigma_u	0.151***	0.149***	0.155***	0.154***	0.147***	0.148***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
sigma_e	0.116***	0.116***	0.115***	0.107***	0.107***	0.104***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
rho	0.630	0.624	0.644	0.677	0.654	0.670
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Prob > = chibar2	0.000	0.000	0.000	0.000	0.000	0.000
n	420	420	420	420	420	420

Note: Standard errors are shown in parentheses.
***, **, * denote the statistical significance at 1%, 5% and 10% separately.

Tables 5 and 6 show that the impacts of resource dependence on carbon emissions efficiency keep unchanged and are still significant negative in both the medium-term and the long-term.[4] Similar to the results in the models with the annual data, the rationalization and advanced of industrial structure promote the carbon emissions efficiency in the medium-term and long-term (see column (2)–(3) in Tables 5 and 6). In the case of introducing cross-items, the positive effect of rationalization is significantly weakened, and the coefficients of cross-items further show that in the resource dependence regions, even the development of industrial structure towards rational and advanced still cannot improve carbon emissions efficiency (see column (4)–(6) in Tables 5 and 6).

In the long run, the resources dependence of economic development in resource-based regions will inevitably lead to “lock-in effect”, which hinders the adjustment and evolution of regional industrial structures. The longer this development model is maintained, the higher resource dependence will be and the greater negative impact on carbon emissions efficiency will be. Even when resources are exhausted, the transformation of development model are still very difficult due to the lack of alternative industries.

For the control variables, the coefficients of economic development, the government intervention, the technology innovation and the energy price are consistent with those in the models with the annual data (short run effect). The coefficient of urbanization become significantly positive from non-significant, suggesting that although the impact of urbanization on carbon emissions efficiency is unclear in the short and medium-term, in the long run, the effect agglomeration and technology spillover of urbanization significantly improves carbon emissions efficiency.

It needs to be noticed that the coefficient of energy-saving and emissions-reduction target is significantly negative in the long-term model, while it is non-significant in the medium-term model and is significantly negative in the models with annual data. Due to the fiscal decentralization system, the interests between the China's central and local governments are not entirely consistent and the pursuit of rapid economic growth is the primary objective of local governments for a long time. Under the constraints of energy saving and emissions reduction targets, local governments are more likely to control current energy consumption through some government interventions and resulting in higher carbon emissions efficiency in the short term. However, if the target constraints cannot be translated into effective environmental regulations to promote innovation and industrial structure upgrading, they cannot continuously and effectively improve carbon emissions efficiency in the long run.

In summary, the empirical analysis shows that rationalization and advancement of the industrial structure improve the carbon emissions efficiency in different time horizon. However, the significantly negative coefficients of resource abundance in all models and the coefficients of interaction-terms all show that higher resource dependence not only hinders the improvement of carbon emissions efficiency directly but also affects the carbon emissions efficiency by distorting the industrial structure and further exacerbates inefficiency.

[4] We also examine the medium-term and long-term effect with the variable of resource dependence in employment (*NRDL*) and the fossil energy endowment (*FEE*). The results are consistent with that in the Tables 5 and 6 except the coefficients of *FEE* become less significant in the long-term effect model with the cross-items.

Table 5
Middle-term analysis of influencing factors of carbon emissions efficiency.

Dependent variable	(1) *lnefficiency*	(2)	(3)	(4)	(5)	(6)
lnNRD	−0.014***	−0.016***	−0.012***	−0.237**	−0.266***	−0.402***
	(0.003)	(0.003)	(0.003)	(0.047)	(0.045)	(0.040)
lnrational		−0.011***		−0.003		0.071***
		(0.004)		(0.010)		(0.011)
lnadvanced			0.134***		0.080**	0.175***
			(0.012)		(0.033)	(0.036)
*lnNRD*lnrational*				0.009***		0.019***
				(0.002)		(0.002)
*lnNRD*lnadvanced*					0.002	−0.006
					(0.008)	(0.009)
lnPGDP				0.152***	0.168***	0.294***
				(0.020)	(0.017)	(0.024)
*lnNRD*lnPGDP*				0.026***	0.028***	0.043***
				(0.005)	(0.004)	(0.004)
lnGOV						0.090***
						(0.017)
lnR&D						0.044***
						(0.011)
lnEPI						0.586***
						(0.107)
lnUR						−0.014
						(0.048)
Regulation						0.005
						(0.014)
_cons	−0.355***	−0.386***	−0.391**	−1.839***	−1.937***	−5.756***
	(0.013)	(0.016)	(0.011)	(0.193)	(0.176)	(0.661)
sigma_u	0.196***	0.134***	0.130***	0.193***	0.195***	0.142***
	(0.006)	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)
sigma_e	0.078***	0.070***	0.067***	0.068***	0.065***	0.054***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
rho	0.864	0.788	0.791	0.889	0.899	0.873
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Prob > = chibar2	0.000	0.000	0.000	0.000	0.000	0.000
n	300	300	300	300	300	300

Note: Standard errors are shown in parentheses.
***, **, * denote the statistical significance at 1%, 5% and 10% separately.

