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Article

Total Factor Energy Efficiency of China's Industrial Sector: A Stochastic Frontier Analysis

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Abstract: Based on stochastic frontier analysis and translog input distance function, this paper examines the total factor energy efficiency of China's industry using input-output data of 30 sub-industries from 2002 to 2014, and decomposes the changes in estimated total factor energy efficiency into the effects of technical change, technical efficiency change, scale efficiency change and input-mix effect. The results show that during this period the total factor energy efficiency in China's industry grows annually at a rate of 3.63%, technical change, technical efficiency change and input-mix effect contribute positively to the change in total factor energy efficiency, while scale efficiency change contributes negatively to it.

Keywords: malmquist productivity index; total factor energy efficiency; stochastic input distance function; China's industry

1. Introduction

China has to optimize its energy consumption structure and improve energy efficiency in order to reduce environmental pressure, ensure energy security, and fulfil its international obligations of dealing with the global climate change. As the world's largest energy consumer, China has a significantly high proportion of fossil energy in primary energy consumption. Although it is slowly decreasing due to the slowdown in economic growth and the rapid development of the renewables in recent years, the share of fossil energy consumption remains 88% in 2015. The industry (especially manufacturing) is the largest economic sector as well as the largest energy use sector in China. According to relevant statistics, the value-added of the manufacturing accounts for one third of China's GDP, and the energy consumption of the industrial sector accounts for 60% of China's total energy consumption in 2015. This situation implies that for China improving the industrial energy efficiency should be the main way to reduce its GHG emissions related to energy consumption.

In order to assess the energy efficiency, and propose assessment-based practical policy, it is essential to figure out how to define and measure the energy efficiency. There is no widely accepted definition of energy efficiency. Most definitions are on basis of the simple ratio of useful output of a process and energy input into that process [1]. Patterson [2] identifies different ways to quantify the outputs and inputs for calculating that ratio. One of those ways is to use economic-thermodynamic indicators, in which outputs measured in monetary values, and the energy input measured in thermodynamic units. The energy-GDP ratio commonly used in energy analysis at a macro level actually is the inverse of this economic-thermodynamic indicator. However, this definition is considered too simplistic. A better way to define energy efficiency is to resort to the microeconomic theory of production. To understand this approach, it is necessary to recognize that the demand for energy is a kind of derived demand, resulting from the demand for outputs, i.e. products and services. Producers or households use energy, capital and labor to produce products and (energy) services. What matters for producers is to provide products and services in an efficient way. Under

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given productive technology, they minimize the production cost of a certain output quantity by choosing the combinations of inputs. In reality, producers may choose non-cost-minimization combination of inputs or use obsolete technology to produce outputs. In these situations, possibly energy and other inputs are used inefficiently. Under this circumstance, productive inefficiency could be discussed using the microeconomic theory of production. What's more, the radial measure of technical, allocative and overall productive efficiency introduced by Farell [3], and the non-radial measure of input specific technical efficiency introduced by Kopp [4] can help to understand the concept of energy efficiency.

Finippini and Hunt [5] present the difference between the radial and non-radial measure of energy efficiency in Figure one. Suppose a producer is using capital (C) and energy (E) to produce a unit energy service (ES). In figure one, IS_0 and IC_0 represent a unit isoquant and an isocost line, respectively. A technically efficient producer will use the combinations of inputs lying on the isoquant IS_0 to produce a unit energy service. If the price ratio of capital and energy, represented by the slope of the isocost line is known, producer can identify the cost-minimization-combination for producing a unit energy service, i.e. the point X^*. If a producer uses combination X_1 to provide one unit energy service, apparently it is technically inefficient. Using input-oriented radial measure, the level of technical inefficiency θ can be measured as the ratio between the distance from the origin to the technically efficient point θX_1 and the distance from the origin to point X_1. Although point θX_1 is technically efficient, it is allocatively inefficient. The allocative efficiency level can be measured as the ratio between the distance from the origin to point αX_1 and the distance from the origin to point θX_1. The overall productive efficiency α can be measured as the ratio between the distance from the origin to point αX_1 and the distance from the origin to point X_1. A producer operating at point X_1 is inefficient technically and allocatively, he could improve the overall productive efficiency by moving towards the optimal input combination point X^*. During the process of movement, the energy input is decreasing because of the substitution between capital and energy.

