Energy and CO_2 emissions performance in China's regional economics: do market-oriented reforms matter?

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Abstract: This paper employs two newly developed non-radial directional distance functions to evaluate China's regional energy and CO_2 emission performance for the period 1997-2009. Moreover, we analyze the impact of China's market-oriented reform on China's regional energy and carbon efficiency. The main findings are as follows. First, most of China's regions did not perform efficiently in energy use and CO_2 emissions. Provinces in the east area generally performed better than those in the central and west areas. By contrast, provinces in the west area generally evidenced the lowest efficiency. Second, Market-oriented reforms, especially the promotion of factor market, were found to have positive effect on the efficiency of energy use and CO_2 emissions. Third, the share of coal in the total energy consumption and the expansion of industrial sector were found to be negatively correlated with China's regional energy and CO2 emissions performance.

Keywords: market-oriented reforms; energy and carbon efficiency; non-radial directional distance function

1. Introduction

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The Chinese government instituted the policy of reform and opening-up in 1978. Since then, China adopted gradual market-oriented reforms and has been transitioning from a planned economy to a market economy. Benefiting from such polies, China's economy has obtained impressive achievement. According to NBSC, China's real GDP has increased by approximately 26-fold from 1978 to 2013. Along with such aggressive economic expansion, China's energy consumption has also been rising substantially which results in uninterruptedly growing emissions of carbon dioxide (CO_2). As shown in Fig. 1, China consumed 2852 million tonnes of oil equivalent (Mtoe) of primary energy in 2013, increasing from 396 Mtoe in 1978. Meanwhile, the amount of China's CO_2 emissions reached 9524 million tonnes which increased from 1429 million tonnes in 1978. Since 2007, China has already surpassed the US as the largest energy consumer and the largest emitter of CO_2 in the world (Choi et al., 2012; Wang et al., 2013c).

[Fig. 1 is about here]

The rapidly rising energy consumption and CO_2 emissions have raised concerns about China's sustainable development. Moreover, China is currently in the stage of industrialization which is inevitably inducing more energy consumption (Li and Lin, 2013), which makes the situation even more serious in the next decade. It is widely recognized that improving energy efficiency and CO_2 emissions efficiency is an important path for China to tackle energy challenges and environmental pollutions. As such, it is of great interest to evaluate China's efficiency performance in energy use and CO_2 emissions. This topic has attracted much attention. Many researchers have devoted to quantitatively measuring energy efficiency and CO_2 emissions efficiency in China's regions and industries. For example, based on the input-oriented DEA model, Hu and Wang (2006) proposed a total factor energy efficiency index to assess China's 29 administrative regions for the period 1995-2002. Wu et al. (2012) constructed both static and dynamic efficiency indices which also take into account undesirable output to measure industrial energy efficiency in China's provinces for the period 1997-2008. Based on the non-radial directional distance function, Wang et al. (2013a) investigated China's provincial energy efficiency and productivity with different production scenarios for the period 2006-2010. Lin and Du (2014) introduced a latent class stochastic frontier approach to measure energy efficiency at China's provincial level for the period 1997-2010.

In terms of CO_2 emission performance, Guo et al. (2011) employed an environmental DEA model to evaluate China's regional CO_2 emission efficiency for the period 2005-2007. Based on different efficiency orientations, Wang et al. (2012) proposed a group of efficiency models to assess China's regional economic efficiency and CO_2 emissions performance. Wang et al. (2013e) used the directional distance function and combined with stochastic frontier analysis (SFA) techniques to estimate the total factor CO_2 emissions performance index at China's provincial level for the period from 1995 to 2009.

Unlike the aforementioned studies which separately analyzed China's energy efficiency and CO_2 emissions efficiency, there are also many studies simultaneously conducting both efficiency analyses in a single model. For instance, Zhang and Choi

(2013b) developed two slack-based measure (SBM) efficiency indices to model China's regional energy and environmental (carbon dioxide, sulfur dioxide, and Chemical Oxygen Demand) performance during the period 2001-2010. Choi et al. (2012) also employed SBM-DEA approach to estimate energy and carbon efficiency and the abatement cost of emissions in China's regions over the period 2001-2010. Wang et al. (2013b) used RAM-DEA model and to evaluate China's provincial energy and carbon performances for the period 2006-2010. Wang et al. (2013c) employed multi-directional DEA model to estimate China's regional energy and carbon efficiency over the period 1997-2010.

It is worth pointing out that there are extensive literatures on this subject and the number of studies has been growing over years. We can not review one by one here. More studies on China's energy efficiency and CO_2 emission efficiency are summarized in Table 1.

[Table 1 is about here]

Thanks to the contribution of the pioneer studies, many insightful conclusions have been obtained. Although there are variations in the methods employed by previous stduies, some common findings include: (1) China's energy efficiency and CO_2 emission efficiency were still at the low stage; (2) most of China's provinces were not energy-efficient or carbon-efficient; (3) the performances of China's provinces varied greatly. However, most existing literature only focused on the measurement of energy efficiency and CO_2 emission efficiency. Very few of them, so far as we know, have analyzed the influential factors of China's regional efficiency performance. Specially, the quantitative evidence on the impact of China's market-oriented reform in the energy and CO_2 emission efficiency performance in China's regions remains unexplored. Without a doubt, conducting such study not only helps us to understand China's regional performance more in depth but also has significance in terms of policy guidance. It is therefore the purpose of this paper attempts to fill the blank through empirically analyzing the role of market driven reforms in China's regional energy and CO_2 efficiency performance. Based on the empirical findings, we provide policy suggestions for enhancing energy and carbon efficiency in China. This paper also adds to the existing literature on the assessment of China's regional energy and CO_2 emission efficiency performance through applying two newly composite efficiency indicators which were recently developed by Zhang et al. (2014) based on the non-radial directional distance function.

The remainder of the paper is structured as follows. In Sec. 2, we give a brief introduction of China's market-oriented reforms. In Sec. 3, we describe the methods, variables and data in detail. In Sec. 4, we present the empirical results and discussion. In Sec. 5, we use two alternative estimation methods to conduct robustness analysis. In Sec. 6, we conclude the paper and provide the policy implications.

2. China's market-oriented reforms

Prior to China's Comprehensive Economic Reform (CER) in 1978, China was a central planned economy which can be summarized in the following aspects. First, the macro economy was operated through commands of the government. In general, the Five Year Plan is set up to direct the operational aspect of the economy. Then the plan was passed on to the Planning Commission at various layers of government for execution and monitoring (Hou, 2011). People's communes (production teams) and state-owned enterprises (SOEs) were organized for production in the agricultural and industrial sectors, respectively. Second, a pure public ownership system wss in place for the property right, which means that means of production (land, capital, mineral resources, and labor services) are all publically owned and allocated by the government according to the economic plan. Third, in the command economy, prices of resources, products and services are set by the government. To pursuit the heavy-industry-oriented development, raw materials, and living necessities were artificially undervalued. Fourth, the Chinese government established an egalitarian system of income distribution. Under the planned economy, people earned identically regardless of their contribution.

It can be seen that before CER, the economic polies of China run against the law of market which made its economy stagnated for decades. To revive the economy, the Chinese government began to carry out CER in 1978. Unlike the shock therapy in Eastern Europe, China's market-oriented reform have often been characterized as a gradual process. The first step of reforms took place in the rural agricultural production with the practice of the Household Responsibility System as the milestone. This system allocated the usage rights of land to farmers and allowed them to make their own production decisions and get most of their harvest. Due to the incentives from the Household Responsibility System (HRS), China's agricultural sector grew dramatically. With the success of the HRS, the reform was then expanded to urban industrial sector (Hou, 2011). Various “managerial responsibility” systems were introduced in the reform of SOEs. Moreover, private enterprises were also allowed to operate and develop (Hou, 2011).

Although the scope of the market for resource allocation were expanded, in the early stage of the reform the basic institutional framework of central planning remained intact (Qian and Wu, 2000). One important fact is the existence of the dual track system of prices. With the advancement of the reform, the dual track system was abolished in 1992. After that, the government decided to abolish the planning system and the establishment of a socialism market system had been regarded as the goal of the reform. Since then, the market has been being completed. Specially, in the product market most commodities’ prices are determined via the interaction of supply and demand. According to Li (2006), the prices of more than 90% of products have been determined by free markets. In this sense, the product market has been basically achieved. However, the development of the factor market lags far behind the product market. Markets for production factors including land, capital, and energy remain distorted. Particularly in the energy market, the reforms are very slow. Over the past decades, energy (e.g., coal, oil, natural gas, and electricity) prices were artificially determined or regulated by the government. Until recent years, there have not been adequate reforms in the energy sector.

Another typical characteristic of China’s reforms are that they often began with experiment in some specific regions and then gradually expanded to the whole country. Specifically, China’s market-oriented reforms were first carried out in the provinces of the eastern area. After their successes, the reforms were promoted in provinces of the central area and then spread to the western area. For instance, the central government established several special economic zones (SEZs) in the coastal provinces and gradually applied their experience to other zones. As a result, the step-wise development strategy makes China's regional marketization particularly uneven. Accordingly, China's regional economies are not envenly developed. As the pioneers of CER, provinces in the east area are economically well-developed. By contrast, provinces in the central area show less developed and those in the west area are generally the least developed (Du et al., 2014).

