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“Neighbors as Competitors” or “Neighbors as Partners”: How does Market Segmentation Affect Regional Energy Efficiency in China?

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Summary

Existing studies have focused on the negative impact of inefficient resource allocation on energy performance in China's factor market, but neglected to further explore the underlying reason for this phenomenon from the perspective of market segmentation. In this paper, the epsilon-based measure model, which combines the merits of radial and non-radial Data Envelopment Analysis, is employed to measure the energy efficiency, and price index method derived from Iceberg Transport Cost model is used to examine the degrees of market segmentation. On the basis, we use the Tobit model to empirically investigate the impact of market segmentation on China's energy efficiency. The results show that although energy efficiency in the eastern region is higher than that in the central and western regions, the energy efficiency gap is narrowing significantly between the eastern and central, but insignificantly between the western and eastern. Although efforts have been made towards a unified national market, the western provinces still have more segmented markets than the eastern still. Econometric analysis indicates that market segmentation is negative to China's energy efficiency significantly. This finding remains robust even if the endogeneity is excluded and the dependent variable is re-measured by the slack-based measure model, but is of a regional heterogeneity. We also find that factor market distortion, enterprises' R&D investment, and industrial agglomeration are three mediation mechanisms through which market segmentation affects energy efficiency. In-depth analysis indicates that there is a Race to the Top competition centering on market segmentation among Chinese local officials in geospatial and economic space, which triggers a long-term inhibition to energy efficiency.

Keywords: Energy efficiency, Market segmentation, Factor market, EBM model, Tobit model, SBM model

JEL Classification: Q43, Q48, O13, P23, P28

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"Neighbors as competitors" or "neighbors as partners": How does market segmentation affect regional energy efficiency in China?

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1. Introduction

Since launching its open-door policy and economic reforms in late 1978, China has experienced spectacular economic growth. In this course, China has been heavily dependent on dirty-burning coal to fuel its rapidly growing economy, and consumed two to three times energy of the United States, Germany and Japan to produce per unit of GDP in 2016, respectively (BP, 2016). Until recently, China had valued economic growth above environmental protection. A combination of these factors has given rise to unprecedented environmental pollution and health risks across the country (Ho and Nielsen, 2007; The World Bank, 2007; Zhang, 2010 and 2015a). Moreover, China overtook the United States as the world's largest carbon emitter in 2006, and surpassed the combined carbon emissions of the United States and the European Union in 2013 (Choi et al., 2012; Wang et al., 2013).

The extensive way of energy utilization and its resulting traditional pollution and carbon pollution not only put China under the tremendous pressure from international community, but also threaten its sustainable development. In order to promote energy efficiency and pursue low-carbon transition, the Chinese government incorporated Green Development as one of the "Five Major Principles" into the 13th Five-Year (2016-2020) Plan. At the 2015 Paris Climate Conference, China committed to capping its carbon emissions around 2030, and to trying to peak early. In addition, China pledged to reduce the carbon intensity of its economy by 60–65% by 2030 compared to 2005 levels. Hence, it can be widely seen that saving energy and controlling carbon emissions have become a key theme in China's economic and social development for some time to come (Zhang, 2015a,b and 2017).

On the related research front, scholars have studied ways to improve China's energy efficiency from the perspectives of urbanization, industrial structure, foreign direct investment, and energy consumption mix (Feng et al., 2009; Guo et al., 2011; Elliott et al., 2013; Li et al., 2012; Zhou et al., 2013; Li and Lin, 2014; Tian et al., 2014; Ma, 2015; Yan, 2015; Elliott, et al., 2017). In recent years, with the transformation of China's economy, they have begun to shift the research focus from the demand side to the supply side and arrive at the consensus that the inefficient resource allocation of factor market is the key to restricting China's energy performance currently (Li and Lin, 2015; Ouyang and Sun, 2015; Dai and Cheng, 2016; Yang et al., 2018b). However, to the best of our knowledge, there is still a lack of in-depth research to investigate the underlying reason for this phenomenon.

In fact, it is widely recognized that fiscal decentralization reform carried out from the 1980s makes great contributions to the early rapid development of China, because local governments were provided with a powerful motivation to grow the economies by being granted with certain fiscal rights. However, this Chinese-style decentralization also drives local officials to split up the unified market. In order to increase GDP, tax revenues and employment within their jurisdiction, local officials often restrict the outflow of local resources and the inflow of non-local products using administrative measures (Poncet, 2005; Shao, et al., 2019). Market segmentation, in theory, makes it impossible for production factors to flow freely in line with price signal, and consequently energy price gaps vary greatly from one region to another, which will bring about a series of grave consequences. Specifically speaking, the low-efficiency enterprises in resource-rich areas are given a greater possibility to survive from market competition by virtue of factor cost advantage. Meanwhile, the high-efficiency enterprises are forced out of the market due to factor cost disadvantage (Kumar et al., 2014; He et al. 2018a). Clearly market segmentation is the underlying reason for the inefficient resource allocation in the factor market and further magnifies the loss of energy efficiency in China. Unfortunately, few previous studies examined this issue from the perspective of market segmentation. Although Li and Lin (2017a) pointed out that market integration is beneficial for improving energy efficiency, they neglected the game behavior hidden behind market segmentation among local governments. They also failed to explore the impact mechanisms between these two variables. Given the shortcomings of previous literatures, this paper innovatively studies the impact of market segmentation on energy efficiency in China and the regional heterogeneity of such effect. On the basis of these, the mediation mechanisms between them are further investigated. Furthermore, we explore the game behavior behind market segmentation among local governments and its long-term impact on energy efficiency. This study contributes to the existing literature by analyzing the reasons for China's low energy efficiency from an institutional perspective, and provides a valuable reference for the Chinese government to promote energy efficiency and accelerate market-oriented reforms.

The rest of this paper is organized as follows. Section 2 is a brief review of previous literature. Section 3 describes variables, model specification and data sources in detail. Section 4 gives the measuring results of energy efficiency and market segmentation in China's regional economies. In Section 5, we empirically examine the impact of market segmentation on energy efficiency and the regional heterogeneity of such effect. The impact mechanism between them are further discussed. We also investigate the game behavior hidden behind market segmentation among Chinese local governments in geospatial and economic space and its long-term impact on energy efficiency. Section 6 concludes with policy implications.

2. Literature review

With widespread local air pollution across China and urgent need to address global climate change, the increasing energy consumption and CO_2 emissions have made China's energy efficiency the focus of a growing number of studies. These studies can be divided into two groups. The first one attempts to use various improved models to measure energy efficiency in China's regions or industries. The second one pays special attention to the factors affecting China's energy efficiency.

In the first group of studies, two kinds of method are usually employed to measure energy efficiency (Wang et al., 2013). One is the parametric method represented by Stochastic Frontier Analysis (SFA), and the other is the non-parametric method represented by Data Envelopment Analysis (DEA). Compared with SFA method, DEA method is used more widely because the explicit relationship between inputs and outputs is unnecessary to pre-determined (Lin and Du, 2015). Hu and Wang (2006) have done a path breaking study in this field. They firstly defined the concept of energy efficiency and built a DEA model with energy, capital, labor and biomass energy as inputs and GDP as output. On the basis, they measured the total factor energy efficiency of China's 29 provinces for the period 1995-2002. It is found that the eastern provinces have a highest energy efficiency score, followed by the western and central. Drawing lessons from Hu and Wang (2006), Zhao et al. (2014) and Song et al. (2015) further discussed China's energy efficiency based on a similar method.

Generally speaking, conventional DEA models used in the aforementioned studies are set to maximize desirable outputs (e.g., GDP) only; undesirable outputs, such as pollutants like SO_2 and

CO_2, however, are not taken into account. This setting is inconsistent with the production process in the real world (Wang and Lin, 2018). To make up for such flaw, Chambers et al. (1996) and Chung et al. (1997) proposed a Directional Distance Function (DDF) in which the constraints of pollution emissions on the production process is simulated scientifically. Wu et al. (2012) used DDF to measure the average annual growth of energy efficiency in industrial sector of China. Along this line, He et al. (2013) evaluated the energy efficiency and productivity change in China's iron and steel industry.

In fact, DDF belongs to the radial DEA with an assumption that inputs and outputs adjust in the same proportion. Clearly, this assumption does not match reality and may have led to the biased result. In view of this, Tone (2001) proposed a non-radial slack-based measure (SBM) model in which slack variables are taken into account to distinguish the different proportion adjustment of inputs and outputs. SBM model makes up for the shortcomings of DDF and many scholars apply it to the studies of energy efficiency (Lin and Yang, 2014). For example, Li and Hu (2012) computed the ecological total-factor energy efficiency (ETFEE) of 30 provinces in China for the period 2005-2009 using SBM model with undesirable outputs. It found that China's regional ETFEE still remains at a low level and is extremely unbalanced across various regions. Using a similar method, Li and Lin (2017b) further measured the ETFEE in the heavy industry and light industry of China. Despite its merits, SBM model discards varying proportions of original inputs and outputs (Avkiran et al., 2008). In order to solve this problem, Tone and Tsutsui (2010) further proposed an epsilon-based measure (EBM) model which combines the merits of radial and non-radial DEA into a unified framework. This model is able to exhibit the original proportion adjustment of the frontier projection value and meanwhile adequately reflect the contrast among the non-radial adjustments of inputs or outputs (He et al., 2018b).