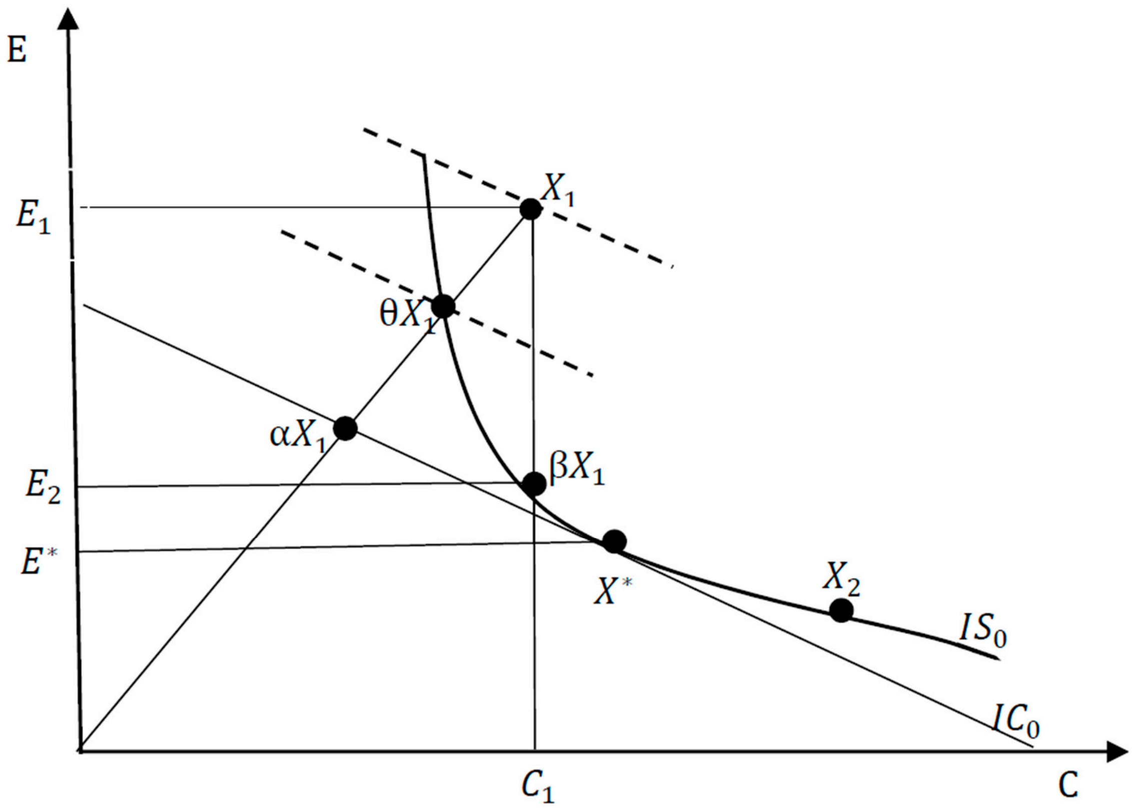

Figure 1. Productive efficiency.

In above-mentioned input oriented radial measure of energy efficiency, an efficiency improvement in input utilization requires a reduction of energy and other inputs proportionally. Of

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course, if researchers are more interested in measuring the technical efficiency of specific input, for instance, energy input, he can turn to non-radial concept of technical efficiency. Non-radial measure of technical efficiency is proposed by Kopp [4], it can be expressed as the ratio between the distance from the technically efficient point βX_1 to point C_1 on the horizontal axis and the distance from point X_1 to point C_1. That means under non-radial technical efficiency framework energy efficiency can be measured as the ratio of minimum feasible energy input (E_2) to the observed use of energy (E_1), conditional on the output and other inputs fixed.

It is important to consider the effects of relative price and technical change on the efficiencies of energy and other inputs when analyzing a producer's productive efficiency. When the relative prices of inputs change, the cost-minimizing combination of inputs will change as well, subsequently resulting in a change in allocative efficiency. If technical change allows a producer to produce the same output level with less energy and capital input, the isoquant move inward. As a result, the technical, allocative and overall productive efficiency all change. In a word, the level of energy efficiency could change due to the changes in relative price and technological progress over time.