3. Methods, variables and data

3.1 Evaluating energy and CO_2 emissions performance based on the non-radial directional distance function

Data envelopment analysis (DEA) has been a powerful tool in the evaluation of energy and environmental efficiency performance[1]. Methodologically, DEA is a nonparametric method which employs linear programming techniques to estimate the best-practice frontier. Consequently, the relative efficiency of the assessed decision-making unit (DMU) can be easily identified through its distance from the frontier (Chen and Golley, 2014). Conventional DEA models are generally built on the Sherphard distance function which expands desirable and undesirable outputs at the same proportion (Zhang and Choi, 2014). It means that reduction of undesirable output is not credited. Thus, conventional DEA models are limited for the

[1] Here we just provide a brief review on the evolution of the methodology. There are already several excellent reviews of data envelopment analysis in energy and environmental studies. See, for example, Zhou et al. (2008), Song et al. (2012), and Zhang and Choi (2014).

measurement of energy and environmental efficiency. To address this issue, Chung et al. (1997) proposed a directional distance function (DDF) method. DDF distinguishes strong disposability and weak disposability between desirable and undesirable outputs. Moreover, DDF allows for increment of desirable output and reduction of undesirable output and inputs simultaneously. As such, DDF has become popular in empirical application. Examples of such studies include Boyd and McClelland (1999), Färe et al. (2007), Oggioni et al. (2011), and Riccardi et al. (2012). Despite its merits, DDF has the limitation that the expansion of desirable output and the contraction of undesirable output/inputs are at the same rate (Du et al., 2014). In this sense, DDF is a radial efficiency measure which may underestimate the inefficiency of the assessed DMU. In view of the limitation of the conventional DDF, Zhou et al. (2012) proposed a non-radial directional distance function (NDDF) method. Compared to DDF, NDDF allows for disproportional adjustments of inputs, desirable output and undesirable output (Zhou et al., 2012). As a result, NDDF has higher discriminating power than DDF. The NDDF method was further developed by Zhang et al. (2013) and Zhang and Choi (2013a) to account for technology heterogeneity and investigate the dynamic change of CO_2 emission performance. Recently, Zhang et al. (2014) proposed two NDDFs for energy/carbon efficiency analysis.

Considering its distinct advantages, the NDDF method is applied in this paper. Suppose that there are N assessed regions and each region is regarded as a DMU. Each DMU uses capital (K), labor (L) and energy (E) to produce desirable goods (Y). Meanwhile, undesirable output CO_2 emissions (C) are generated as byproduct in the process of production. According to the joint production framework proposed by Färe et al. (1989), the production technology can be expressed as:

$$P = \{(K, L, E, Y, C) : (K, L, E) \text{ can produce } (Y, C)\}$$

Technically, the set P is usually assumed to possess the following properties.

(1) P is closed and bounded, which means that only finite amounts of output can be generated by finite amounts of input.

(2) If $C = 0$ and $(K, L, E, Y, C) \in P$, then $Y = 0$. It is termed as null-jointness of desirable output and undesirable output which means that desirable goods cannot be produced without generating undesirable output.

(3) If $(K, L, E, Y, C) \in P$ and $Y' < Y$, then $(K, L, E, Y', C) \in P$. This property is termed as strong disposability of input and desirable output, indicating that redundant input and desirable output can be disposed without any cost.

(4) If $(K, L, E, Y, C) \in P$ and $\alpha \in [0,1]$, then $(K, L, E, \alpha Y, \alpha C) \in P$. This condition is termed as weak disposability of undesirable output, suggesting that undesirable output can be cleaned up at the cost of desirable output.

According to Zhou et al. (2012), Zhang et al. (2013) and Zhang and Choi (2013a), the non-radial directional distance function is defined as:

$$\vec{D}(K, L, E, Y, C; g) = \sup_{\beta \geq 0} \left\{ w^T \beta : (K, L, E, Y, C) + diag(\beta) \cdot g \in P \right\} \qquad (1)$$

where $\beta = (\beta_K, \beta_L, \beta_E, \beta_Y, \beta_C)^T$ is a vector of scaling factors which measures the departure of real production activity from the optimal state; $diag(\beta)$ represents a diagonal matrix with β; $g = (g_K, g_L, g_E, g_Y, g_C)^T$ is a directional vector determining the directions in which each input/output is scaled; $w = (w_K, w_L, w_E, w_Y, w_C)^T$ is a vector denoting the weights assigned to each inputs/outputs.

Note that the directional vector g and the weight vector w can be set in different ways to serve different policy goals. To evaluate the energy and CO_2 emission performance in China's regional economies, we employ two indicators developed by Zhang et al. (2014). The first one is the unified efficiency index (UEI) which sets the directional vector g and the weight vector w as $(-K,-L,-E,Y,-C)$ and $(1/9,1/9,1/9,1/3,1/3)$, respectively. Let $\beta^* = (\beta_K^*, \beta_L^*, \beta_E^*, \beta_Y^*, \beta_C^*)$ denotes the solution to Eq. (1) under the scenario that $g = (-K,-L,-E,Y,-C)$ and $w = (1/9,1/9,1/9,1/3,1/3)$. According to Zhang et al. (2014), the unified efficiency index can be formulated as follows:

$$UEI = \frac{1/4[(1-\beta_K^*) + (1-\beta_L^*) + (1-\beta_E^*) + (1-\beta_C^*)]}{1+\beta_Y^*} \tag{2}$$

Eq. (2) shows that the unified efficiency index takes account of all inefficiencies of inputs, desirable output and undesirable output (CO_2 emissions). Unlike the unified efficiency index, the second indicator emphasizes on the inefficiencies of energy input, desirable output and CO_2 emissions, and removes the diluting effect of other inputs (capital and labor)[2]. In this sense, it is termed energy-environmental performance index (EEPI) in which the directional vector g is set as $(0,0,-E,Y,-C)$ and the weight vector w is set as $(0,0,1/3,1/3,1/3)$. Suppose that $\beta^{**} = (\beta_E^{**}, \beta_Y^{**}, \beta_C^{**})$ is the solution to Eq. (1) under the scenario that $g = (0,0,-E,Y,-C)$ and $w = (0,0,1/3,1/3,1/3)$. According to Zhang et al. (2014), the energy-environmental performance index (EEPI) can be formulated as follows:

[2] It is reasonable to fix non-energy inputs since labor and capital do not contribute to CO_2 emissions directly (Zhang et al., 2014).

$$EEPI = \frac{1/2[(1-\beta_E^{**})+(1-\beta_C^{**})]}{1+\beta_Y^{**}} \tag{3}$$

It can be easily derived that both *UEI* and *EEPI* range from 0 to 1. The higher score of the index means the better energy and CO_2 performance. The assessed DMU is located in the production frontier and regarded as the best performance when *UEI* (EEPI) is equal to 1.

Technically, *UEI* and *EEPI* can be estimated through DEA-type models. For comparability of evaluated results between different years, this paper employs the global environmental DEA method which proposed by Oh (2010). The global DEA method uses the whole sample to construct a fixed benchmark technology frontier. This idea can date back to Berg et al. (1992). According to Oh (2010), the global production technology with constant returns to scale can be formulated as:

$$\begin{aligned} P^g = \Big\{(K,L,E,Y): & \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}K_{n,t} \le K \\ & \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}L_{n,t} \le L \\ & \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}E_{n,t} \le E \\ & \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}Y_{n,t} \ge Y \\ & \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}C_{n,t} = C \\ & \lambda_{n,t} \ge 0, n=1,\ldots,N, t=1,\ldots,T\Big\} \end{aligned} \tag{4}$$

Then, *UEI* and *EEPI* can be calculated after solving the following linear programmings (LPs).

$$\vec{D}(K,L,E,Y,C) = \max \frac{1}{9}\beta_K + \frac{1}{9}\beta_L + \frac{1}{9}\beta_E + \frac{1}{3}\beta_Y + \frac{1}{3}\beta_C$$

$$\begin{aligned}
s.t.\quad & \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}K_{n,t} \le K - \beta_K K \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}L_{n,t} \le L - \beta_L L \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}E_{n,t} \le E - \beta_E E \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}Y_{n,t} \ge Y + \beta_Y Y \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}C_{n,t} = C - \beta_C C \\
& \lambda_{n,t} \ge 0, n = 1,\ldots,N, t = 1,\ldots,T \}
\end{aligned} \tag{5}$$

$$\vec{D}(K,L,E,Y,C) = \max \frac{1}{3}\beta_E + \frac{1}{3}\beta_Y + \frac{1}{3}\beta_C$$

$$\begin{aligned}
s.t.\quad & \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}K_{n,t} \le K \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}L_{n,t} \le L \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}E_{n,t} \le E - \beta_E E \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}Y_{n,t} \ge Y + \beta_Y Y \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_{n,t}C_{n,t} = C - \beta_C C \\
& \lambda_{n,t} \ge 0, n = 1,\ldots,N, t = 1,\ldots,T \}
\end{aligned} \tag{6}$$

3.2 Econometric model, variables and data

For the empirical study, we collect a panel data set of 30 provinces in China from 1997 to 2009[3]. Regional gross domestic product (GDP) is chosen as the proxy of output variable. Raw data on regional GDP are obtained from China Premium Database and adjusted by the gross domestic product deflator so that they are measured by the constant prices in 1997. Since there are no official data of China's

[3] Due to data unavailability, Tibet is not included in this study.

regional CO_2 emissions, we estimate the data according to the method described in Wu et al. (2012).