The second group of research focuses on the factors affecting energy efficiency in China. For example, Li et al. (2012), Ma (2015) and Yan (2015) suggested that urbanization is conducive to promoting China's energy efficiency. Elliott et al. (2017) drew a similar conclusion and further explored intrinsic impact mechanisms between them. Zhou et al. (2013), Li and Lin (2014) and Tian et al. (2014) studied the impact of industrial structure on China's energy efficiency, and pointed out that an effective way to improve China's energy efficiency is to upgrade and optimize industrial structure through technological innovation. Guo et al. (2011) and Feng et al (2009) studied the relationship between energy consumption structure and energy efficiency. From the perspective of foreign trade, Elliott et al. (2013) proposed that there is a negative correlation between FDI and China's energy intensity because foreign enterprises prefer to invest in energy-intensive industries.

To sum up, most of existing studies have explored ways to promote China's energy efficiency from the demand-side perspective, such as urbanization, industrial structure, energy consumption structure, and FDI. However, in line with the transformation of China's economic structure, scholars found that the pull effect of demand-side factors on energy efficiency is restricted, and supply-side factors are becoming a key driving force for China's energy efficiency (Zhang et al., 2018). Therefore, research focus shifts from the demand side to the supply side. For example, Dai and Cheng (2016) proposed that China's energy industry has a serious factor market distortion, which leads to a great loss of energy efficiency. Particularly, Ouyang and Sun (2015) pointed out that China's industry-wide energy savings potential resulted from energy allocative inefficiency was about 9.71% during 2001-2009. Li and Lin (2015) and Yang et al. (2018b) carried out in-depth research in this field. We notice that a common problem reflected in these studies investigating China's energy efficiency from a supply-side perspective is that the irrational resource allocation of factor market is the key to restricting China's energy efficiency. However, few studies further explore the underlying reason for this phenomenon.

It is widely recognized that the Chinese fiscal reform carried out from the 1980s plays a positive role in promoting the rapid economic growth (Lin and Liu, 2000; Qiao et al., 2008). Before the reform, Chinese local governments' fiscal revenue must be handed over to the central government, and the expenditure is uniformly allocated by the central as planned (Liu and Alm, 2016). In that period, local governments are less motivated to grow the economies, because both the expenditure and revenue powers belong to the central government. In the early 1980s, China began to implement the fiscal decentralization reform so that local governments were provided with certain fiscal powers (Song, 2013). Specifically, if a local government's revenue exceeds its expenditure, the surplus amount is owned by local government and needs not be handed over to the central (Jin et al., 2005). Similarly, if a local government's expenditure exceeds its revenue, the excess amount is not subsidized by the central (Han and Kung, 2015). Through a series of reforming measures, local governments have an increasing motivation to grow their economies to broaden a tax base. Especially after the implementation of tax-sharing reform in 1994, local fiscal power gets a further match with local administrative responsibilities (He, 2015; Yang, 2016). However, with the deepening of reform, some drawbacks of Chinese-style decentralization began to appear. The long-term goal of fiscal reform is inconsistent with the short-term goal of local government (Pang et al., 2019). In particular, in order to broaden the tax base, local governments often adopt a beggar-thy-neighbour policy to restrict the entry of non-local products and the outflow of local resources during their term of office, which will result in a loss of energy efficiency (Poncet, 2005; Shao et al., 2019).

In theory, energy prices are lower in resource-rich areas, while those are higher in resource-poor areas. There is a natural energy price gap between two areas. If market segmentation does not exist, the price gap will be filled up due to the free flow of production factors (Kumar et al., 2014, Ke, 2015). However, in the real word, the price gap can be maintained because local governments often split market to protect local economy (Anderson and Nelgen, 2012). The beggar-thy-neighbour measures taken by local governments bring about a series of grave consequences. The low-efficiency enterprises in resource-rich areas are given a greater possibility to survive from the market competition, benefiting from factor cost advantage. By contrast, the high-efficiency enterprises in resource-poor areas are forced out of the market due to factor cost disadvantage (He et al., 2018a). Clearly, market segmentation is a very important reason for inefficient resource allocation in Chinese factor market and further enhances the loss of energy efficiency. But unfortunately, few studies examine this issue from the perspective of market segmentation. Li and Lin (2017a) once pointed out that regional integration is conducive to improving energy and environment performance in China. However, they deconstructed this problem from the perspective of economic integration, which result in a neglection of the game behavior hidden behind market segmentation among Chinese local governments. In addition, they also failed to examine the internal mechanisms through which market segmentation affects energy efficiency.

In summary, scholars have done a lot of studies on China's energy efficiency and its affecting factors, whereas there are still some shortcomings. First, most of previous studies measure China's regional energy efficiency bases on a radial or non-radial DEA model. However, both of them have some defects in the theoretic logic, which could result in a biased energy efficiency score. Second, previous studies pay attention to the negative impact of inefficient resource allocation on energy performance in Chinese factor market, but neglect to explore the underlying reason for this phenomenon from the perspective of market segmentation. As would be expected, such literature could not provide theoretical guidance to solve this problem fundamentally. Third, due to the constraint of research perspective, previous literature which examines the relationship between regional economic integration and energy performance neglects the game behavior hidden behind market segmentation among local governments. Therefore, these studies cannot explain the self-reinforcing effect of market segmentation in China and its negative impact on energy efficiency.

Compared with previous studies, the contributions of this paper are mainly reflected in the following aspects. First, we employ the EBM model that combines the merits of radial and non-radial DEA to measure China's energy efficiency more accurately. Second, the paper empirically investigates the impact of market segmentation on energy efficiency and the regional heterogeneity of such effect. Moreover, we use mediating effect model to further explore the internal impact mechanism. Third, on the basis of Promotion Tournament Model, we further examine the Race to the Top competition centering on the market segmentation in geospatial and economic space of China and its long-term negative impact on energy efficiency.

3. Method

This section introduces the EBM model employed to measure energy efficiency and the price index method used to measure market segmentation. We also establish an econometric model to examine the relationship between market segmentation and energy efficiency, and then discuss the variable selection as well as data sources.

3.1. The EBM model for measuring energy efficiency

In contrast with conventional DEA method, EBM model combines the merits of radial and non-radial DEA into a unified framework. Therefore, we use it to measure the energy efficiency in each province of China.

Suppose that there are K (k=1, 2, …, K) provinces concerned and each province is regarded as a Decision Making Unit (DMU). Each DMU uses N (n=1, 2, …, N) inputs to produce M (m=1, 2, …, M) desirable outputs. The matrices of inputs and outputs are denoted as $\mathbf{X}=\{x_{nk}\}\in R^{N\times K}$, $\mathbf{Y}=\{y_{mk}\}\in R^{M\times K}$. We assume $\mathbf{X}>0$ and $\mathbf{Y}>0$. The EBM model established by Tone and Tsutsui (2010) is as follows:

$$\min \gamma = \frac{\theta_o - \varepsilon^x_{no}(1/\sum_{n=1}^{N}\omega^x_{no})\sum_{n=1}^{N}(\omega^x_{no}s^x_{no}/x_{no})}{\varphi_o + \varepsilon^y_{mo}(1/\sum_{m=1}^{M}\omega^y_{mo})\sum_{m=1}^{M}(\omega^y_{mo}s^y_{mo}/y_{mo})}$$

$$\begin{aligned} s.t. \quad & \sum_{k=1}^{K}\lambda_k x_{nk} + s^x_{no} = \theta_o x_{no} \qquad (n=1,2,\cdots,N) \\ & \sum_{k=1}^{K}\lambda_k x_{mk} - s^y_{mo} = \varphi_o y_{mo} \qquad (m=1,2,\cdots,M) \\ & \lambda_k \geq 0, s^x_{no} \geq 0, s^y_{mo} \geq 0 \end{aligned} \tag{1}$$

where λ is the linear coefficient of DMUs; subscript o denotes the DMU to be assessed; θ_o and φ_o are the planning parameters of radial part; s^x_{no} and s^y_{mo} are non-radial slack variables of inputs and desirable outputs, respectively; ε denotes the importance of non-radial part and satisfies $0 \leq \varepsilon \leq 1$; ω is the weights of inputs or outputs. Before measuring the energy efficiency, ε and ω need to be pre-determined. Here we take ε^x_{no} and ω^x_{no} as an example to introduce the calculation process briefly[2]. Firstly, use the SBM model to measure the projected inputs $\bar{\mathbf{x}}_{\mathbf{n}}$ in the frontier. Secondly, construct the correlation matrix $\mathbf{S} = [s_{pq}] \in R^{N\times N}$, where s_{pq} (p, q=1, 2, ⋯, N) is the "affinity index" of $\bar{\mathbf{x}}_{\mathbf{p}}$ and $\bar{\mathbf{x}}_{\mathbf{q}}$ [3]. Thirdly, Solve the largest eigenvalue β and eigenvector $\boldsymbol{\omega} = (\omega_1, \ \omega_2 \ldots, \ \omega_N)$ of matrix $\mathbf{S}$. Finally, we can get ε^x_{no} and ω^x_{no} by plugging above results into Eq. (2).