China's industrial economy has been growing rapidly since 1990s. According to *China Industrial Statistics Yearbook*, at 1990 constant price, the value-added of the above-scale industrial enterprises expands 4.76 times from 1993 to 2007, with an average annual growth rate of 12.38%; the gross output value increases by 12 times from 1990-2011 with a yearly averaged growth rate of 12.75%. With the rapid growth of output and factors demand, the relative prices of factor inputs have been changing over time. Figure 2 shows the trends in price indices of labor, capital and energy (1990=100) from 1990-2015. We notice that the real wage index has been rising since 1990, especially the real wage growth obviously has been accelerating after 2000. This reflects the fact that the labor cost of the industrial sector has been escalating since 2000. Although during the same period the capital goods price index[1] has been rising as well, but it almost keeps stable compared with the rapid rise of real wage index. The energy price index[2] shows a different evolution picture. Generally, the energy price index goes up at an average annual rate of 9.27% from 2002-2011, but it begins entering a declining path after 2011. These trends in factor price indices mean that the relative price of labor to capital has been going up, labor becomes more expensive relative to capital factor, that leads to a significant increase in capital-labor ratio. For example, the net fixed assets value per worker in the industry sector was only 18.1 thousand yuan (at 1990 constant price) in 1991, but it reached 106.7 thousand yuan (at 1990 constant price) in 2010, expanding 4.89 times during this period with an annually averaged growth rate of 19.4%. This number shows the pace of capital deepening in China's industry sector has been very high.

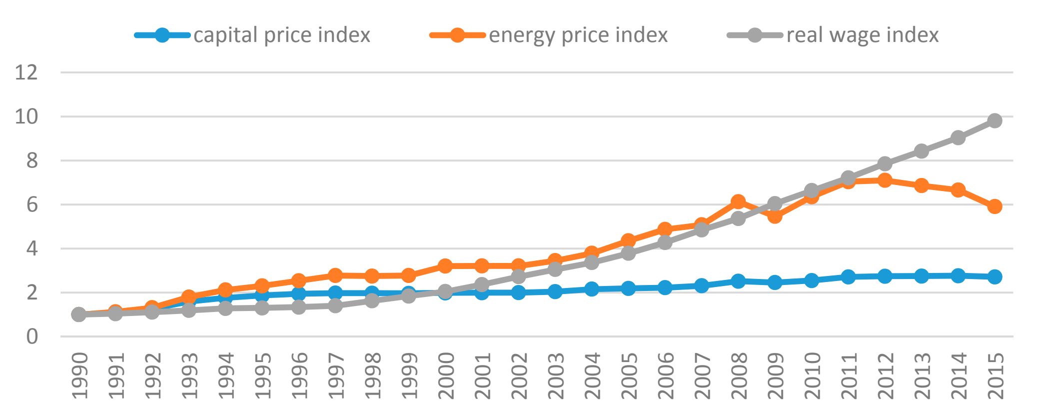

Figure 2. Factor price indices

Source: authors' calculation with the original data from CEIC China Premium Database.

[1] The fixed assets investment price index is used to approximate the capital goods price index.

[2] The fuel and power price index is used to represent the capital goods price index.

Meanwhile, China's industry sector has witnessed dramatic structure change since 1990s. For example, in terms of sectoral share of manufacturing value added, the three largest sectors are basic metals and metal products, food, beverages and tobacco , and textiles and textiles products sector in 1987, accounting for 15%, 14.9% and 14.3% respectively; while in 2008 the three largest sectors are electrical and optical equipment, basic metals and metal products, and machinery NEC, accounting for 16.7%, 13.1% and 11.2% , respectively（Naudé et al. ）[6]. That indicates the status of the labor-intensive sectors such as food processing, textiles in manufacturing has been dropping gradually, while capital-intensive sectors, such as machinery, electrical and optical equipment etc., have become increasingly more important, the manufacturing is gradually transforming into a more capital-intensive sector from a more labor-intensive one. The most significant change in China's industry sector should be the change in ownership structure. Although the state-owned enterprises still predominate in assets size, but in terms of output and employment, private and foreign investment enterprises have already surpassed the state-owned enterprises. For instance, according to *China Industrial Statistical Yearbook*, the share of total assets held by state-owned and state holding enterprises was 68.64% in 1998, but it has rapidly dropped to 40.29% in 2013; at the same time, the share of private and foreign investment enterprises rose to 42.37% in 2013, it was only 20.97% in 1998.

In sum, China's industrial sector has experienced profound structure change over past decades. Ownership structure has transformed into a co-existing pattern of various ownership economies from past predominance of state-owned economy, the share of state capital has declined dramatically, while the share of private and foreign capital has increased substantially; output structure has changed into a more capital-intensive sector from a more labor-intensive one. The factor prices and capital-labor ratio also have been changing along with the structure change of this sector. All these changes necessarily influence the energy efficiency of china's industrial sector. This paper aims at estimating and decomposing the total factor energy efficiency of that sector.