Data on energy consumption and labor force are directly collected from China Premium Database. Raw Data on capital stock for the period of 1997-2006 are directly obtained from Shan (2008) and then are extended to 2009 using the perpetual inventory method (PIM) as described in Shan (2008). Data on Capital stock are also converted into the constant prices in 1997 using the price index of investment in fixed assets.

To gain deeper insight into the role of market-oriented reform in China's regional energy and CO_2 emissions performances, we consider the following reduced form econometric model.

$$y_{it} = \beta_0 + \beta_1 Mak_{it} + Z_{it}^{'}\gamma + \varepsilon_{it} \tag{7}$$

where the dependent variable ***y*** denotes the score of energy and CO_2 emissions performance (UEI or EEPI); ***Mak*** represents the marketization variable; ***Z*** represents a vector of control variables which are used to single out the influences from other specific characteristics of China's regional economies; ε is the stochastic error term.

We select three proxy variables to reflect the process of marketization in China's administrative regions. They are **Composite Index of Marketization (*CIM*)**, **Index of Product Marketization (*IPM*)**, and **Index of Factor Marketization (*IFM*)**. These indices are drawn from Fan et al. (2012), which captures the development of the entire market, product market and factor market in China's regional economies, respectively. The higher score of the index means the higher level of the market development. Fig.

2 plots the marketization in China's regional economies. It is can be seen that there ae large variations in the development of the market in China's provinces. The provinces in the east area, which are the pioneers of the policy of reforming and opening-up, evidence the highest scores of marketization. On the contrary, the provinces in the west area generally show the lowest level of market development. Comparing the pictures in Panels (A) and (B), we can find there were less diverse across the provinces in the development of product market than in the development of factor market. Fig. 3 plots the dynamic change of the distribution of the three indices over years. From Fig. 3, we can observe the position of the distributions of marketization indices were shifting to the right side over years which indicates that the degree of China's regional markets was gradually improving.

[Fig.2 is about here]

[Fig.3 is about here]

The control variables (***Z***) in the regression model are selected and constructed as follows.

Energy price (denoted as ***Price*****).** In theory, a raise in energy price increases the cost of energy use so that producers would response by improving energy efficiency (Wu, 2012), which helps to reduce CO_2 emissions. Thus, energy price is expected to be positively correlated with energy and CO_2 emissions performance. As data on China's regional energy price are unavailable, we follow Wu (2012) to use the fuel price index as the proxy of energy price. Data on regional fuel price index are obtained from China Premium Database.

Energy consumption structure (denoted as ***ECS*****).** Physically, different types of energy vary in quality[4]. Electricity is more productive than oil which is in turn more productive than coal (Liddle, 2012). Some studies (e.g., Schurr, 1982; Wang, 2007) have found that the composition of energy consumption is correlated with energy efficiency. Specifically, more consumption of energy of high quality can significantly improve energy productivity. Additionally, different types of energy also have different CO_2 emission coefficients. For example, burning coal would emit 1.2 and 1.6 times of CO_2 as the consumption of oil and natural gas, respectively (Du et al., 2012). Given this, the share of coal in total energy consumption is expected to be negatively correlated with the energy and CO_2 emissions performance. Thus, we include the variable of energy consumption structure to control provincial variations and use the share of coal in total energy consumption as the proxy. Raw data are obtained from China Energy Statistics Yearbook.

Industrial structure (denoted as ***IS*****).** Generally speaking, the secondary industry is more energy intensive than the first and tertiary industries. At present, most of China's regions are still in the process of industrialization, which might be an unfavorable factor for improving their energy and CO_2 emissions performances. In this paper, industrial structure is measured by the share of the secondary industry accounting for regional GDP. Raw data are collected from China Premium Database.

Trade openness (denoted as ***Trade*****).** The existing studies (e.g., Ang, 2009; Jalil and Mahmud, 2009) have extensively explored the impact of international trade on

[4] It means that the one unit of different types of energy generates different amounts of work.

the environmental pollutions. On the one hand, local producers benefit from the diffusion of technology and managerial experience through international trade which promotes the growth of resource productivity. On the other hand, international trade generally allocates the production of energy and pollution intensive commodities toward China's regions. This phenomenon is usually termed "pollution refuge hypothesis". It means that larger trade openness might lead to more energy consumption and CO_2 emissions. In summary, trade openness may influence the energy and CO_2 emissions performance in China's regional economies in two opposing sides and the net effect is unclear. Following Du et al. (2012), we measure the trade openness by the share of the sum of import and export in GDP. The corresponding data are collected from China Premium Database.

Urbanization (denoted as ***Urban*****).** Similar to the impact of trade openness, Du et al. (2012) pointed out that urbanization also has two different effects. In the process of urbanization, the construction of infrastructure including road, railway, and airport consumes a lot of energy and results in more emissions of CO_2. Meanwhile, urbanization helps to bring production agglomeration which is widely regarded as an important contributor to economic growth. The change of production mode would affect the energy and CO_2 emissions performance at the economy-wide level through the scale effect and spillover effect. In this paper, the percentage of non-agricultural population is employed as the proxy of urbanization level. Raw data are collected from China Employment Statistics Yearbook and China Population Statistics Yearbook China Population.

Policy dummy (denoted as ***Policy*****).** Considering that in "Eleventh Five-year (2006-2010) Plan" the Chinese government had laid more stress on the energy savings and environmental protection and issued various policies to achieve the target. Following Du and Zou (2011) and Lin and Du (2013a), we set up a dummy variable to examine the impact of the polies. Specifically, ***Policy*** is set to one for the observations during the period from 2006 to 2009 and to 0 during other periods.

Provincial dummies. Except the aforementioned variables, there are also some other factors which also influence the energy and CO_2 emissions performances in China's regional economies, but might not be observed. In view of this fact, we also add provincial dummies in the econometric model which would help us to further control the regional heterogeneity.

The descriptive statistics of the variables are reported in Table 2. As the dependent variable in Eq. (7) is censored at 0 and 1, the tobit regression method is employed in this paper to get the consistent estimates.

[Table 2 is about here]

4. Results and discussion

We use Matlab 7.6 to solve the LPs presented in Eqs. (5) and (6). The estimation results of the unified efficiency index (UEI) in China's regional economies are reported in Table 3. It can be observed that a few scores of the UEI are equal to unity, indicating most of China's provinces did not perform efficiently in their production activities. The average score of UEI in China during the sample period was only 0.563, which was still at a low stage. It implies that as a whole there is still a long way for

China to develop an energy-efficiency and environmental-friendly economy.

[Table 2 is about here]

Table 3 also reveals that the scores of the UEI vary significantly across China's provinces. Among the 30 provinces, Guangdong shows the best performance with an average score of 0.972, followed by Fujian (0.864) and Shanghai (0.781). These three provinces are all from the east area of China. In general, the provinces in the east area were more efficient than those in the central and west areas. The provinces in the west area generally evidenced the lowest scores of UEI. Taking Ningxia and Guizhou as examples, their average values only reached 0.285 and 0.293, which were at the bottom among China's provinces. Basically, these results are in line with the findings of previous studies such as Choi et al. (2012), Wang et al. (2013b), and Wang et al. (2013c).

[Fig. 3 is about here]

Fig. 4 plots the trends of the average scores of the UEI in the three grand areas. From Fig. 4, we can find that the score of the UEI in east area was not only the highest but also grew fastest, which increased from 0.641 in 1997 to 0.79 in 2009, indicating an average growth rate of 1.8%. In contrast, the growth of the score in the west area which was backward in the unified efficiency index was very limited. Therefore, the UEI gap between the leader and the backward was inclined to be widened.

Table 4 reports the estimation results of the EEPI in China's regional economies. The trends of the average scores of the UEI in the three grand areas are presented in

Fig. 5. It can be seen that the results from the EEPI are very similar to the case of the UEI. Thus, we here do not discuss them in detail.

Fig. 6 plots the binary relationship between energy and CO_2 emissions performance and marketization in China's regional economies. It can be observed that either *UEI* or *PEEI* is positively correlated with the marketization indices. It means that the regions with higher degree of marketization were inclined to perform more efficiently in energy use and CO_2 emissions.

The intuitive relationship shown in Fig. 6 is further examined by the multivariable regression model presented in Eq. (7). The corresponding estimation results are reported in Table 5. The dependent variables of Models I-III and Models IV-VI are UEI and EEPI, respectively. In Models I and IV, the coefficients of CIM are estimated as 0.013 and 0.018 respectively, both significant at 1% level. The result suggests that overall marketization had significantly positive effect on the energy and CO_2 emissions performances of China's regions.