$$\begin{aligned} \varepsilon^x_{no} &= \begin{cases} \dfrac{N-\beta}{N-1} & (if \ \ N>1) \\ 0 & (if \ \ N=1) \end{cases} \\ \omega^x_{no} &= \frac{\omega_n}{\sum_{n=1}^{N}\omega_n} \end{aligned} \tag{2}$$

Due to the limitations of current technology, inputs cannot be converted into desirable outputs 100%. Some "by-products", such as CO_2 and SO_2, would be generated in the process of energy utilization inevitably. If these emissions are neglected, we may get a biased result. Thus, it is necessary to add undesirable outputs into EBM model on the basis of Tone and Tsutsui (2010).

Suppose that there are J (j=1, 2, ⋯, J) undesirable outputs in production. The matrix of undesirable outputs is $\mathbf{B} = \{b_{jk}\} \in R^{J\times K}$. $P(x)$={($\mathbf{y}$, $\mathbf{b}$): $\mathbf{x}$ can produce ($\mathbf{y}$, $\mathbf{b}$)} denotes production possibility set. In order to describe production process more reasonably, Färe et al. (2007) suggested that two additional assumptions should be imposed on $P(x)$:

(1) Weak disposability of undesirable output. If ($\mathbf{y}$, $\mathbf{b}$)∈$P(x)$ and $0 \leq \theta \leq 1$, then ($\theta\mathbf{y}$, $\theta\mathbf{b}$)∈$P(x)$, which means that the reduction of undesirable outputs comes at the expense of desirable outputs.

(2) Null-jointness of desirable and undesirable outputs. If ($\mathbf{y}$, $\mathbf{b}$)∈$P(x)$ and $\mathbf{b}$=$\mathbf{0}$, then $\mathbf{y}$=$\mathbf{0}$, which means that desirable outputs cannot be generated without undesirable outputs.

By introducing the above assumptions into Eq. (1), EBM model with undesirable outputs is

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[2] ε^y_{mo} and ω^y_{mo} of outputs could be calculated by similar methods.

[3] Tone and Tsutsui (2010) defined the "affinity index" of vectors **a** and **b** in the following way: S(**a**, **b**)=1-2D(**a**, **b**), where $D(\mathbf{a},\mathbf{b}) = \begin{cases} \dfrac{\sum_{j=1}^{n}|c_j - \bar{c}|}{n(c_{\max} - c_{\min})} & (if \ \ c_{\max} > c_{\min}) \\ 0 & (if \ \ c_{\max} = c_{\min}) \end{cases}$, $c_j = \ln(\frac{b_j}{a_j})$, $\bar{c} = \frac{1}{n}\sum_{j=1}^{n} c_j$, $c_{\max} = \max(c_j)$, $c_{\min} = \min(c_j)$.

established as follows:

$$\min \rho = \frac{\theta_o - \varepsilon_{no}^x (1/\sum_{n=1}^{N} \omega_{no}^x) \sum_{n=1}^{N} (\omega_{no}^x s_{no}^x / x_{no})}{\varphi_o + \varepsilon_{mo}^y (1/\sum_{m=1}^{M} \omega_{mo}^y) \sum_{m=1}^{M} (\omega_{mo}^y s_{mo}^y / y_{mo}) + \varepsilon_{jo}^b (1/\sum_{j=1}^{J} \omega_{jo}^b) \sum_{j=1}^{J} (\omega_{jo}^b s_{jo}^b / b_{jo})}$$

$$\begin{aligned} s.t. \quad & \sum_{k=1}^{K} \lambda_k x_{nk} + s_{no}^x = \theta_o x_{no} \qquad (n = 1, 2, \cdots, N) \\ & \sum_{k=1}^{K} \lambda_k y_{mk} - s_{mo}^y = \varphi_o y_{mo} \qquad (m = 1, 2, \cdots, M) \\ & \sum_{k=1}^{K} \lambda_k b_{jk} + s_{jo}^b = \varphi_o b_{jo} \qquad (j = 1, 2, \cdots, J) \\ & \lambda_k \geq 0, s_{no}^x \geq 0, s_{mo}^y \geq 0, s_{jo}^b \geq 0 \end{aligned} \tag{3}$$

where s_{jo}^b denotes the slack variables of undesirable outputs; ε_{jo}^b and ω_{jo}^b are parameters of undesirable outputs, and their calculation process is similar to ε_{no}^x and ω_{no}^x; other symbols have the same meaning as Eq. (1).

It should be pointed out that there are two forms of energy efficiency measured by DEA models: static one and dynamic one. The former's reference technology is limited to a fixed period, so it can not describe dynamic changes between two DUMs in different periods. The latter one not only measures the energy efficiency of a DMU relative to other DMUs in the same period, but also reflects the dynamic trend of efficiency change for assessed DMU in different time windows. Thus, it is necessary to apply DEA window analysis to Eq. (3). Before starting the efficiency measuring, we need to pre-determine the length of the window. In fact, DEA window analysis has an implicit assumption that there is no technical improvement within each window period (Sueyoshi et al., 2013). In order to narrow the measurement errors, we set the window length to 2, following Yang et al. (2018a), which means that annual reference technology set is composed of inputs and outputs in current and last year.

On the basis of the study above, referring to Hu and Wang (2006) and Bhat et al. (2018), we define energy efficiency as follows:

$$ee_{it} = \frac{tei_{it}}{e_{it}} = \frac{e_{it} - eei_{it}}{e_{it}} = \frac{e_{it} - (s_{it}^e + \theta e_{it})}{e_{it}} \tag{4}$$

where ee_{it} is the energy efficiency of t period in region i; tei_{it} is the target energy input measured by EBM model in the efficiency frontier, e_{it} is the actual energy input; eei_{it} is the excess energy input relative to the efficiency frontier, and is compose of slack adjustment (s_{it}^e) and proportionate adjustment (θe_{it}).

3.2. Measuring China's market segmentation

The methods of measuring market segmentation include production structure method (Young, 2000), trade flow method (Poncet, 2003), economic correlation method (Xu, 2002) and price index method (Parsley et al., 2001). The first three methods are difficult to be consistent in logic (Shao et al., 2019). Therefore, we use price index method to measure market segmentation in China. In fact, this method is derived from Iceberg Transport Cost model that traded goods value will "melt" like glaciers in transport due to the transaction cost between two areas (Samuelson, 1954). So even if there is a complete arbitrage, the prices cannot be equal absolutely in two markets. The price gap will fluctuate within a certain interval. If this fluctuation tends to converge, market segmentation is decreasing, and vice versa. It can be seen that the key of constructing a market segmentation index is to measure the variance of relative prices between two regions. The detailed method is as follows.

First, it is essential to calculate the relative price between two regions:

$$\left|\Delta Q_{ijt}^k\right| = \left|\ln(p_{it}^k / p_{jt}^k) - \ln(p_{it-1}^k / p_{jt-1}^k)\right| \tag{5}$$

where *i* and *j* denote two regions respectively; *t* denotes a period to be investigated; *k* is a type of commodity; *p* is the retail price index of commodity *k*. Relative price has a bearing on the order of two regions, so we need to calculate the absolute value $\left|\Delta Q_{ijt}^k\right|$.

Secondly, the price gap is relevant to not only market segmentation, but also individual characteristics of commodity *k*. It is very necessary to remove fixed effects associated with the commodity *k* from Eq. (5). Specifically speaking, we calculate the average relative price $\overline{\left|\Delta Q_t^k\right|}$ for all the investigated regions, and then subtract $\overline{\left|\Delta Q_t^k\right|}$ at both ends of Eq. (5):

$$q_{ijt}^k = \left|\Delta Q_{ijt}^k\right| - \overline{\left|\Delta Q_t^k\right|} \tag{6}$$

q_{ijt}^k is the relative price used to calculate variance. It is only relevant to market segmentation and some random errors.

Finally, market segmentation index could be obtained by calculating the variance of q_{ijt}^k for all types of commodity, and then merging the results by provinces, which is formulated as Eq. (7):

$$seg_{it} = \frac{1}{N}\sum_{i \neq j} \mathrm{var}(q_{ijt}^k) \tag{7}$$

where *N* denotes the number of merged provinces.