2. Literature review

China has been the world's fastest growing economy over past decades. Considering the huge amount of its energy consumption and GHG emissions, researchers have paid much more attentions to the energy efficiency of China. Generally, the literature relating to China's energy efficiency can be divided into two categories by theme. One category mainly examines regional difference of China's energy efficiency. Another one mainly focuses on identifying the sources of its energy efficiency change. However, a few studies simultaneously involve in those two topics. Due to the economic, technical and institutional variety in different regions, there must be difference in energy efficiency among them. Hu and Wang [7] define total factor energy efficiency as the ratio of target energy input to actual energy input for a given output, and use nonparametric techniques to measuring it. They find regions in the east area have the highest rank of total factor energy efficiency, while regions in the central area have the worst one of efficiency. It is worth pointing out that Hu and Wang's definition is a radial measure of technical efficiency under multiple-inputs framework. Shi et al. [8] estimate the industrial energy efficiency of China's 28 provincially administrated districts using nonparametric data envelopment analysis. Their results show that during 2000-2006, the industry sector of eastern region has the best energy efficiency. Similar conclusions are made by Wang et al. [9], Yao et al. [10], and Lin and Zhao [11].

Above literatures using nonparametric method to estimate the energy efficiency of China's economy. This method attributes all deviations from frontier to inefficiency. Moreover, the result of nonparametric method is highly sensitive to outliers in data. To avoid these drawbacks, parametric techniques can be used as an alternative method. Zhou et al. [12] propose a parametric frontier method to measure China's energy efficiency. Lin and Du [13] use parametric meta-frontier approach to estimate total factor energy efficiency for China's 30 provincial units. Again, it is worth noting that the definition of total factor energy efficiency in Lin and Du [13] is a non-radial measure of technical efficiency. Lin and Wang [14] explore energy efficiency in China's iron and steel sector using stochastic frontier analysis. Similarly, Hu [15], Ouyang and Sun [16], Li et al. [17] also use SFA to measure the total factor energy efficiency or energy-saving potentials of China's industrial sector.

Malmquist productivity index introduced by Caves et al. [18] is the commonly used method to identify the sources of TFP. Fare et al. [19] develop nonparametric method to estimate TFP, and further decompose it into two sources, i.e. technical change and technical efficiency change. In contrast, Coelli et al.[20], Rossi [21], Balk [22] , Fuentes et al.[23], Orea [24], Pantzios et al. [25] use alternative parametric techniques to estimate and decompose Malmquist productivity index. We note that Pantzios et al. [25] extend the framework of Fuentes et al. [23], and decompose Malmquist productivity index into technical change, technical efficiency change, scale efficiency change and input-mix effect. Compared with traditional decomposition techniques, the decomposition approach in Pantzios et al. [25] are helpful to estimate the effect of scale efficiency related to input combination on total factor productivity.

Under Malmquist productivity index framework, a few literature estimate and decompose the total factor energy efficiency of China's industry. He et al. [26] use DEA-Malmquist productivity index techniques to measure the energy efficiency and productivity change for 50 iron and steel enterprises from 2001 to 2008. The results show that inefficiency is present in most surveyed enterprises, average energy efficiency is only 61.1%, and the annual growth rate of total factor productivity averages of 7.96% during this period, technical change is the main source of this growth. Similarly, Shao et al. [27] also find that technical change is the largest contributor to the growth of total factor productivity for China's nonferrous metal industry, followed by the improvement in scale efficiency. Li and Lin [28], Li and Lin [29] measure green productivity growth in China's industrial sector and manufacturing using an improved Malmquist-Luenberger productivity index.

We find that among the literature relating to the energy efficiency of China, most estimate the non-radial total factor energy efficiency by using nonparametric techniques. Measuring the level of non-radial total factor energy efficiency is necessary, since producers occasionally do not want or have no ways to reduce other inputs of production process, only care about saving energy. But in some cases, the radial total factor energy efficiency is more reasonable. First, output is produced using labor, capital and energy. Producers not only need to concern energy saving, but also need to concern other inputs saving. Second, there is a complicated relationship between capital and energy use economically and technologically in production process. The relationship can be either substitutional or complementary one. If it is substitutional, then reducing capital input requires an increase in energy use; if it is complementary, reducing energy input needs to reduce capital input synchronously. Historic experiences from developed countries confirm that the relationship between capital and energy is more of complementary one. Particularly, China's industry has been suffering from severe overcapacity. Removing excess capacity needs to reduce capital and energy input as well. Hence, for China the radial measure of total factor energy efficiency is more suitable than non-radial one.