In Models II and V, the coefficients of IPM are negative but not significant even at 10% level, which means we do not find evidences to support that during the research period China's regions had benefited from the promotion of product market in terms of energy and CO_2 emissions performances. At the first sight, it is somehow out of our expectation. Recalling that marketization of product has been largely achieved in 1990s and the prices of most commodities are determined by the market. At the current stage the imperfection of product market mainly lies in local protection which is originated from the interaction of local governments. It is understood that local protection benefits local economic growth in the short run but inhabits technological innovations in the long run (Lu and Chen, 2009). In the short run, the situation for efficiency performance in energy use and CO_2 emissions might be complicated. On the one hand, local protection hinders the diffusion of clean production technology. On the other hand, to some extent it can prevent the backward regions from specialized division with production of energy and pollution intensive commodities. In addition, as shown in Fig. 2 the disparities in the product market of China's regions are relative small which means the variations of efficiency performances in energy use and CO_2 emissions might not be explained by the disparities in China's regional product markets. Therefore, it is not surprising to find that during the sample period the promotion of product market does not play a significant role in energy and CO_2 emissions performance. This result might be limited to the sample period of this study. In the early stage of China's market-oriented reforms, markets for products experienced great transformation from a planned system to a market system. For this period, it would be expected to show a different picture from our finding.

Contrary to the case of regressions against IPM, in Models III and VI the coefficients are estimated as 0.005 and 0.013 respectively, both also significant at 1% level. Unlike the development of product market, factor market is still heavily regulated by the government. Factor market distortions are found to result in productivity losses (Brandt et al., 2013; Hsieh and Klenow, 2009). Moreover, the undeveloped factor market would induce inefficiency of resource allocation. It is also not in favor of industrial upgrade. Because that underpricing of resources makes the backward production survive. As a result, the promotion of factor market can contribute to the improvement of energy and CO_2 emissions performance.

As to the estimation results of the control variables, several results can be drawn from Table 5. First, the coefficients of energy price in all models are at least significant at 10% level, suggesting that increasing energy price helps to enhance the energy and CO_2 emissions performance. This result is consistent with the commenon sense that an increase in energy price benefits energy conservation and emission reduction. Second, the share of coal in total energy consumption (referred to *ECS*) and the share of the secondary industry in GDP (referred to *IS*) have negative effects on energy and CO_2 emissions performance which is in line with our expectation. Third, the coefficients of trade openness are significantly positive. As we discussed above, trade openness has two opposing forces. This result suggests that its negative effect contributes to the improvement of energy and CO_2 emissions performance. Fourth, the coefficients of urbanization in most of the models are not significant. Thus, the two opposing effects of urbanization may offset each other. Fifth, although the Chinese government took more measures to promote energy conservation and emission reduction in the "Eleventh Five-Year", the effect of such polies are not found to be significant. This result is consistent with the findings of Du and Zou (2011) and Lin and Du (2013a). One possible explanation is that most measures taken by the government were mainly command-and-control measures such as "blackout with force" which interrupted the normal production activities. Therefore, they are not effective policies and cannot contribute to the improvement of China's regional efficiency performances in terms of energy use and CO_2 emissions.

5. Robustness analysis

To examine the robustness of the results we discussed above, this section conducts the estimation of Eq. (7) using two alternative methods. First, we use random effect tobit model to estimate Eq. (7). Unlike the treatment of unobserved individual factors with dummy variables in the previous section, random effect tobit model does not introduce the dummy variables. It captures unobserved individual factors with a random variable which is often assumed to be a normal distribution. When unobserved individual factors are not correlated with the regressors, random effect model is not only consistent but also more efficient. The estimation results are reported in Table 6. Compared with Table 5, we can find that the results are very similar in terms of the sign and significance of the coefficients.

Our another concern is the possibility of the bidirectional influencing relationship between marketization and energy and CO_2 emissions performance which would lead to endogeneity. To address this issue, we use instrumental variable (IV) method. The instrumental variables we used are the lag variables of CIM, IPM and IFM. This strategy is similar to the idea of General Moment Method (GMM) for dynamic panel model. It is reasonable as the lag variables have been historical such that they would not be influenced and changed by the current energy and CO_2 performance. The estimation results are reported in Table 7. We can observe that for CIM, IPM, IFM, ECS, and IS, our previous results still hold while the coefficients of

Price and Trade become insignificant in some models.

6. Conclusions and policy implications

This paper empirically explores whether market-oriented reforms can contribute to improving energy and CO_2 emissions performances in China's regional economies. To serve this purpose, we first employed two newly developed indicators of Zhang et al. (2014) to evaluate China's regional efficiency performance in energy use and CO_2 emissions. Our main findings are as follows. First, most of China's region did not perform efficiently in energy use and CO_2 emissions. Second, provinces in the east area generally performed better than those in the central and west areas. Provinces in the west area generally evidenced the lowest efficiency. Third, during the research period the efficiency scores in most of provinces showed an increasing trend. Moreover, provinces in the east area grew faster than those in the other areas.

Multivariable regression model is then used to analyze the relationship between China's regional energy and CO_2 emissions performance and marketization. Several different estimation methods are also employed to examine the robustness of our findings. Taking together results from different estimation methods, we can draw some robust conclusions as follows.

(1) Market-oriented reform, especially the promotion of factor market was found to have positive effect on the efficiency of energy use and CO_2 emissions. In other words, the different performances in China's regions can be explained by the variation in their processes of marketization.

(2) The share of coal in the total energy consumption and the expansion of

industrial sector were found to have negative effects on China's regional energy and CO_2 emissions performances.

Based on the above findings, some important policy implication can be proposed. First, the Chinese government should further promotion the marketization in China's regions, especially for the provinces in the central and west areas. Second, as the factor market plays a basic role in resource allocation for production activity, the Chinese government is suggested to complete factor market system. Specifically, the government should slack control over factor price and enhance the functions of market in resource pricing. Additionally, as all mineral resources in China belongs to the state, the government should adopt a more open and transparent way to allocate the initial use right and strengthen the supervision and administration so that producers with higher efficiency are given priority to resource use. Third, the government is also suggested to optimize energy consumption structure through increasing the share of energy which is higher quality and more clean. More financial support should be spent on the development of renewable energy. Forth, the Chinese government should also take measures to adjust the structure of industries and support the development of industries with low energy consumption and less environmental pollutions. Last but not the least, the disparities of China's regional efficiency performances imply variations in the abatement costs of CO_2 emissions. Thus, establishing carbon emission trade systems (ETS) can also play an important role in the development of "low-carbon economy".

Finally, there are some limitations in this paper which should be duly noted.

Restricted to data availability, our research period began at 1997. However, for the product market, great transformations had been accomplished in 1990s. As such, in our sample period we do not find evidences on the general relief that market systems for products can contribute to energy and CO_2 emission performance. This result should be further investigated for a longer time span including the early stage of China's reforms. We leave this issue for the future study.

Reference

Ang, J.B., 2009. CO_2 emissions, research and technology transfer in China. Ecological Economics 68, 2658-2665.

Berg, S.A., Førsund, F.R., Jansen, E.S., 1992. Malmquist indices of productivity growth during the deregulation of Norwegian banking, 1980-89. The Scandinavian Journal of Economics, S211-S228.

Boyd, G.A., McClelland, J.D., 1999. The impact of environmental constraints on productivity improvement in integrated paper plants. Journal of Environmental Economics and Management 38, 121-142.

BP, Statistical Review of World Energy 2014. http://www.bp.com/statisticalreview.

Brandt, L., Tombe, T., Zhu, X., 2013. Factor market distortions across time, space and sectors in China. Review of Economic Dynamics 16, 39-58.

Chen, S., Golley, J., 2014. 'Green' productivity growth in China's industrial economy. Energy Economics 44, 89-98.

China Premium Database; 05/07/2014.

Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related

CO_2 emissions in China: A slacks-based efficiency measure. Applied Energy 98, 198-208.

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. journal of Environmental Management 51, 229-240.

Du, K., Lu, H., Yu, K., 2014. Sources of the potential CO_2 emission reduction in China: A nonparametric metafrontier approach. Applied Energy 115, 491-501.

Du, K., Zou, C., 2011. The Regional Differences of CO_2 Emission Efficiency, Influential Factors and Convergence Analysis: An Empirical Research Based on the Stochastic Frontier Model and Panel Unit Roots Test. Zhejiang Social Science 11, 32-43.

Du, L., Wei, C., Cai, S., 2012. Economic development and carbon dioxide emissions in China: Provincial panel data analysis. China Economic Review 23, 371-384.

Färe, R., Grosskopf, S., Lovell, C.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. The review of economics and statistics, 90-98.

Färe, R., Grosskopf, S., Pasurka Jr, C.A., 2007. Environmental production functions and environmental directional distance functions. Energy 32, 1055-1066.

Fan, G., Wang, X., Zhu, H., 2012. NERI Index of Marketization of China'a Provinces 2011 Report. Economic Science Press, Beijing.

Guo, X.-D., Zhu, L., Fan, Y., Xie, B.-C., 2011. Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. Energy Policy

39, 2352-2360.

Hou, J.W., 2011. Economic reform of China: Cause and effects. The Social Science Journal 48, 419-434.