3.3 Model specification, variables construction and data sources

In order to examine the impact of market segmentation on energy efficiency, we construct the following econometric model:

$$ee_{it} = \alpha + \beta seg_{it} + \gamma \mathbf{X}_{it} + \lambda_i + \varepsilon_{it} \tag{8}$$

where ee_{it} denotes energy efficiency of period *t* in province *i*; seg_{it} denotes the market segmentation index which is the core dependent variable in this paper and β is its estimated coefficient; λ_i denotes regional fixed effect; ε_{it} is the perturbation term. $\mathbf{X}_{it}$ denotes a set of control variables, including industrial structure, foreign direct investment, environmental regulation, energy consumption structure, ownership, and $\boldsymbol{\gamma}$ is the coefficient vector.

In this paper, the dependent variable is obtained by DEA-EBM model. Specifically speaking, the inputs are energy (*E*), labor (*L*), capital (*K*). The desirable output is GDP (*Y*). The undesirable outputs are carbon dioxide (CO_2) and sulfur dioxide (SO_2). Capital stock needs to be estimated by perpetual inventory method as described in Shan (2008), because of the unpublished data in China's official statistical yearbook. Data on GDP and capital stock have been deflated to constant price in 2000. The accounting method of CO_2 refers mainly to Chen and Golley (2014).

The independent variable is obtained by price index method. Drawing lessons from Shao et al. (2019), we select the retail price indexes of grain, fresh vegetables, tobacco and alcohol, clothing, office supplies, articles for daily use, medicine, newspaper and magazine, fuel to construct market segmentation index.

In order to reduce the bias of omitted variables, some control variables affecting energy efficiency should be added into Eq. (8):

(1) Industrial structure (*ind*). In contrast with other industries, the tertiary industry has a relatively low energy intensity. In pace with the development of China's economy, it plays an increasing role in promoting energy efficiency to upgrade industrial structure. Following Cheng et al. (2018), we use the share of the tertiary industry output in gross output to measure industrial structure in each province.

(2) Foreign direct investment (*fdi*). There are mainly two competing views about how FDI affects energy efficiency. One view is that FDI could bring advanced technology and management experience to the host country, which is positive to local energy efficiency. Another view is that since developed countries adopt a stricter environmental regulation, a large number of industries with heavy CO_2 emissions would be transferred to developing countries, which is negatively related to local energy efficiency. Thus, the impact of FDI on China's energy efficiency is unpredictable. Following Li and Lin (2017a), we use the share of FDI in regional GDP as the proxy variable.

(3) Environmental regulation (*reg*). According to the Potter hypothesis, environmental regulation could stimulate enterprises to enhance technological innovation, and thus promote energy efficiency in the long run. However, in order to meet the regulatory standards, enterprises have to bear added cost to control emissions in the short run, which may hinder technological innovation by crowding out R&D investment (Jaffe, 1995). From this point of view, environmental regulation is negative to energy efficiency. We use the share of the investment for pollution control in GDP to measure environmental regulation in each province of China (Lanoie et al., 2008).

(4) Energy consumption structure (*ene*). To a great extent, energy consumption structure is an important variable affecting regional energy efficiency. In contrast with clean energy, conventional energy, such as coal and fuel oil, has a higher emission intensity and a lower thermal efficiency. It can be predicted that there is a negative correlation between conventional energy consumption and energy efficiency. We use the ratio of coal in total energy consumption as the proxy (Lin and Du, 2015).

(5) Ownership (*own*). For the state-owned and private enterprises of China, management mode and motivational method vary greatly. Previous research suggests that due to the public ownership, there is a lack of organizational vitality and tech-innovation motive in state-owned enterprises, which is unbeneficial to the promotion of China's energy efficiency (Han et al., 2007). Thus, drawing lessons from Li and Lin (2017a)，we use the share of state-owned enterprise output in the gross output to measure the ownership in various provinces.

This paper selects 30 provincial-level administrative units in mainland China as the sample. Tibet is excluded due to incomplete data. All the original data comes from *China Statistical Yearbook*, *China Environment Yearbook*, and *China Energy Statistical Yearbook*, from 2004 to 2016. The descriptive statistics of the variables mentioned above are shown in Table 1.

Table 1

The descriptive statistics of variables.

Variable	Symbol	Number	Mean	Sd	Min	Max
Labor	*L*	390	2574.027	1705.967	290.420	6726.000

Capital	*K*	390	11384.430	8505.224	1317.067	36772.890
Energy	*E*	390	12369.970	7960.684	742.000	38899.250
GDP	*Y*	390	10843.300	9774.385	403.666	52310.540
CO_2	CO_2	390	34725.370	24968.610	1626.025	142432.900
SO_2	SO_2	390	71.522	43.880	1.696	200.300
Market segmentation	*seg*	390	0.083	0.082	0.018	0.915
Industrial structure	*ind*	390	0.413	0.087	0.286	0.802
Foreign direct investment	*fdi*	390	0.024	0.019	0.000	0.082
Environmental regulation	*reg*	390	0.013	0.007	0.003	0.042
Energy structure	*ene*	390	0.684	0.265	0.087	1.449
Ownership	*own*	390	0.454	0.175	0.100	0.981

4. Main results

This section gives the measuring results of energy efficiency and market segmentation in China, and provides a brief analysis of the regional differences and trends for these two variables.

4.1 Measuring energy efficiency

We use MaxDEA to solve the linear programming presented in Eq. (3). Table 2 only shows measuring results for some years due to the space limitation. Energy efficiency scores measured by SBM model (see Appendix A) are also given in Table 2 for the sake of robustness. *ee_ebm* and *ee_sbm* denote the energy efficiency scores measured by EBM and SBM model, respectively. As shown in Table 2, there are huge differences for *ee_ebm* in the eastern, central and western regions. The *ee_ebm* in the eastern region is generally higher than that in the central and western regions. Specifically speaking, Fujian performs best in 30 provinces with an average *ee_ebm* of 0.992, followed by Shanghai (0.988) and Guangdong (0.984). These three provinces all belong to the eastern region of China. Qinghai (0.379) and Ningxia (0.481) are the two western provinces with the lowest *ee_ebm*. Similar conclusions can be also drawn from the *ee_sbm* in Table 2.

Table 2

Estimation of *ee_ebm* and *ee_sbm* across China's provinces.

	EBM					**SBM**				
	2004	2008	2012	2016	*average*	2004	2008	2012	2016	*average*
Eastern region										
Beijing	0.981	0.983	0.949	0.988	0.977	0.919	0.960	0.922	0.971	0.947
Fujian	1.000	1.000	0.978	0.990	0.991	1.000	1.000	0.975	0.985	0.996
Guangdong	0.997	0.983	0.960	0.962	0.981	1.000	0.978	0.949	0.957	0.976
Hainan	0.999	0.991	0.831	0.862	0.924	1.000	0.988	0.797	0.808	0.910
Hebei	0.494	0.510	0.617	0.759	0.601	0.451	0.436	0.523	0.496	0.480
Jiangsu	0.976	0.956	0.960	0.961	0.959	0.972	0.919	0.937	0.982	0.939
Liaoning	0.770	0.826	0.817	0.793	0.814	0.768	0.826	0.817	0.628	0.788
Shandong	0.744	0.724	0.868	0.869	0.788	0.674	0.662	0.754	0.778	0.717
Shanghai	0.999	0.985	0.973	0.986	0.988	0.998	0.969	0.963	0.974	0.979

Tianjin	0.778	0.975	0.939	0.973	0.928	0.760	0.885	0.916	0.967	0.900
Zhejiang	0.931	0.945	0.929	0.910	0.934	0.891	0.923	0.888	0.928	0.911
Central region										
Anhui	0.757	0.799	0.818	0.854	0.824	0.728	0.758	0.723	0.816	0.773
Henan	0.604	0.628	0.775	0.798	0.705	0.577	0.597	0.652	0.732	0.638
Heilongjiang	0.831	0.682	0.823	0.865	0.774	0.823	0.661	0.783	0.745	0.733
Hubei	0.731	0.767	0.847	0.876	0.805	0.654	0.692	0.735	0.869	0.743
Hunan	0.770	0.650	0.665	0.831	0.714	0.753	0.630	0.595	0.795	0.682
Jiangxi	0.915	0.833	0.937	0.886	0.879	0.901	0.813	0.832	0.808	0.834
Jilin	0.521	0.609	0.736	0.839	0.689	0.477	0.564	0.702	0.771	0.644
Shanxi	0.497	0.725	0.701	0.662	0.655	0.235	0.267	0.289	0.252	0.267
Western region										
Chongqing	0.739	0.625	0.683	0.735	0.675	0.636	0.537	0.656	0.719	0.613
Gansu	0.597	0.574	0.493	0.691	0.597	0.366	0.369	0.433	0.413	0.391
Guangxi	0.763	0.726	0.705	0.731	0.742	0.703	0.679	0.628	0.689	0.682
Guizhou	0.436	0.669	0.606	0.656	0.572	0.235	0.290	0.335	0.351	0.315
Inner Mongolia	0.747	0.974	0.904	0.986	0.941	0.747	0.887	0.880	0.975	0.893
Ningxia	0.431	0.508	0.503	0.432	0.472	0.179	0.191	0.192	0.154	0.183
Qinghai	0.396	0.390	0.358	0.365	0.375	0.302	0.259	0.268	0.231	0.267
Shaanxi	0.648	0.643	0.729	0.757	0.690	0.523	0.526	0.604	0.532	0.554
Sichuan	0.590	0.620	0.674	0.709	0.657	0.552	0.567	0.571	0.698	0.609
Xinjiang	0.488	0.535	0.443	0.530	0.522	0.416	0.374	0.331	0.244	0.342
Yunnan	0.583	0.575	0.654	0.652	0.618	0.517	0.484	0.486	0.552	0.504
east	0.879	0.898	0.893	0.914	0.898	0.858	0.868	0.858	0.861	0.868
central	0.703	0.712	0.788	0.826	0.756	0.644	0.623	0.664	0.723	0.664
west	0.583	0.622	0.614	0.659	0.624	0.471	0.469	0.489	0.505	0.487
average	0.724	0.747	0.762	0.797	0.760	0.659	0.656	0.671	0.694	0.674

Source: Own calculations.