In summary, the majority of previous literatures relating to China's energy efficiency estimate the non-radial measure of total factor energy efficiency using nonparametric techniques. Following the method proposed by Pantzios et al. [25], this paper will use parametric techniques to estimate and decompose the radial measure of the total factor energy efficiency in China's industry. Our results show that the total factor energy efficiency in China's industry grows at an annual average rate of 3.63% from 2002 to 2014, technical change, technical efficiency change and input-mix effect contribute positively to the change in total factor energy efficiency, while scale efficiency change contributes negatively to it.

The contributions of this paper lie in two aspects. First, different from most previous studies, this study estimates the level of radial total factor energy efficiency by using parametric techniques. Second, it examines the effect of scale efficiency associated with output and input-mix change on energy efficiency in China's industry, finding that the deterioration of scale efficiency related to output is the key factor refraining the growth of China's industrial energy efficiency. The remainder of this paper is organized as follow: section 3 introduces an input-oriented Malmquist productivity index and its parametric decomposition proposed by Pantzios et al. [25]; section 4 estimates and decomposes the total factor energy efficiency of China's industry; section 5 concludes.

3. Decomposition and parametric estimation of the input-oriented Malmquist productivity index

3.1 Decomposition

According to Pantzios et al. (2011)[25] and Balk (2001)[22], for any two successive time periods t and t+1, the input-oriented Malmquist productivity index M_I^t can be expressed as:

$$M_I^t(x^{t+1},y^{t+1},x^t,y^t) = TC_I^{t,t+1}(x^{t+1},y^{t+1}) \times TEC_I(x^{t+1},y^{t+1},x^t,y^t) \times SEC_I^t(x^t,y^{t+1},y^t) \times ME_I^t(x^{t+1},x^t,y^{t+1}) \quad (1)$$

where x and y denote inputs and outputs, respectively, the subscript I refers to input orientation. The four components on the right-hand side of (1) are defined as:

$$TC_I^{t,t+1} = \frac{D_I^{t+1}(x^{t+1},y^{t+1})}{D_I^t(x^{t+1},y^{t+1})} \quad \text{(2a)} \qquad TEC_I = \frac{D_I^t(x^t,y^t)}{D_I^{t+1}(x^{t+1},y^{t+1})} \quad \text{(2b)}$$

$$SEC_I^t = \frac{ISE^t(x^t,y^{t+1})}{ISE^t(x^t,y^t)} \quad \text{(2c)} \qquad ME_I^t = \frac{ISE^t(x^{t+1},y^{t+1})}{ISE^t(x^t,y^{t+1})} \quad \text{(2d)}$$

ISE^t in (2c) is the input-oriented scale efficiency measure, evaluating the productivity of an observed input-output bundle (x^t, y^t) relative to that of technically optimal scale.

$TC_I^{t,t+1}$, representing the technical change component, captures the radial shift in the input requirement set measured with period t+1 data. If the same output level can be produced with less inputs, technical progress occurs and the values of $TC_I^{t,t+1}$ are greater than one. Fare et al. [30] shown that (2a) can be rewritten as:

$$TC_I^{t,t+1}(y^{t+1},x^{t+1}) = TCM(y^t,x^t) \times OB(y^t,x^{t+1},y^{t+1}) \times IB(x^t,y^t,x^{t+1}) \quad (3)$$

$TCM(y^t,x^t)$, Pantzios et al. (2011) [25] referring to as technical change magnitude index, measures the rate of technical change locally. The values of TCM will be greater than one when the input requirement set contract along a ray through period t data. The terms $OB(y^t,x^{t+1},y^{t+1})$ and $IB(x^t,y^t,x^{t+1})$ are the output and the input bias indices, respectively. The specific definitions of these two terms can be found in Pantzios et al. [25]. Generally, the bias indices compare the magnitude of technical change along a ray through period t+1 data to the magnitude of technical change along a ray through period t data. If technical change is neutral, the input requirement set will shift inward or outward by the same proportion along a ray through period t+1 data as it does along the ray through period t data. The input bias index equals one and does not have contribution to productivity when implicit Hicks input-neutral technical change prevails. Similarly, the output bias index equals one and has no contribution to productivity change when implicit Hicks output-neutral technical change and CRS prevail [25].