Hsieh, C.-T., Klenow, P.J., 2009. Misallocation and Manufacturing TFP in China and India. The Quarterly Journal of Economics 124, 1403-1448.

Hu, J.-L., Wang, S.-C., 2006. Total-factor energy efficiency of regions in China. Energy policy 34, 3206-3217.

Jalil, A., Mahmud, S.F., 2009. Environment Kuznets curve for CO_2 emissions: A cointegration analysis for China. Energy Policy 37, 5167-5172.

Li, A., Lin, B., 2013. Comparing climate policies to reduce carbon emissions in China. Energy Policy 60, 667-674.

Li, X., 2006. Assessing the extent of China's marketization. Ashgate Publishing, Ltd.

Liddle, B., 2012. The importance of energy quality in energy intensive manufacturing: Evidence from panel cointegration and panel FMOLS. Energy Economics 34, 1819-1825.

Lin, B., Du, K., 2013a. The energy effect of factor market distortion in China. Economic Research Journal 9, 125-136.

Lin, B., Du, K., 2013b. Technology gap and China's regional energy efficiency: A parametric metafrontier approach. Energy Economics 40, 529-536.

Lin, B., Du, K., 2014. Measuring energy efficiency under heterogeneous technologies using a latent class stochastic frontier approach: An application to Chinese energy economy. Energy.

Lu, M., Chen, Z., 2009. Fragmented Growth: Why Economic Opening May Worsen Domestic Market Segmentation ? Economic Research Journal 3, 42-52.

National Bureau of Statistics of China (NBSC), China Energy Statistical Yearbook , 2013. China Statistics Press, Beijing.

Oggioni, G., Riccardi, R., Toninelli, R., 2011. Eco-efficiency of the world cement industry: a data envelopment analysis. Energy Policy 39, 2842-2854.

Oh, D.-h., 2010. A global Malmquist-Luenberger productivity index. Journal of Productivity Analysis 34, 183-197.

Qian, Y., Wu, J., 2000. China's transition to a market economy: How far across the river? . Stanford Univertsity Working Paper NO. 69.

Riccardi, R., Oggioni, G., Toninelli, R., 2012. Efficiency analysis of world cement industry in presence of undesirable output: application of data envelopment analysis and directional distance function. Energy Policy 44, 140-152.

Schurr, S.H., 1982. Energy efficiency and productive efficiency: some thoughts based on American experience. The Energy Journal, 3-14.

Shan, H., 2008. Reestimating the capital stock of China: 1952-2006. The Journal of Quantitative & Technical Economics 10, 17-31.

Shi, G.-M., Bi, J., Wang, J.-N., 2010. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Policy 38, 6172-6179.

Song, M., An, Q., Zhang, W., Wang, Z., Wu, J., 2012. Environmental efficiency evaluation based on data envelopment analysis: A review. Renewable and Sustainable

Energy Reviews 16, 4465-4469.

Wang, C., 2007. Decomposing energy productivity change: A distance function approach. Energy 32, 1326-1333.

Wang, H., Zhou, P., Zhou, D.Q., 2013a. Scenario-based energy efficiency and productivity in China: A non-radial directional distance function analysis. Energy Economics 40, 795-803.

Wang, K., Lu, B., Wei, Y.-M., 2013b. China's regional energy and environmental efficiency: A Range-Adjusted Measure based analysis. Applied Energy 112, 1403-1415.

Wang, K., Wei, Y.-M., Zhang, X., 2013c. Energy and emissions efficiency patterns of Chinese regions: A multi-directional efficiency analysis. Applied Energy 104, 105-116.

Wang, Q., Zhao, Z., Zhou, P., Zhou, D., 2013d. Energy efficiency and production technology heterogeneity in China: A meta-frontier DEA approach. Economic Modelling 35, 283-289.

Wang, Q., Zhou, P., Zhou, D., 2012. Efficiency measurement with carbon dioxide emissions: The case of China. Applied Energy 90, 161-166.

Wang, Q.W., Zhou, P., Shen, N., Wang, S.S., 2013e. Measuring carbon dioxide emission performance in Chinese provinces: A parametric approach. Renewable and Sustainable Energy Reviews 21, 324-330.

Wei, C., Ni, J., Shen, M., 2009. Empirical Analysis of Provincial Energy Efficiency in China. China & World Economy 17, 88-103.

Wu, F., Fan, L.W., Zhou, P., Zhou, D.Q., 2012. Industrial energy efficiency with CO_2 emissions in China: A nonparametric analysis. Energy Policy 49, 164-172.

Wu, Y., 2012. Energy intensity and its determinants in China's regional economies. Energy Policy 41, 703-711.

Zhang, N., Choi, Y., 2013a. A comparative study of dynamic changes in CO_2 emission performance of fossil fuel power plants in China and Korea. Energy Policy 62, 324-332.

Zhang, N., Choi, Y., 2013b. Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. The Social Science Journal 50, 225-234.

Zhang, N., Choi, Y., 2014. A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013. Renewable and Sustainable Energy Reviews 33, 50-59.

Zhang, N., Kong, F., Choi, Y., Zhou, P., 2014. The effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants. Energy Policy 70, 193-200.

Zhang, N., Zhou, P., Choi, Y., 2013. Energy efficiency, CO_2 emission performance and technology gaps in fossil fuel electricity generation in Korea: A meta-frontier non-radial directional distance functionanalysis. Energy Policy 56, 653-662.

Zhou, P., Ang, B.W., Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. European Journal of Operational Research 189, 1-18.

Zhou, P., Ang, B.W., Wang, H., 2012. Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. European Journal of Operational Research 221, 625-635.

Table 1 Previous studies on China's energy and carbon efficiency

Literature	Methodological approaches	Field of research	DMUs	Period
Hu and Wang (2006)	CCR-DEA model	Energy efficiency	China's 29 provinces	1995-2002
Wei et al. (2009)	CCR-DEA model	Energy efficiency	China's 29 provinces	1997-2006
Shi et al. (2010)	DEA model of fixing non-energy inputs	Industrial energy efficiency	China's 28 provinces	2000-2006
Wu et al. (2012)	Environmental DEA model	Industrial energy efficiency	China's 28 provinces	1997-2008
Wang et al. (2013a)	NDDF	Energy efficiency and productivity	China's 28 provinces	2005-2010
Lin and Du (2013b)	Parametric metafrontier approach	Energy efficiency	China's 30 provinces	1997-2010
Wang et al. (2013d)	Metafrontier DEA approach	Energy efficiency	China's 28 provinces	2000-2010
Lin and Du (2014)	Latent class stochastic frontier approach	Energy efficiency	China's 30 provinces	1997-2010
Guo et al. (2011)	Environmental DEA model	Carbon efficiency and potential reductions	China's 29 provinces	2005-2007
Du et al. (2014)	Non-parametric metafrontier approach	Carbon efficiency and potential reductions	China's 30 provinces	2006-2010
Wang et al. (2013e)	DDF and SFA	Carbon efficiency	China's 28 provinces	1995-2009
Choi et al. (2012)	SBM-DEA model	Energy and carbon efficiency, abatement cost of emissions	China's 30 provinces	2001-2010
Zhang and Choi (2013)	SBM-DEA model	Energy and environmental efficiency	China's 30 provinces	2001-2010
Wang et al. (2012)	Environmental DEA model	Economic and energy efficiency	China's 28 provinces	2001-2007
Wang et al. (2013b)	RAM-DEA model	Energy and carbon efficiency	China's 30 provinces	2006-2010
Wang et al. (2013c)	Multi-directional DEA model	Energy and carbon efficiency	China's 30 provinces	1997-2010

Table 2 The descriptive statistics of the variables

Variable	Symbol	Unit	Mean	Sd	Min	Max
GDP	***Y***	Billion RMB	521.2	501.8	20.28	3122
CO_2	***C***	10 thousand tons	18172	14221	705	83382
Capital	***K***	100 million RMB	9643	8898	459.4	53860
Energy	***E***	Mtce	74.19	55.23	3.9	324.2
Labor	***L***	Million persons	22.22	14.69	2.304	59.49
CIM	***CIM***	-	5.788	2.12	1.29	11.8
IPM	***IPM***	-	7.111	1.886	0.16	10.61
IFM	***IFM***	-	4.015	2.231	0.4	11.93
Energy price	***Price***	%	148.5	47.58	89.6	288.3
Energy consumption structure	***ECS***	%	73.13	14.83	27.7	99.32
Industrial structure	***IS***	%	46.03	7.355	19.76	61.5
Trade openness	***Trade***	%	30.84	39.91	3.204	172.1
Urbanization	***Urban***	%	33.26	15.85	14.04	88.25

Table 3 Estimation results of the unified efficiency index (UEI) in China's regional economics