Fig. 2 depicts the historical trends of *ee_ebm* for the national average and the three regions (east, central and west). It can be seen that *ee_ebm* is high in the eastern region, but the growth rate is low. During the 13-year period from 2004 to 2016, the average annual growth rate is only 0.4%. By contrast, although *ee_ebm* in central region is lower than that in eastern region, the growth rate is relatively high, and reaches 1.6% per yaer. Therefore, the *ee_ebm* gap between central and eastern region is narrowing gradually. The average annual growth rate is also high in the western region, reaching 1.4%. However, the absolute level of *ee_ebm* in this region is still low, and threfore the *ee_ebm* gap between the western and eastern region is narrowing insignificantly. In the same way, we can draw the similar conclusions from the averaged trends of *ee_sbm* depicted in Fig. 3.

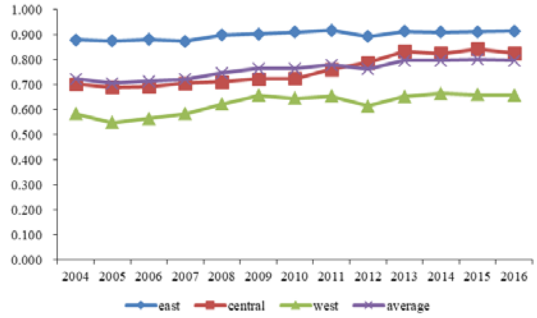

Fig. 2. The averaged trends of *ee_ebm*.

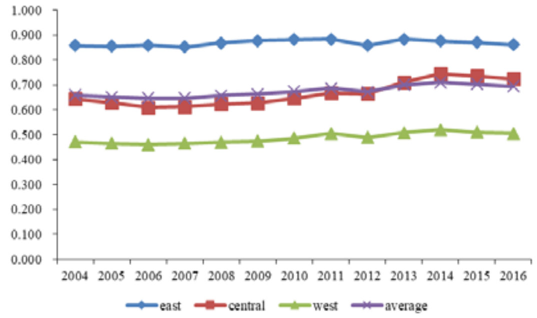

Fig. 3. The averaged trends of *ee_sbm*.

4.2 Measuring market segmentation

Fig. 4 depicts the average degrees of market segmentation in China's provinces. A darker color indicates that there is a more severe market segmentation problem. As can be seen that the degrees of market segmentation vary greatly across China, but certain regularities could be grasped. The average degree of market segmentation in the western region is generally higher than that in the eastern. The reason lies mainly in the economic gap between two regions. The eastern China has a developed market due to the advanced economy, but a poor resource endowment. Local governments, therefore, have a burning desire to expand market openness in order to make the best use of resources from other regions. On the contrary, the western local governments are inclined to adopt protectionist measures giving priority to enterprises within their jurisdiction.

Fig. 5 depicts the kernel density evolution paths of market segmentation in China. Each curve shows the density of data on the coordinate axis. A higher peak indicates that the data is denser at this point. A wider peak suggests that there is a set of data with greater diversity in this interval (Herrerias, 2012; Jeon and Taylor, 2016). According to the distribution, morphology and evolution of curves in Fig. 5, we can make some basic judgments about market segmentation in China. From the positional point of view, the density curve is moving to the left, indicating that market segmentation index is declining year by year. From the distributive point of view, the curves skew to the left, suggesting that the market segmentation problem in some provinces are more serious than that in the rest. From the morphological point of view, the height of the peak is rising with time, and the width is decreasing, suggesting that the degrees of market segmentation show a convergence in China.

Fig. 4. The degrees of market segmentation in China's provinces.

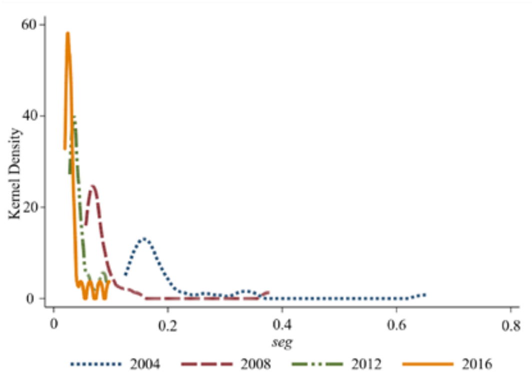

Fig. 5. Kernel density evolution of market segmentation in China.

5. Results and discussion

In this section, we empirically investigate the impact of market segmentation on energy efficiency and the regional heterogeneity of such effects. On this basis, the internal impact mechanisms between them are further explored. Considering the characteristics of China's current administrative system, we also examine the Race to the Top competition centering on market segmentation among Chinese local governments in geospatial and economic space and its long-term negative impact on energy efficiency.

5.1 Baseline results

When DEA method is used to measure energy efficiency, it is inevitable that one or more DMUs are in the efficiency frontier. Therefore, the dependent variable in this paper no longer meets a continuous distribution, but becomes a mixed distribution composed of one discrete point and one continuous distribution. If conventional methods, such as OLS or Fixed Effect model, are used to estimate Eq. (8), we may get an inconsistent estimator. In order to solve this problem, Tobin (1958) constructed an indicator function which could tell the differences between the points in and within the efficiency frontier, and proposed that the model with limited dependent variable could be estimated by maximum likelihood method. Following Tobin (1958), we use a similar method (also known as the Tobit model) to study the impact of market segmentation on energy efficiency. Table 3 shows the estimated results. The dependent variables in column (1) and (2) are *ee_ebm*, and the dependent variables in column (4) and (5) are *ee_sbm*. Control variables are not added to column (1) and (4). According to column (1) and (2), the estimated coefficient of market segmentation is negative with the significant level of 1%, indicating that market segmentation, as a beggar-thy-neighbour policy, has a negative effect on regional energy efficiency in China. The preceding analysis is verified to some extent. Furthermore, we could draw similar conclusions from the estimated results in columns (4) and (5).

Regarding the control variables, the coefficient of industrial structure (*ind*) is positive in the 1% level of significance. Compared with other industries, the tertiary industry has a lower energy intensity and less pollution emissions. Thus, an increasing share of tertiary industry is contribution to promoting regional energy efficiency in China (Cheng et al., 2018). The estimated coefficient of foreign direct investment (*fdi*) is also significantly positive. In recent years, the Chinese government has paid more attention to the quality of economic development. Most regions have gradually abandoned the extensive economic growth, and encouraged local enterprises to import energy-efficient, low-carbon equipment as well as technology actively, which is conducive to the promotion of energy efficiency (Zhang and Zhou, 2016). In column (5), the coefficient of energy consumption structure (*ene*) is negative with the significant level of 1%. Conventional energy, such as coal and crude oil, has a lower thermal efficiency. Thus, an increasing share of conventional energy consumption inhibits China's energy efficiency. This finding is consistent with Lin and Du (2015). The coefficient of ownership is also significantly negative. In China, state-owned enterprises perform a relatively low operational efficiency and innovative vitality due to the public ownership (Han et al., 2007). An increase share of state-owned economy is unbeneficial to the promotion of energy efficiency. This finding is consistent with Li and Lin (2017a). It is unexpected that the coefficient of environmental regulation (*reg*) is negative but not significant. The reason may lie in that in contrast with the fast-growing GDP, the investment used to control pollution is still insufficient in China, and could not significantly reduce CO_2 emissions in each region (Zhao and Luo, 2017).

Table 3

Estimation results of Tobit model and GMM.

