Energy efficiency measures in China: A three-stage DEA analysis

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Abstract. This paper measures energy efficiency of 30 regions in China during 2010-2014 by using the three-stage data envelopment analysis (DEA) model. The results indicate that environmental factors and random error both have significant impacts on energy efficiency. After eliminating these influences, the results present that the energy efficiency in developed regions is almost higher than that in undeveloped or resource-rich regions and low scale technical efficiency is the main constraining factor in inefficient regions. Based on the efficiency characteristics, this paper divides all regions into four types and provide differential energy strategies.

1. Introduction
Since China has become the biggest emitter, the pressure to reduce carbon emissions is severe than ever. However, for China is still accelerating the process of industrialization and urbanization, energy is the material basis for development. Therefore, it is of practical significance to explore an optimal path for China's low-carbon development. Considering China is a vast territory with big differences in economic scale, resource endowment, urbanization level and the degree of openness among different regions, to achieve the national reduction targets, it is necessary to begin by elucidating the characteristics of regional carbon emissions, such as using the form of efficiency index.

Current research on the energy efficiency including two categories: one is single factor index represented by carbon intensity, which is defined as the energy consumption divided by the economic output [1]. Although single factor index has the advantages of simple calculation and easy interpretability, these indicators simply measure the proportional relationship between energy and economic output without considering the substitution effects among energy, capital, labor force and other factors [2]. Another measure is the total-factor energy efficiency method [3], including the parametric method and non-parametric method. Data envelopment analysis (DEA) [4], which can assess the relative efficiency of a set of decision-making units (DMUs) with multiple inputs and outputs, has gained increasingly popularity in energy efficiency measurements.

At present, many scholars pay great attention to China’s regional efficiency by using traditional DEA method or extending methods, such as Wang H et al [5], and Zhang et al [6]. Although they have made
huge progress towards understanding China's energy efficiency, they fail to fully consider the effects of environmental heterogeneity and stochastic factors. Stochastic frontier analysis (SFA) is a parametric method which can provide a specific function form to void heterogeneity for DMUs. Following the pioneering work of Fried\textsuperscript{10} who proposed the three-stage DEA approach combining DEA and SFA, several studies have applied this model to evaluate efficiency considering environmental heterogeneity. Such as Yang et al\textsuperscript{7} and Li et al\textsuperscript{8}. All these researches validated that environmental factors and statistical error have impact on efficiency.

The paper is organized as follows: Section Two describes the data. Section 3 presents the empirical analysis. Section 4 gives our conclusions and policy implications.

2. Data

Based on data availability, this paper takes the 30 provinces of China as the sample set over the period 2010–2014(Hong Kong, Macao, Tibet, and Chinese Taiwan are not included) with capital stock, labor force, energy and carbon emissions as inputs and the GDP of each province as output. Capital stock data are estimated using the perpetual inventory method \textsuperscript{9}. Labor force, represented by the number of employed persons by the end of a year, are collected from the China Statistical Yearbooks. The energy data are from The Energy Statistical Yearbook and different energy types are converted into standard coal. Carbon emissions are calculated based on the carbon-emission coefficients provided by IPCC (2006). GDP data are obtained from the China Statistical Yearbook and are converted into standard prices using a price index (2010.100).

3. Empirical application and results

3.1 Results of Traditional DEA in the First Stage

From Table\textsuperscript{1}, (1) without considering the influence of environmental factors and random error, the mean comprehensive technical efficiency(CTE) is 0.668, with the mean of pure technical efficiency (TE) and scale efficiency(SE) are 0.899 and 0.756, respectively. (2) The results show a large variation in efficiency values across regions. Beijing lies on the efficiency frontier during the studied period while other provinces somewhat further away from optimal efficiency. (3) CTE presents a divergent trend, with the difference between the maximum and the minimum efficiency value between 30 regions widened from 0.466 in 2010 to 0.648 in 2014. (4) The CTE of most regions present downward trends year by year. The average efficiency values fell from 0.720 in 2010 to 0.580 in 2014, which is not in line with the actual development situation of our country. (5) The average value of SE is higher than TE in most regions, meaning that carbon inefficiency in most provinces emerges from pure technical inefficiency. Contrarily, the economic scale is much different between regions, therefore, it is necessary to strip environment factors and random error to obtain more reliable results. 3.2 Results of SFA Regression Analysis in the Second Stage

From Table\textsuperscript{1}, the coefficients on economy structure are all significantly positive, suggesting that this is an unfavourable factor. This is consistent with the viewpoints that the secondary industries are the most intensive energy-consumption part of the economy. The same result is applied to the energy structure. The increase of the proportion of primary energy counts against reductions in input slacks. Urbanization rate and foreign trade are found to have different coefficients for different variables.
3.3 Results Following an Adjustment of Input Variables in the Third Stage