Province	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
(E)Beijing	0.508	0.504	0.535	0.569	0.591	0.612	0.631	0.668	0.700	0.732	0.774	0.895	1.000	0.671
(E)Fujian	1.000	1.000	0.957	0.835	1.000	0.820	0.806	0.794	0.766	0.792	0.815	0.841	0.800	0.864
(E)Guangdong	1.000	1.000	0.930	0.954	0.946	0.951	0.960	0.981	0.948	0.968	1.000	1.000	1.000	0.972
(E)Hainan	0.632	0.622	0.653	0.661	0.670	0.632	0.606	0.586	0.641	0.639	0.678	0.690	0.707	0.647
(E)Hebei	0.460	0.466	0.467	0.460	0.481	0.470	0.476	0.488	0.491	0.503	0.520	0.527	0.497	0.485
(E)Jiangsu	0.641	0.658	0.691	0.717	0.748	0.776	0.790	0.771	0.727	0.730	0.781	0.810	0.828	0.744
(E)Liaoning	0.450	0.486	0.507	0.511	0.534	0.564	0.585	0.585	0.598	0.607	0.611	0.580	0.593	0.555
(E)Shandong	0.620	0.628	0.644	0.655	0.679	0.637	0.635	0.634	0.605	0.625	0.639	0.659	0.669	0.641
(E)Shanghai	0.580	0.621	0.638	0.675	0.703	0.730	0.757	0.799	0.816	0.869	0.965	1.000	1.000	0.781
(E)Tianjin	0.487	0.527	0.523	0.533	0.560	0.596	0.631	0.647	0.676	0.709	0.748	0.772	0.807	0.632
(E)Zhejiang	0.676	0.697	0.714	0.703	0.727	0.716	0.730	0.724	0.727	0.758	0.773	0.777	0.789	0.732
(C)Anhui	0.509	0.514	0.528	0.535	0.549	0.567	0.577	0.597	0.604	0.612	0.632	0.645	0.661	0.579
(C)Heilongjiang	0.486	0.503	0.519	0.538	0.574	0.610	0.622	0.649	0.677	0.680	0.710	0.729	0.734	0.618
(C)Henan	0.578	0.531	0.524	0.529	0.535	0.534	0.526	0.507	0.504	0.505	0.507	0.514	0.521	0.524
(C)Hubei	0.464	0.475	0.482	0.491	0.516	0.517	0.513	0.513	0.523	0.509	0.555	0.588	0.608	0.520
(C)Hunan	0.515	0.532	0.604	0.638	0.618	0.606	0.588	0.562	0.523	0.536	0.561	0.586	0.608	0.575
(C)InnerMog	0.503	0.569	0.539	0.554	0.556	0.529	0.477	0.461	0.466	0.478	0.431	0.432	0.436	0.495
(C)Jiangxi	0.647	0.652	0.626	0.599	0.627	0.604	0.581	0.572	0.573	0.569	0.583	0.617	0.634	0.606
(C)Jilin	0.415	0.458	0.483	0.494	0.510	0.506	0.547	0.514	0.524	0.510	0.499	0.500	0.509	0.498
(C)Shanxi	0.348	0.357	0.354	0.361	0.357	0.361	0.375	0.390	0.398	0.402	0.423	0.424	0.409	0.381
(W)Chongqing	0.477	0.467	0.458	0.534	0.533	0.574	0.604	0.589	0.551	0.562	0.589	0.580	0.616	0.549
(W)Gansu	0.428	0.430	0.415	0.413	0.418	0.412	0.405	0.403	0.405	0.410	0.421	0.424	0.441	0.417
(W)Guangxi	0.694	0.715	0.689	0.651	0.657	0.671	0.655	0.606	0.599	0.600	0.606	0.628	0.623	0.646
(W)Guizhou	0.317	0.314	0.295	0.289	0.287	0.285	0.267	0.267	0.280	0.283	0.296	0.310	0.313	0.293

(W)Ningxia	0.295	0.309	0.316	0.289	0.285	0.282	0.269	0.266	0.268	0.274	0.282	0.290	0.284	0.285
(W)Qinghai	0.324	0.341	0.316	0.333	0.329	0.334	0.334	0.330	0.340	0.340	0.358	0.366	0.371	0.340
(W)Shananxi	0.389	0.404	0.440	0.460	0.445	0.440	0.436	0.430	0.435	0.446	0.461	0.478	0.497	0.443
(W)Sichuan	0.420	0.443	0.476	0.503	0.521	0.521	0.511	0.499	0.523	0.535	0.551	0.551	0.573	0.510
(W)Xinjiang	0.358	0.366	0.380	0.389	0.398	0.401	0.406	0.405	0.410	0.408	0.423	0.436	0.432	0.401
(W)Yunnan	0.500	0.489	0.505	0.517	0.515	0.501	0.484	0.549	0.447	0.446	0.452	0.468	0.474	0.488
Average	0.524	0.536	0.540	0.546	0.562	0.559	0.559	0.560	0.558	0.568	0.588	0.604	0.614	0.563

Note: E, C,and W in parentheses represent to the east, central, and west areas respectively.

Table 4 Estimation results of the unified efficiency index (UEI) in China's regional economics

Province	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
(E)Beijing	0.417	0.453	0.486	0.529	0.553	0.604	0.640	0.689	0.734	0.784	0.845	0.932	1.000	0.667
(E)Fujian	1.000	1.000	0.980	0.901	1.000	0.869	0.835	0.809	0.757	0.795	0.821	0.869	0.885	0.886
(E)Guangdong	1.000	1.000	0.929	0.934	0.934	0.954	0.964	0.965	0.932	0.960	1.000	1.000	1.000	0.967
(E)Hainan	0.829	0.795	0.845	0.841	0.839	0.753	0.708	0.673	0.776	0.764	0.744	0.751	0.775	0.776
(E)Hebei	0.305	0.316	0.332	0.320	0.354	0.320	0.311	0.311	0.301	0.315	0.333	0.356	0.376	0.327
(E)Jiangsu	0.581	0.607	0.654	0.695	0.748	0.783	0.797	0.733	0.667	0.688	0.740	0.794	0.851	0.718
(E)Liaoning	0.261	0.283	0.296	0.287	0.314	0.346	0.361	0.351	0.377	0.399	0.415	0.451	0.469	0.355
(E)Shandong	0.522	0.566	0.608	0.614	0.648	0.555	0.539	0.520	0.456	0.470	0.499	0.533	0.577	0.547
(E)Shanghai	0.489	0.543	0.562	0.607	0.641	0.679	0.703	0.748	0.763	0.822	0.930	1.000	1.000	0.730
(E)Tianjin	0.354	0.393	0.421	0.425	0.456	0.496	0.547	0.543	0.570	0.603	0.647	0.706	0.754	0.532
(E)Zhejiang	0.667	0.691	0.722	0.697	0.744	0.714	0.729	0.706	0.700	0.723	0.746	0.801	0.840	0.729
(C)Anhui	0.424	0.433	0.454	0.465	0.480	0.506	0.517	0.543	0.548	0.570	0.590	0.608	0.633	0.521
(C)Heilongjiang	0.293	0.336	0.356	0.373	0.424	0.474	0.472	0.481	0.497	0.508	0.523	0.537	0.583	0.451
(C)Henan	0.450	0.437	0.452	0.457	0.463	0.461	0.444	0.401	0.397	0.407	0.424	0.458	0.480	0.441
(C)Hubei	0.327	0.354	0.382	0.402	0.450	0.450	0.434	0.424	0.435	0.439	0.460	0.509	0.543	0.431
(C)Hunan	0.441	0.465	0.598	0.663	0.629	0.609	0.578	0.522	0.439	0.459	0.482	0.521	0.561	0.536
(C)InnerMog	0.259	0.350	0.304	0.311	0.299	0.284	0.259	0.233	0.230	0.234	0.239	0.249	0.273	0.271
(C)Jiangxi	0.580	0.609	0.610	0.580	0.629	0.583	0.551	0.545	0.557	0.566	0.574	0.623	0.649	0.589
(C)Jilin	0.233	0.294	0.321	0.328	0.344	0.338	0.399	0.342	0.366	0.384	0.415	0.455	0.478	0.361
(C)Shanxi	0.167	0.187	0.204	0.213	0.193	0.178	0.183	0.191	0.196	0.199	0.215	0.225	0.227	0.198
(W)Chongqing	0.394	0.367	0.349	0.484	0.478	0.557	0.619	0.596	0.527	0.542	0.571	0.553	0.593	0.510
(W)Gansu	0.240	0.244	0.242	0.253	0.282	0.289	0.286	0.285	0.290	0.297	0.290	0.305	0.337	0.280
(W)Guangxi	0.696	0.709	0.694	0.671	0.698	0.715	0.678	0.575	0.563	0.577	0.592	0.641	0.661	0.652
(W)Guizhou	0.157	0.155	0.179	0.186	0.200	0.213	0.185	0.184	0.208	0.209	0.222	0.230	0.235	0.197

(W)Ningxia	0.201	0.224	0.225	0.184	0.174	0.170	0.135	0.142	0.144	0.145	0.150	0.150	0.159	0.169
(W)Qinghai	0.236	0.253	0.240	0.268	0.268	0.265	0.268	0.272	0.283	0.267	0.281	0.269	0.282	0.266
(W)Shananxi	0.289	0.330	0.404	0.443	0.414	0.403	0.396	0.373	0.371	0.391	0.412	0.435	0.458	0.394
(W)Sichuan	0.356	0.386	0.447	0.488	0.515	0.504	0.476	0.443	0.479	0.490	0.509	0.518	0.538	0.473
(W)Xinjiang	0.238	0.253	0.277	0.276	0.291	0.301	0.305	0.292	0.292	0.288	0.299	0.308	0.300	0.286
(W)Yunnan	0.392	0.402	0.443	0.471	0.473	0.443	0.419	0.533	0.361	0.363	0.375	0.396	0.409	0.422
Average	0.427	0.448	0.467	0.479	0.498	0.494	0.491	0.481	0.474	0.489	0.511	0.539	0.564	0.489

Note: E, C,and W in parentheses represent to the east, central, and west areas, respectively.