Variable	EBM			SBM		
	Tobit	Tobit	GMM	Tobit	Tobit	GMM
	(1)	(2)	(3)	(4)	(5)	(6)
seg	-0.216***	-0.165***	-0.083***	-0.118**	-0.092**	-0.068***
	(0.043)	(0.043)	(0.012)	(0.037)	(0.037)	(0.011)
ind		0.302***	-0.141***		0.147	-0.086
		(0.099)	(0.053)		(0.090)	(0.060)
fdi		2.448***	0.105		1.904***	-0.111
		(0.405)	(0.304)		(0.357)	(0.396)
reg		0.135	0.530		-0.179	0.025
		(0.729)	(0.353)		(0.627)	(0.508)
ene		-0.026	0.042*		-0.145***	-0.038*
		(0.040)	(0.024)		(0.037)	(0.022)
own		-0.213***	-0.079***		-0.112**	0.073***
		(0.055)	(0.018)		(0.051)	(0.023)
$ee_{it\text{-}1}$			0.843***			1.058***
			(0.028)			(0.027)
AR (1)			0.007			0.001
AR (2)			0.141			0.703
Sargan			24.988			28.651
			(1.000)			(1.000)
Wald	25.57	102.43	3184.37	10.42	70.85	4375.15
test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Standard errors in parentheses.

* Denote coefficient significant at 10%.

** Denote coefficient significant at 5%.

*** Denote coefficient significant at 1%.

Due to the diversities of geography, climate, and culture in various regions of China, some variables that are difficult to be measured accurately, such as development outlook, market volatility, may affect energy efficiency. If Eq. (8) is estimated by Tobit model only, an endogenous problem brought about by omitted variables is unavoidable. Therefore, we use the Generalized Method of Moments (GMM) to re-estimate Eq. (8) for the sake of robustness. The basic idea of GMM is to calculate the first-order difference for original equation, and then use the lagged variable as the instrumental variable in the difference equation. GMM estimation can not only correct the omitted variable bias resulted from the correlation between unobservable variables and dependent variable by difference transform, but also overcome the bidirectional causality, another kind of endogeneity, between independent variable and dependent variable by instrumental variables (Blundell and Bond, 2000).

When we use GMM to estimate Eq. (8), two statistical tests are needed: one is Sargan test with null hypothesis that instrumental variables are valid, while the other is Arellano-Bond test for AR(1) and AR(2) with null hypothesis that there is not an autocorrelation in perturbation term ε_{it}. In Table 3, columns (3) and (6) show the estimated results by GMM. The dependent variables in column (3) is *ee_ebm*, and the dependent variables in column (6) is *ee_sbm*. According to AR (2) tests at the bottom of Table 3, there is no second order autocorrelation in the perturbation term. The Sargan tests indicate that all instrumental variables are valid. Therefore, the estimated results by GMM are reliable in this paper. In columns (3) and (6), the estimated coefficients of market segmentation are all significantly negative at the significance level of 1%, suggesting that market segmentation does inhibit regional energy efficiency in China. Therefore, the conclusions drawn above are robust.

5.2 The test of regional heterogeneity

Up to now, we have verified that market segmentation significantly inhibits energy efficiency already. However, the Chinese economic development is characterized by regional imbalance. The policy objectives and intensities will vary greatly, when local governments take protectionist actions. Thus, there should be an asymmetrical inhibition of market segmentation on energy efficiency in different regions of China. In order to examine such effect, we group the study sample into three sub-samples (east, central and west) and make empirical tests. Table 4 shows the test results of regional heterogeneity.

Table 4

Test results of regional heterogeneity

Variable	**EBM**			**SBM**		
	East	West	Central	East	West	Central
	(1)	(2)	(3)	(104)	(105)	(106)
seg	-0.076	-0.402***	-0.125**	-0.055	-0.271***	-0.072*
	(0.107)	(0.101)	(0.054)	(0.104)	(0.091)	(0.038)
ind	0.171	-0.116	0.341*	0.188	-0.546***	0.302**
	(0.147)	(0.199)	(0.192)	(0.160)	(0.179)	(0.136)
fdi	1.651***	1.183	1.482	1.903***	0.601	-0.011
	(0.521)	(1.062)	(0.945)	(0.510)	(0.984)	(0.671)
reg	0.577	1.633	-2.244*	1.083	-0.818	-1.826**
	(1.174)	(1.524)	(1.183)	(1.086)	(1.333)	(0.837)
ene	-0.266***	-0.178*	0.130**	-0.350***	-0.370***	-0.044
	(0.093)	(0.099)	(0.057)	(0.090)	(0.088)	(0.042)
own	-0.064	-0.384***	-0.235**	0.102	-0.587***	-0.004
	(0.078)	(0.113)	(0.096)	(0.082)	(0.100)	(0.072)
Wald test	34.01	75.65	30.01	48.81	84.75	19.28
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Standard errors in parentheses.

* Denote coefficient significant at 10%.

** Denote coefficient significant at 5%.

*** Denote coefficient significant at 1%.

As can be seen from Table 4, market segmentation significantly inhibits energy efficiency in the central and western regions. This finding is consistent with the regression results that the three regions are taken as a whole. However, such inhibitory effect is insignificant in the eastern. To trace its root, the eastern region has been at the forefront of China's reform and opening up for a long time, which triggers an advanced market economy. The resources and commodities in this region flow more frequently and freely than other regions. Thus, the degree of market segmentation is relatively low and is unable to significantly inhibit energy efficiency. However, due to backward economy, the governments in the central and western regions are inclined to take protectionist measures for the sake of their own development interests. Therefore, the problem of market segmentation is relatively serious, and has a significant inhibitory effect on local energy efficiency in the regions.

5.3 The test of impact mechanisms.

The above two sections have examined the inhibitory effect of market segmentation on energy efficiency and the regional heterogeneity of such effect, but the internal impact mechanisms between them has not been thoroughly discussed yet. In this section, we will explore the mediation mechanism through which market segmentation affects energy efficiency. In fact, as mentioned above, factor market distortion is a mediation mechanism. Due to market segmentation, low-efficiency enterprises in resource-rich areas could survive from market competition by virtue of factor cost advantage. However, high-efficiency enterprises in resource-poor areas have no choice but to exit from the market because of factor cost disadvantage (He et al., 2018a). Therefore, market segmentation distorts the resources allocation in factor markets and consequently brings about the energy efficiency loss. Besides, this paper argues for the two further mediation mechanisms. The first one is enterprises' R&D investment. The enterprises protected by local government using market segmentation measures would be prevented from normal and essential market competition. They earn high profits by virtue of policy bonuses, which undermines their innovation impetus and is unbeneficial to the promotion of energy efficiency (Parello, 2008). The second one is industrial agglomeration. Previous literature showed that industrial agglomeration plays an important role in promoting the growth of energy efficiency by bringing about scale economies and knowledge spillovers (Lu and Tao, 2009). However, market segmentation hinders the sharing of technology and information among intra-industry and inter-industry enterprises, and thereby restricts industrial agglomeration (Ke, 2015).

In order to test above impact mechanisms, we use the method described in Yao et al. (2018) to establish mediating effect model as follows:

$$dis_{it} = \alpha + \beta seg_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \lambda_i + \varepsilon_{it} \tag{9}$$

$$rd_{it} = \alpha + \beta seg_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \lambda_i + \varepsilon_{it} \tag{10}$$

$$agg_{it} = \alpha + \beta seg_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \lambda_i + \varepsilon_{it} \tag{11}$$

$$ee_{it} = \alpha + \beta_1 seg_{it} + \beta_2 dis_{it} + \beta_3 rd_{it} + \beta_4 agg_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \lambda_i + \varepsilon_{it} \tag{12}$$

where dis_{it} is factor market distortion, which is denoted by "(Product Market Development Index−Factor Market Development Index)/Product Market Development Index"[4] (Yin, 2018);

[4] "Product Market Development Index" and "Factor Market Development Index" are both derived from Wang

rd_{it} is the enterprises' R&D investment, which is denoted by the R&D internal expenditure of enterprises; agg_{it} is industrial agglomeration, which is denoted by location quotient index (O'Donoghue and Gleave, 2004)[5]. Table 5 shows the test results of impact mechanism[6].

Table 5

Test results of impact mechanism.

Variable	Factor market distortion	*ee*	Enterprises' R&D investment	*ee*	Industrial agglomeration	*ee*	*ee*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
seg	0.359***		-0.224***		-0.278***		-0.039
	(0.099)		(0.067)		(0.045)		(0.043)
dis		-0.128***					-0.100***
		(0.024)					(0.025)
rd				0.169***			0.173***
				(0.031)			(0.041)
agg						0.276***	0.146**
						(0.044)	(0.061)
ind	-1.097***	0.336***	1.200***	0.196*	-1.541***	0.737***	0.413**
	(0.306)	(0.121)	(0.172)	(0.101)	(0.114)	(0.110)	(0.170)
fdi	-2.305**	2.346***	-3.664***	3.039***	-0.179	2.394***	3.025***
	(1.125)	(0.493)	(0.634)	(0.415)	(0.420)	(0.390)	(0.479)
reg	-5.144***	0.563	0.262	0.475	1.631**	-0.069	-0.001
	(1.845)	(0.785)	(1.165)	(0.710)	(0.772)	(0.706)	(0.754)
ene	-0.231*	-0.042	-0.165**	-0.008	-0.056	-0.023	-0.021
	(0.120)	(0.046)	(0.071)	(0.040)	(0.047)	(0.039)	(0.044)
own	0.425**	-0.177***	0.123	-0.213***	-0.287***	-0.152***	-0.142**
	(0.174)	(0.068)	(0.097)	(0.053)	(0.064)	(0.055)	(0.064)
Wald test/	11.28	89.65	35.23	121.70	38.80	132.98	141.26
F test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Standard errors in parentheses.