Table 6
Long-term analysis of influencing factors of carbon emissions efficiency.

Dependent variable	(1) *lnefficiency*	(2)	(3)	(4)	(5)	(6)
lnNRD	−0.071***	−0.068***	−0.064***	−0.856**	−0.751***	−0.594**
	(0.018)	(0.018)	(0.017)	(0.327)	(0.255)	(0.247)
lnrational		−0.051**		0.019		0.188**
		(0.022)		(0.040)		(0.069)
lnadvanced			0.173***		−0.074	0.455**
			(0.062)		(0.195)	(0.217)
*lnNRD*lnrational*				0.013		0.018
				(0.008)		(0.015)
*lnNRD*lnadvanced*					−0.052	0.075
					(0.045)	(0.077)
lnPGDP				0.383***	0.360***	0.218
				(0.127)	(0.102)	(0.132)
*lnNRD*lnPGDP*				0.081**	0.068***	0.059**
				(0.032)	(0.024)	(0.026)
lnGOV						0.315***
						(0.098)
lnR&D						0.229***
						(0.064)
lnUR						0.842**
						(0.352)
Regulation						−0.660***
						(0.137)
_cons	−0.606***	−0.711***	−0.566**	−4.384***	−4.184***	−3.134*
	(0.077)	(0.090)	(0.076)	(1.270)	(1.046)	(1.582)
n	30	30	30	30	30	30

Note: Standard errors are shown in parentheses.
***, **, * denote the statistical significance at 1%, 5% and 10% separately.

6. Conclusion and policy implications

Given China's ongoing efforts implement a national emission trading scheme, investigating potential and ways to achieve low carbon transition are common challenges for all regions and enterprises. These challenges are particular important for the resource-based regions, in which resource-intensive industries are both the pillar and leading industries. With the continuous strengthening of global climate governance, the low-carbon transition of resource-based regions is particularly imperative and will become a new obstacle to the future sustainable development of resource based regions.

This paper uses SBM with windows analysis approach to estimate carbon emissions efficiency and abatement potential for China's 30 provinces from 2003 to 2016. The panel Tobit model is further employed to analyze the direct and indirect effects of resource abundance on emissions efficiency. The paper finds that : (1) The natural resource abundance in the middle Yellow River regions means lower carbon emissions efficiency and larger abatement potential. (2) From the direct effect, there is a negative correlation between resource abundance and carbon emissions efficiency. The more abundant the resources in a region, the lower the emissions efficiency, and the larger the abatement potential. (3) From the indirect effect, resource abundance is not conducive to the rationalization and advancement of the industrial structure, and indirectly affects the carbon emissions efficiency, which decreases the dividend of industrial structure.

Given the continuous advancement of climate change efforts, resource-based regions must regard the industrial structure transformation as an important development strategy in the medium and long term, otherwise which may become a huge challenge for their sustainable development. These regions should take the low-carbon transition as an important factor in their long-term development strategy. Therefore, the conclusions of this paper have important implications to resource-based regions in China, which is applicable to other countries, including:

(1) The resource-based regions should take improving emissions efficiency and tapping abatement potentials as the top priority of actions for low-carbon transition. Resource-based regions should set strict criteria of entrance of new projects for carbon emissions efficiency when conducting environmental impact assessments.
(2) Resource-based regions need to promote the rationalization, and advancement of industrial structures, so as to obtain a double dividend in sustainable development and carbon emissions efficiency. Resource-based regions could gradually phase out outdated industries and/or retrofit those resource intensive industries with new abatement technologies.
(3) The central government should further accelerate the construction of the carbon market, so that the resource-based regions can sell the allowances saved through technological improvement, thereby obtain financial compensation for their abatement investment. The government could also reserve fund from auction of carbon allowances to support industry upgrading and development of low carbon emissions.

The current study at the provincial level has a limitation in that the spatial distribution of natural resources is extremely uneven within any given province. Therefore, the impact of resource dependence on carbon emissions efficiency needs to be further decomposed geographically so that the relationship can be described more accurately. In future, we will employ panel data at the city level for empirical analysis.

Acknowledgements

This work was supported by the National Social Science Fund of China on “Energy Consumption and Efficiency in New Urbanization Process” (Grant no. 15BTJ021), National Natural Science Foundation of China on “Modelling Industrial Capacity Cut under a Cap and Trade Mechanism and Policy Issues: A case study of coal sector” (Grant no. 71828401), National Social Science Fund of China on “Study of Measurement of Statistical Misreporting and Correction Mechanism: Based on Incentive of Local Government” (Grant no. 17BJL070), Humanity and Social Science Youth Foundation of Ministry of Education of China on “GDP Misreporting and Formation Mechanism under Official Evaluation: Study Based on Satellite Light Data” (Grant no. 16YJC790136), and Major Projects of the National Social Science Fund of China on “Supply-side Structural Reform and New Developing Impetus” (Grant no. 16ZDA006).

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