Table 5 Estimation results of tobit models

Variable	UEI			EEPI		
	Model I	Model II	Model III	Model IV	Model V	Model VI
CIM	0.0124***			0.0178***		
	(0.00399)			(0.00503)		
IPM		-0.000434			-4.40e-05	
		(0.00222)			(0.00282)	
IFM			0.00555**			0.0127***
			(0.00270)			(0.00338)
Price	0.000230*	0.000475***	0.000371***	0.000322*	0.000666***	0.000440***
	(0.000132)	(0.000115)	(0.000119)	(0.000167)	(0.000146)	(0.000149)
ECS	-0.00363***	-0.00390***	-0.00382***	-0.00557***	-0.00594***	-0.00578***
	(0.000603)	(0.000610)	(0.000602)	(0.000762)	(0.000774)	(0.000754)
IS	-0.00625***	-0.00620***	-0.00625***	-0.00770***	-0.00764***	-0.00773***
	(0.000752)	(0.000767)	(0.000757)	(0.000952)	(0.000975)	(0.000949)
Trade	0.000804***	0.00113***	0.000910***	0.000571*	0.00104***	0.000544*
	(0.000244)	(0.000228)	(0.000246)	(0.000311)	(0.000291)	(0.000310)
Urban	-0.00175*	-0.000699	-0.000618	-0.00325***	-0.00181	-0.00153
	(0.000910)	(0.000873)	(0.000856)	(0.00115)	(0.00111)	(0.00108)
Policy	0.0142	0.0150	0.0144	0.0138	0.0152	0.0135
	(0.00909)	(0.00925)	(0.00916)	(0.0115)	(0.0117)	(0.0115)
Constant	1.105***	1.144***	1.135***	1.276***	1.330***	1.312***
	(0.0603)	(0.0610)	(0.0597)	(0.0764)	(0.0775)	(0.0748)

Note: To converse space, estimation results of provincial dummies are not reported.

Standard errors in parentheses; *, ** and ***denote coefficient significant at10, 5 and 1% respectively.

Table 6 Estimation results of random-effects tobit models

Variable	UEI			EEPI		
	Model I	Model II	Model III	Model IV	Model V	Model VI
CIM	0.0142***			0.0202***		
	(0.00399)			(0.00502)		
IPM		0.000350			0.000828	
		(0.00229)			(0.00289)	
IFM			0.00633**			0.0138***
			(0.00280)			(0.00351)
Price	0.000128	0.000418***	0.000312**	0.000187	0.000597***	0.000366**
	(0.000139)	(0.000119)	(0.000122)	(0.000176)	(0.000150)	(0.000152)
ECS	-0.00349***	-0.00372***	-0.00366***	-0.00559***	-0.00588***	-0.00574***
	(0.000596)	(0.000606)	(0.000600)	(0.000746)	(0.000763)	(0.000744)
IS	-0.00571***	-0.00574***	-0.00576***	-0.00712***	-0.00716***	-0.00721***
	(0.000781)	(0.000793)	(0.000785)	(0.000980)	(0.00100)	(0.000976)
Trade	0.000928***	0.00128***	0.00104***	0.000784**	0.00128***	0.000758**
	(0.000249)	(0.000234)	(0.000253)	(0.000318)	(0.000300)	(0.000320)
Urban	-0.00157*	-0.000748	-0.000600	-0.00309***	-0.00200*	-0.00166
	(0.000834)	(0.000825)	(0.000814)	(0.00104)	(0.00104)	(0.00101)
Policy	0.0155	0.0167*	0.0157*	0.0158	0.0177	0.0155
	(0.00948)	(0.00964)	(0.00954)	(0.0120)	(0.0122)	(0.0119)
Constant	0.999***	1.015***	1.007***	1.155***	1.177***	1.159***
	(0.0588)	(0.0602)	(0.0594)	(0.0724)	(0.0749)	(0.0728)

Note: Standard errors in parentheses; *, **and ***denote coefficient significant at10, 5 and 1% respectively.

Table 7 Estimation results of instrumental variable (IV) tobit models

Variable	UEI			EEPI		
	Model I	Model II	Model III	Model IV	Model V	Model VI
CIM	0.0224***			0.0331***		
	(0.00572)			(0.00732)		
IPM		-0.00161			-0.00347	
		(0.00385)			(0.00492)	
IFM			0.0222***			0.0396***
			(0.00559)			(0.00721)
Price	-1.95e-05	0.000421***	5.12e-06	-7.73e-05	0.000587***	-0.000163
	(0.000153)	(0.000121)	(0.000151)	(0.000196)	(0.000155)	(0.000196)
ECS	-0.00365***	-0.00408***	-0.00392***	-0.00524***	-0.00591***	-0.00560***
	(0.000665)	(0.000671)	(0.000691)	(0.000852)	(0.000858)	(0.000891)
IS	-0.00596***	-0.00588***	-0.00616***	-0.00741***	-0.00725***	-0.00776***
	(0.000773)	(0.000786)	(0.000812)	(0.000991)	(0.00101)	(0.00105)
Trade	0.000412	0.00104***	0.000143	3.09e-05	0.000986***	-0.000623
	(0.000272)	(0.000242)	(0.000321)	(0.000351)	(0.000311)	(0.000416)
Urban	-0.00228**	-0.000453	0.000304	-0.00432***	-0.00159	-0.000262
	(0.000979)	(0.000897)	(0.000938)	(0.00126)	(0.00115)	(0.00122)
Policy	0.0160*	0.0183**	0.0151	0.0184	0.0215*	0.0160
	(0.00900)	(0.00904)	(0.00945)	(0.0115)	(0.0115)	(0.0122)
Constant	1.086***	1.162***	1.131***	1.229***	1.347***	1.288***
	(0.0658)	(0.0678)	(0.0669)	(0.0844)	(0.0868)	(0.0865)

Note: To converse space, estimation results of provincial dummies are not reported.

Standard errors in parentheses; *, ** and ***denote coefficient significant at10, 5 and 1% respectively.

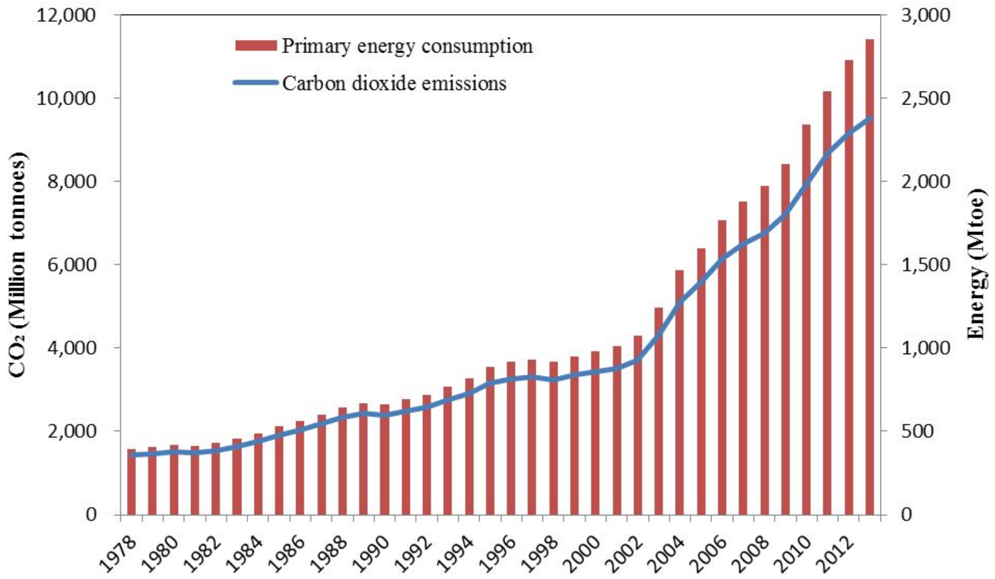

Fig. 1 China's energy consumption and CO_2 emissions over years

Data source: BP Statistical Review of World Energy 2014

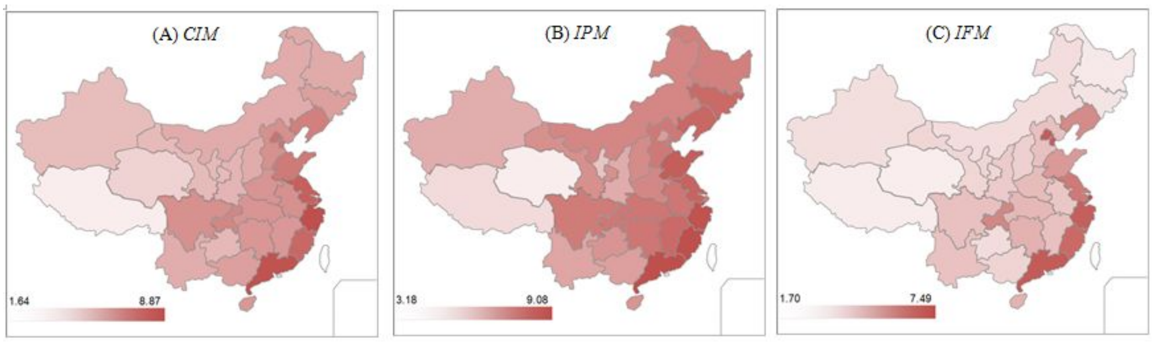

Fig. 2 Marketization in China's regions

Note: The data for plotting are average scores of the three indices of regional marketization. Data source: Fan and Wu (2011).