* Denote coefficient significant at 10%.

** Denote coefficient significant at 5%.

*** Denote coefficient significant at 1%.

As can be seen from column (1) in Table 5, market segmentation significantly exacerbates

et al. (2017). The latest data published in that book is in 2014, so the time interval of data samples is 2004-2014 for Eq. (9) and (12).

5 The formula used to calculate location quotient index is $agg = (\frac{e_{ir}}{\sum_i e_{ir}}) / (\frac{\sum_i e_{ir}}{\sum_i \sum_r e_{ir}})$, where e_{ir} denotes the added value of industry r in i province. Here, we focus mainly on the secondary industry.

6 Due to space limits, Table 5 only shows the test results with *ee_ebm* as dependent variables. It should be noted that the robustness of conclusions is unaffected when the dependent variables are replaced by *ee_sbm* (See Appendix Table B1 for details).

distortion in factor market. Column (2) indicates that factor market distortion has a negative effect on energy efficiency. Therefore, market segmentation inhibits China's regional energy efficiency by enhancing distortion in factor market. According to column (3), market segmentation is negative to enterprises' R&D investment. Column (4) indicates that enterprises' R&D investment is positive to the promotion of energy efficiency. Therefore, market segmentation inhibits energy efficiency by reducing enterprises' R&D investment. Similarly, from column (5), it can be seen that market segmentation is unbeneficial to industrial agglomeration. Column (6) indicates that industrial agglomeration has a positive effect on regional energy efficiency. Therefore, market segmentation inhibits energy efficiency by hindering industrial agglomeration. In column (7), three mediation mechanisms are added into Eq. (8) together. We find that the estimated coefficient of market segmentation becomes insignificant, and the coefficients of dis_{it}, rd_{it} and agg_{it} are still significant. It demonstrates that factor market distortion, enterprises R&D investment and industrial agglomeration are indeed the three mediation mechanisms through which market segmentation inhibits regional energy efficiency in China.

5.4 Further research: Race to the Top tournament centering on market segmentation and its impact on energy efficiency.

In fact, there is a promotion tournament in the current administrative system in China. In other words, a Chinese local official will compete with other local officials at the same level, and whether he could achieve success in the tournament or not determines his political career promotion. Because the yardstick of this tournament is the relative economic performance, one Chinese local official cares more about the relative positioning of himself and the competitors, rather than the absolute economic quantity within his jurisdiction (Li and Zhou, 2005). As a result, local officials prefer a competitive rather than a cooperative strategy in the tournament, which ultimately brings about a typical Prisoner's Dilemma game (Caldeira, 2012).

The pressure of promotion tournament drives local governments to compete on a variety of fronts. In existing literatures, scholars have investigated the political competition centering on environmental regulation and technological innovation already (Bai et al., 2019; Wang et al., 2019), but they ignored that there is a similar tournament centering on market segmentation in China. Specifically speaking, if one Chinese local official employs measures to split up market, it will become difficult for non-local products to enter the market in this region. Enterprises within his jurisdiction receive some protection, and as a result local economy could perform better than other regions (Poncet, 2005; Shao et al., 2019). This local official, consequently, establishes a political advantage so that he is more likely to be promoted in contrast with the officials in "adjacent" regions. In order to turn from such unbenefited situation, officials in "adjacent" regions have to adopt a competitive strategy as well, and the policies carried out by them to split market are more aggressive protective than the former (Lu, et al., 2004). In this way, the degrees of market segmentation get severer and severer due to the repeated game among the Chinese local governments, which should eventually result in a Race to the Top tournament and an inhibition of energy efficiency. In order to verify such effect, we establish the following spatial econometric model:

$$ee_{it} = \alpha + \rho_1 \mathbf{W} \times \mathbf{seg_{it}} + \gamma \mathbf{X}_{it} + \lambda_i + \varepsilon_{it} \tag{12}$$

$$seg_{it} = \alpha + \rho_2 \mathbf{W} \times \mathbf{seg_{it}} + \gamma \mathbf{X}_{it} + \lambda_i + \varepsilon_{it} \tag{13}$$

where **W** is a spatial weight matrix (30×30) which denotes a competitive relationship among local officials in China and w_{ij} is one of the elements in **W**. $\mathbf{seg_{it}}$ is a column vector representing market segmentation index; $\mathbf{W}\times\mathbf{seg_{it}}$ denotes the average degree of market segmentation of all "adjacent" regions. ρ_1 and ρ_2 denote the impact of market segmentation employed by officials in "adjacent" regions on local energy efficiency and market segmentation.

In general, the promotion tournament take place mainly in two spatial dimensions of China: the first one is geographic space, in which a local government official plays a promotion game with the officials in adjoining or near provinces geographically; the second is economic space, where there is a promotion game among local officials in the provinces with an approximate economy. In order to explore such two competitive relationships, we construct the following three spatial weight matrices: (i) The Geographically-Adjoining Weight Matrix (GAWM). If province *i* and *j* are adjoining geographically, then w_{ij}=1; otherwise w_{ij}=0. (ii) Geographical Distance Weight Matrix (GDWM). w_{ij} is defined as the inverse square of great-circle distance between province *i* and *j*, which is formulated as $w_{ij}=1/d_{ij}^{2}$[7]. (iii) Economic Distance Weight Matrix (EDWM). w_{ij} is defined as the gap of real GDP per capita between province *i* and *j* after row-standardization, which is formulated as $w_{ij}=(1/|Y_i-Y_j|)/\Sigma_j(1/|Y_i-Y_j|)$.

Table 6 shows the estimated results of Race to the Top tournament centering on market segmentation and its impact on energy efficiency. Columns (1) and (2) are the results based on GAWM. Columns (3) and (4) are based on GDWM. Columns (5) and (6) are based on EDWM[8].

Table 6

Test results of Race to the Top tournament centering on market segmentation and its impact on energy efficiency

Variable	GAWM		GDWM		EDWM	
	ee	*seg*	*ee*	*seg*	*ee*	*seg*
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{W}\times\mathbf{seg_{it}}$	-0.424***	0.536***	-0.435***	0.758***	-0.333***	0.544***
	(0.060)	(0.056)	(0.067)	(0.050)	(0.059)	(0.049)
ind	0.194*	-0.327***	0.137	-0.158	0.179*	-0.247**
	(0.103)	(0.118)	(0.107)	(0.110)	(0.107)	(0.114)
fdi	1.852***	0.449	2.006***	0.116	2.017***	0.128
	(0.378)	(0.436)	(0.384)	(0.406)	(0.390)	(0.419)
reg	0.105	-1.762**	0.016	-1.203	0.068	-1.391*
	(0.697)	(0.800)	(0.708)	(0.743)	(0.720)	(0.768)
ene	-0.048	0.074	-0.025	0.038	-0.050	0.081*
	(0.042)	(0.049)	(0.043)	(0.045)	(0.043)	(0.047)
own	-0.170***	-0.037	-0.178***	-0.025	-0.169***	-0.041
	(0.058)	(0.067)	(0.058)	(0.062)	(0.059)	(0.064)
Wald test	118.17	152.64	109.11	301.02	97.24	192.11
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

[7] The method used to calculate great-circle distance is $d_{ij}=6378\times arccos\{sin(lat_i\times\pi/180)\times sin(lat_j\times\pi/180)+cos(lat_i\times\pi/180)\times cos(lat_j\times\pi/180)\times cos[(long_i-long_j)\times\pi/180]\}$, where *lat* and *long* are the latitude and longitude of capital cities in province *i* or *j*; π=3.14.

[8] Limited by space, Table 6 only shows the estimated results with *ee_ebm* as dependent variables. It should be noted that the robustness of conclusions is unaffected when the dependent variables are replaced by *ee_sbm* (See Appendix Table B2 for details).

Notes: Standard errors in parentheses.

* Denote coefficient significant at 10%.