From table 2, (1) pure technical efficiency is improved in most regions, but comprehensive technical efficiency changes little, mainly due to the decline of scale efficiency in these regions. Comparatively speaking, scale efficiency has much space for improvement in most regions by continuing expansion of the input scale. (2) The differences of efficiency between regions are significant. Jiangsu and Guangdong, perform efficiently, as both scores of comprehensive technical efficiencies are 1. The scores of the other 28 provinces range from 0.137 to 0.877, with Qinghai ranking last among the inefficient provinces. (3) The efficiency does not show the downturn as the first stage during studied period, which conforms to China’s actual conditions. (4) However, the variation between maximum and minimum of the efficiency scores expanded, which shows that some bad performances have been “reward”, relying on their advantages of energy resources or the foreign trade level.

Table 2 Energy efficiency results in the first stage and the third stage.

| Variable | Capital stock | Labour force | Energy | Carbon |
|----------|--------------|--------------|--------|--------|
| Constant | -37294.77*** | 87.49**      | -13013.84*** | -52356.01*** |
| Economy structure | 50193.50*** | 566.12*** | 9966.44*** | 53529.68*** |
| Energy structure | 23988.94*** | 2986.99*** | 18126.21*** | 46500.23*** |
| Urbanization rate | 17383.40*** | -2500.62*** | 7327.88*** | 34260.45*** |
| Foreign trade | -23821.07*** | 237.25*** | -7954.20*** | -35755.53*** |
| Sigma Squared | 394247820.00*** | 1825160.10*** | 33758624.00*** | 347714400.00*** |
| Gamma | 0.90** | 0.93*** | 0.90** | 0.94*** |
| Log likelihood function | 1535.58 | 1110.12 | 1349.48 | 1501.31 |
| LR test of the one-sided | 195.76*** | 233.53*** | 197.05*** | 238.60*** |

**Table 1.** The regression results of the second stage.
There are significant regional differences of energy efficiency in China. In general, energy efficiency in China between 2010 and 2014. The results indicate that: (1) When using the SFA method in the second stage, environmental factors and statistical error both have significant impacts on energy efficiency. (2) There are significant regional differences of energy efficiency in China. In general, energy efficiency in China divided China into four areas based on the geographic distribution. But we believe specific regional characteristics would be ignored and the corresponding strategies would be far from convincing. Thus, taking the efficiency value of 0.9 as a critical point, we divide China into four areas based on their carbon efficiency characteristics. First type is "high-high", that is TE and SE are all above 0.9. These regions have a relative optimal performance and can serve as the example for other regions. Thus, steady improvement of the energy efficiency in these regions should be guaranteed to improve the overall efficiency. The second type is "high-low", namely high TE but low SE, which should pay attention to improve regional investment attractiveness and expand product scale, tapping the energy savings potential of high-energy consumption sectors. A third type of "low-high" is, that TE below 0.9 while SE above 0.9. These technically inefficient regions can cooperate with adjacent technically efficient regions to actively learn advanced energy saving technologies, then update equipment, adopt advanced process, and strengthen energy management. The fourth type is "low-low", whereby TE and SE are both under 0.9. It is difficult for these regions to improve the TE and SE simultaneously, thus we suggest to emphasis on expanding the scale of production to lay a basis for technological progress. Furthermore, governments should formulate relevant supporting policies to promote the efficient flow of capital, technology, and talent, breaking barriers to improve energy efficiency.

### Table 4 The division of 30 regions

| Type       | Region                                                                 |
|------------|------------------------------------------------------------------------|
| high-high  | Beijing, Inner Mongolia, Liaoqing, Shanghai, Jiangsu, Zhejiang, Anhui, Hubei, Hunan, Guangdong |
| high-low   | Shanxi, Jilin, Jiangxi, Chongqing, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang |
| low-high   | Shanxi, Jilin, Jiangxi, Chongqing, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang |
| low-low    | Tianjin, Heilongjiang, Guangxi, Hainan and Yunnan                       |
developed regions is higher than undeveloped regions or resources endowment regions, indicating that the developed economy, technology, and human resources in former regions greatly promote the improvement of efficiency, while the latter regions always characterized high energy consuming industries as the pillar industry. (3) The average of TE is higher than SE, namely that SE is the primary cause constraining energy efficiency and has great space for improvement in inefficient regions. (4) Based on the efficiency characteristics, we provide differentiated energy strategies to different types. Steadily improve the energy efficiency of “high-high” regions and update equipment, adopt advanced technology in “high-low” regions. The “high-low” regions should accelerate the transfer of intensive growth by attracting investment and expanding product scale. The “low-low” regions should expand the economy scale and introduce energy-saving technologies.

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