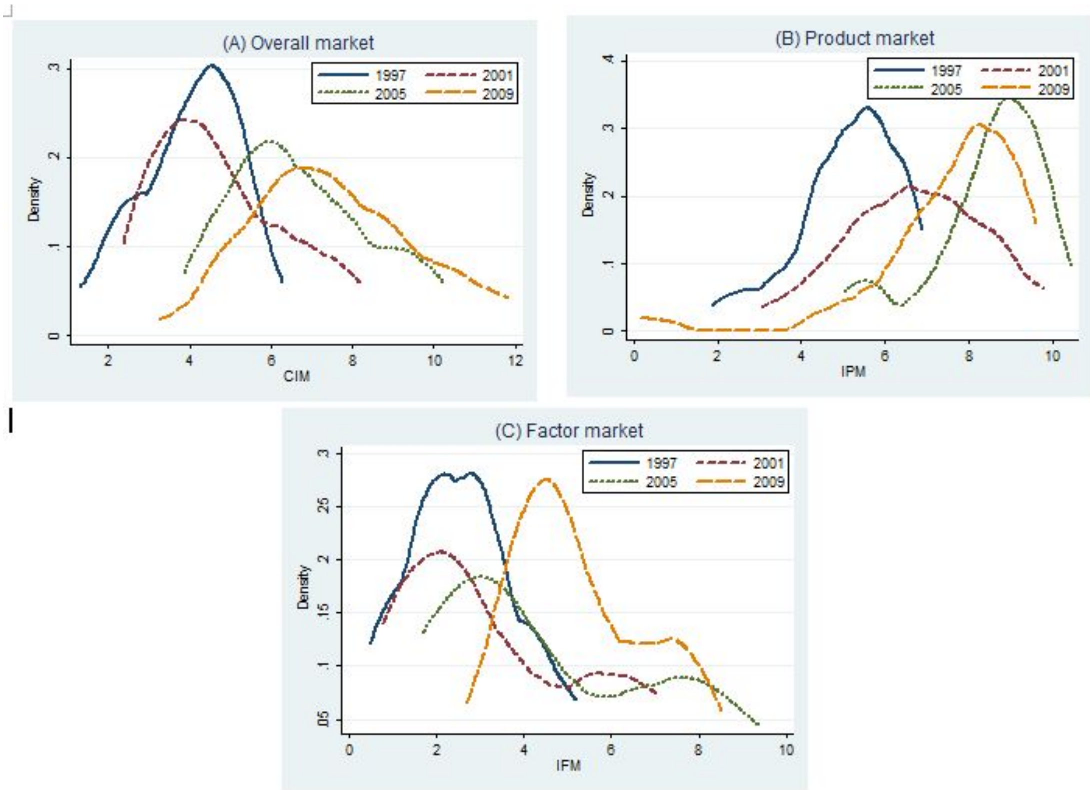

Fig. 3 Kernel density evolution of Marketization in China's regions

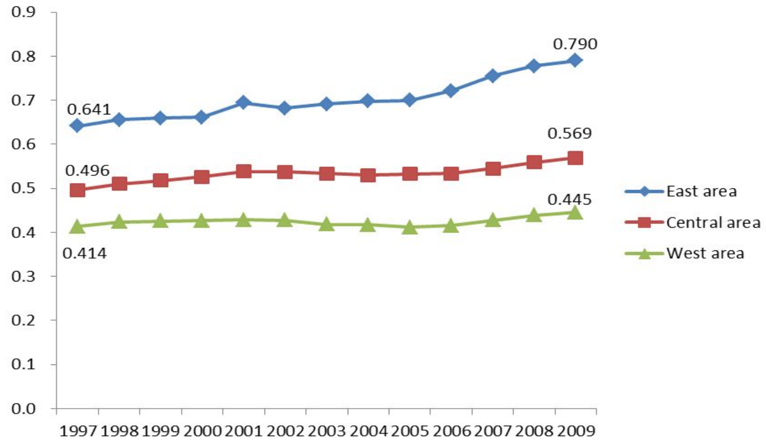

Fig. 4 The average scores of UEI of different regions over years

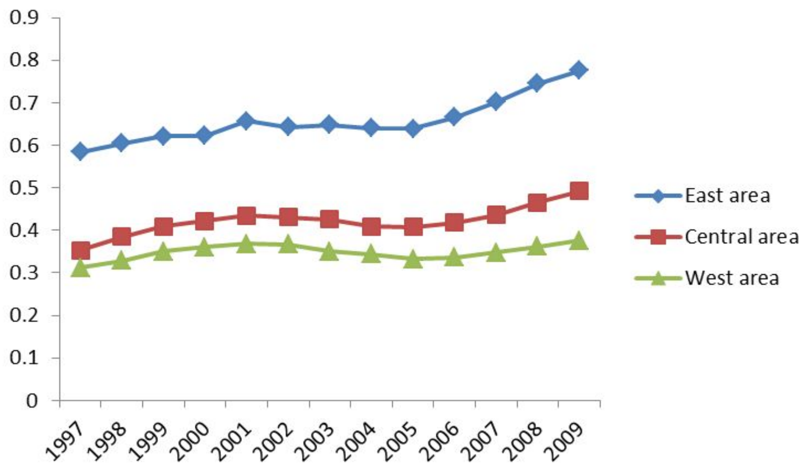

Fig. 5 The average scores of EEPI of different regions over years

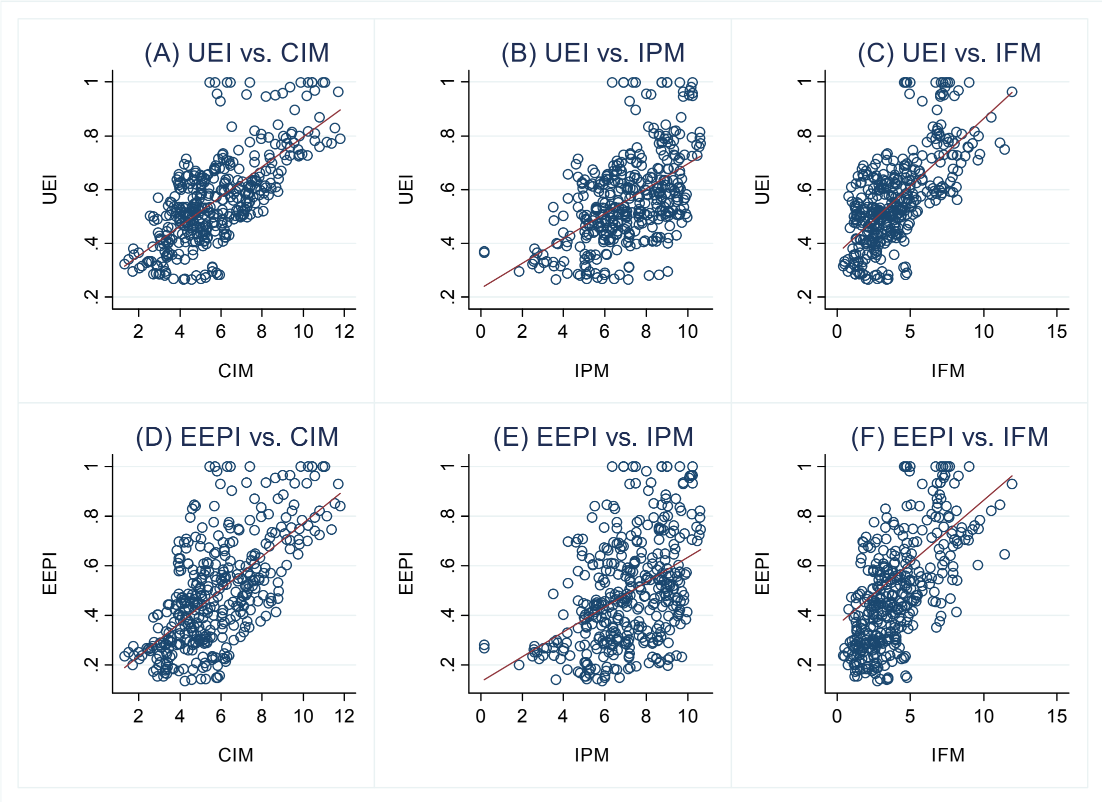

Fig. 6 Correlation between energy and CO_2 emissions performance and marketization