** Denote coefficient significant at 5%.

*** Denote coefficient significant at 1%.

As can be seen from columns (1) and (3) in Table 6, the market segmentation of adjoining or near provinces is negative to local energy efficiency significantly. The reason lies in that the protectionist actions employed by officials in adjoining or near provinces allow it easier for them to get a political promotion, which enforces local officials to increase market segmentation and consequently is not conducive to energy efficiency. Columns (2) and (4) provide empirical evidence for this explanation. In addition, we can get similar conclusions from the estimated results based on EDWM. According to column (5), market segmentation of economically-adjacent provinces is significantly negative to local energy efficiency at the 1% significant level. The reason lies in that the market-segmentation actions taken by officials in the provinces with an approximate economy induce local government officials to increase market segmentation within their jurisdiction due to the pressure from political promotion, which is unfavorable to local energy efficiency. This explanation is supported by the empirical results in column (6). In summary, there is a Race to the Top tournament centering on market segmentation in geospatial and economic space for current administrative system in China, which triggers a long-term inhibition on energy efficiency.

6. Conclusions and policy implications

Increasing energy efficiency is crucial for China to address increasing concerns about a range of environmental problems from burning fossil fuels and steeply rising oil consumption and import in China and global climate change. Previous studies have noticed a negative impact of inefficient resource allocation on energy performance in China's factor market, but neglected to explore the underlying reason for this phenomenon from the perspective of market segmentation. In this paper, the EBM model, which combines the merits of radial and non-radial DEA, is employed to measure the energy efficiency in China, and price index method derived from Iceberg Transport Cost model is used to examine the degrees of market segmentation in China's provinces. On the basis, we use Tobit model to analyze the impact of market segmentation on China's energy efficiency empirically.

Our results show that of the three broadly geographical regions of China, the eastern region has a highest energy efficiency score but a lowest growth rate, and thereby the energy efficiency gap is narrowing gradually between the eastern and central regions. The growth rate in the western region is almost as high as the central, but the efficiency score is the lowest of the three regions. Thus, the efficiency gap is narrowing insignificantly between the western and eastern regions.

There is still a severe market segmentation problem in China, and the western provinces have more segmented markets than the eastern. The reason may lie in the economic gap between two regions. In addition, the market segmentation index of China is declining as time goes by, and also shows a convergence in various provinces.

Market segmentation is significantly negative to energy efficiency in China. This holds even if the endogeneity is excluded and the energy efficiency is remeasured by SBM model. The test of regional heterogeneity shows that market segmentation significantly inhibits energy efficiency in the central and western provinces, but such inhibitory effect is insignificant in the eastern. This may be associated with the non-balanced economy and resource endowment in various provinces of China. The test of impact mechanism shows that factor market distortion, enterprises' R&D investment, and industrial agglomeration are three mediation mechanisms through which market segmentation affects energy efficiency. Further research indicates that there is a Race to the Top competition centering on market segmentation among local officials in geospatial and economic space, which triggers a scrambling increase of market segmentation in China and a long-term inhibition on energy efficiency.

Based on the above findings, some important policy implications and suggestions can be proposed. First, the Chinese central government should push for eliminating local protection and accelerate market integration to the extent possible. Specifically, it is necessary to clear away all kinds of local rules and regulations that prevent the establishment of a unified national market, and to specify the powers and responsibilities of local governments to avoid frequent interference in the market economy. In addition, the central government needs to accelerate market integration by setting up a cross-regional cooperation and information sharing platform of energy economy to achieve regional complementarity. Second, it is extremely important to replace the intermediary mechanism through which market segmentation inhibits energy efficiency. Specifically speaking, the Chinese government should further undertake market reforms in the factor market by reducing the direct intervention and enabling the market to play a decisive role in the allocation of resources. Incentives are needed to encourage enterprises to increase investment in energy-saving and low-carbon technology. In pursuit of the economies of scope and scale, the Chinese central government should support industrial cooperation among provinces by establishing the cross-regional industrial and science parks. Finally, given the past performance evaluation that local officials have been promoted based on how fast they expand their local economies, evaluation for local governments needs to incorporate the overall economic, social, energy and environmental performance into consideration, rather than just take economic growth as the predominate criteria for evaluating local officials' performance.

Appendix A. Linear programming of SBM model

Tone (2001) proposed the SBM model in which radial assumption is avoided effectively by introducing non-radial slack variables. The SBM model with undesired outputs is as follows:

$$\begin{aligned}
&\min \rho = \frac{1-\dfrac{1}{N}\sum_{n=1}^{N}(s_{no}^{x}/x_{no})}{1+\dfrac{1}{M+J}\left[\sum_{m=1}^{M}(s_{mo}^{y}/y_{mo})+\sum_{j=1}^{J}(s_{jo}^{b}/b_{jo})\right]} \\
&s.t. \quad \sum_{k=1}^{K}\lambda_k x_{nk} + s_{no}^{x} = x_{no} \qquad (n=1,2,\cdots,N) \\
&\qquad \sum_{k=1}^{K}\lambda_k y_{mk} - s_{mo}^{y} = y_{mo} \qquad (m=1,2,\cdots,M) \\
&\qquad \sum_{k=1}^{K}\lambda_k b_{jk} + s_{jo}^{b} = b_{jo} \qquad (j=1,2,\cdots,J) \\
&\qquad \lambda_k \geq 0, s_{no}^{x} \geq 0, s_{mo}^{y} \geq 0, s_{jo}^{b} \geq 0
\end{aligned} \tag{14}$$

where each symbol has the same meaning as Eq. (3) described in Section 3.1.

In addition, drawing lessons from Li and Hu (2012) and Li and Lin (2017b), we define *ee_sbm* as follows:

$$ee_{it} = \frac{tei_{it}}{e_{it}} = \frac{e_{it} - s^{e}_{it}}{e_{it}} \tag{15}$$

where each symbol has the same meaning as Eq. (4).

Appendix B.

Table B1

Test results of impact mechanism with *ee_sbm* as dependent variables

Variable	Factor market distortion	*ee*	Enterprises R&D investment	*ee*	Industrial agglomeration	*ee*	*ee*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
seg	0.359***		-0.224***		-0.278***		0.029
	(0.099)		(0.067)		(0.045)		(0.034)
dis		-0.093***					-0.074***
		(0.020)					(0.020)
rd				0.197***			0.176***
				(0.026)			(0.033)
agg						0.268***	0.139***
						(0.038)	(0.051)
ind	-1.097***	0.142	1.200***	-0.050	-1.541***	0.560***	0.226
	(0.306)	(0.104)	(0.172)	(0.089)	(0.114)	(0.099)	(0.147)
fdi	-2.305**	1.515***	-3.664***	2.642***	-0.179	1.896***	2.273***
	(1.125)	(0.413)	(0.634)	(0.354)	(0.420)	(0.336)	(0.407)
reg	-5.144***	-0.123	0.262	-0.083	1.631**	-0.548	-0.547
	(1.845)	(0.630)	(1.165)	(0.583)	(0.772)	(0.591)	(0.597)
ene	-0.231*	-0.112***	-0.165**	-0.118***	-0.056	-0.133***	-0.089**
	(0.120)	(0.040)	(0.071)	(0.035)	(0.047)	(0.035)	(0.037)
own	0.425**	-0.135**	0.123	-0.127***	-0.287***	-0.037	-0.102*
	(0.174)	(0.058)	(0.097)	(0.048)	(0.064)	(0.049)	(0.055)
Wald test/	11.28	63.94	35.23	126.96	38.80	120.30	119.30
F test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Standard errors in parentheses.

* Denote coefficient significant at 10%.

** Denote coefficient significant at 5%.

*** Denote coefficient significant at 1%.

Table B2

Test results of Race to the Top tournament centering on market segmentation and its impact on energy efficiency with *ee_sbm* as dependent variables

Variable	GAWM	GDWM	EDWM

	ee	*seg*	*ee*	*seg*	*ee*	*seg*
	(1)	(2)	(3)	(4)	(5)	(6)
W×seg$_{it}$	-0.310***	0.536***	-0.302***	0.758***	-0.202***	0.544***
	(0.051)	(0.056)	(0.057)	(0.050)	(0.050)	(0.049)
ind	0.082	-0.327***	0.047	-0.158	0.090	-0.247**
	(0.087)	(0.118)	(0.090)	(0.110)	(0.091)	(0.114)
fdi	1.530***	0.449	1.632***	0.116	1.614***	0.128
	(0.319)	(0.436)	(0.325)	(0.406)	(0.331)	(0.419)
reg	-0.339	-1.762**	-0.371	-1.203	-0.257	-1.391*
	(0.588)	(0.800)	(0.599)	(0.743)	(0.610)	(0.768)
ene	-0.147***	0.074	-0.131***	0.038	-0.148***	0.081*
	(0.036)	(0.049)	(0.036)	(0.045)	(0.037)	(0.047)
own	-0.080	-0.037	-0.086*	-0.025	-0.080	-0.041
	(0.049)	(0.067)	(0.049)	(0.062)	(0.050)	(0.064)
Wald test	92.24	152.64	82.04	301.02	68.34	192.11
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Standard errors in parentheses.

* Denote coefficient significant at 10%.

** Denote coefficient significant at 5%.

*** Denote coefficient significant at 1%.

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