The technical efficiency change component, TEC, measures enterprises' ability to improve technical efficiency from one period to the next. For input-oriented technical efficiency, TEC will be greater than one as the technical efficiency improves.

The remaining two components, SEC_I^t and ME_I^t, are defined in terms of the input-oriented scale efficiency measure (ISE^t). If a producer is operating at technically optimal scale, its production technology exhibits CRS and average ray-productivity reaches its maximum. The expression of the component $SEC_I^t(x^t,y^{t+1},y^t)$ can be found in Pantzios et al. [25] formula (6). If SEC_I^t is greater than one, then the output bundle at period t+1 lies closer to the point of technical optimal scale than the output bundle of period t does, thus scale efficiency increases. Therefore, SEC_I^t measures how the input-oriented measure of scale efficiency changes over time when input mix is fixed.

ME_I^t, the input-mix effect, measures how the distance of a frontier-point to the frontier of so-called the cone technology changes when input mix changes, conditional on the same output bundle. Specifically, it measures the change in the input-oriented measure of scale efficiency from a change in input mix when outputs remain unchanged. If the values of ME_I^t are greater than one, that indicates a positive contribution of the input-mix effect to productivity changes. The product of SEC_I^t and ME_I^t measures the combined effect of the scale efficiency change and of input-mix, in nature, it is an overall scale effect. It is worth noting that if technology exhibits CRS, then both SEC_I^t and ME_I^t are equal to one.

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3.2 Parametric estimation

In order to estimate the Malmquist productivity index using parametric techniques, it is necessary to specify a specific function form for the input distance function. Researchers often choose a flexible function form such as translog function. Suppose a producer uses k (k=1,⋯,K) inputs to produce m (m=1,⋯,M) outputs at time t (t=1,⋯, T). The translog input distance function can be defined as:

$$\ln D_I^t(x^t,y^t) = \alpha_0 + \sum_{k=1}^{K} \alpha_k \, lnx_k^t + 0.5\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \, lnx_k^t lnx_l^t + 0.5\sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} \, lnx_k^t \ln y_m^t$$
$$+\sum_{m=1}^{M} \beta_m \, lny_m^t + 0.5\sum_{m=1}^{M}\sum_{m=1}^{M} \beta_{mn} \, lny_m^t lny_n^t + \gamma_0 t + 0.5\gamma_{00} t^2$$
$$+\sum_{k=1}^{K} \eta_k \, lnx_k^t t + \sum_{m=1}^{M} \mu_m \, lny_m^t \mathrm{t} \qquad (4)$$

The regularity conditions related to input distance function require that it should be homogeneous of degree one in input quantities and symmetrical. That means the following restrictions on the parameters of (4):

$$\sum_k^K \alpha_k = 1,\ \sum_k^K \alpha_{kl} = 0,\ \sum_k^K \delta_{km} = 0,\quad \sum_k^K \eta_k = 0 \qquad (5)$$

$$\alpha_{kl} = \alpha_{lk}, \beta_{mn} = \beta_{nm} \qquad (6)$$

The linear homogeneity restriction is imposed by dividing all input quantities in the right-hand side of (4) by the quantity of that input used as a numeraire, for example, here supposing to be x_1, then (4) can be written as:

$$\ln[\frac{D_I^t(x^t,y^t)}{x_1^t}] = \alpha_0 + \sum_{k=2}^{K} \alpha_k \ln(\frac{x_k^t}{x_1^t}) + 0.5\sum_{k=2}^{K}\sum_{l=2}^{K} \alpha_{kl} \ln(\frac{x_k^t}{x_1^t}) ln(x_l^t/x_1^t)$$
$$+0.5\sum_{k=2}^{K}\sum_{m=1}^{M} \delta_{km} \, ln(x_k^t/x_1^t)\ln y_m^t + \sum_{m=1}^{M} \beta_m \, lny_m^t$$
$$+0.5\sum_{m=1}^{M}\sum_{m=1}^{M} \beta_{mn} \, lny_m^t lny_n^t + \gamma_0 t \ +0.5\gamma_{00} t^2 \qquad (7)$$
$$+\sum_{k=2}^{K} \eta_k \ln(\frac{x_k^t}{x_1^t}) t + \sum_{m=1}^{M} \mu_m \, lny_m^t \mathrm{t}$$

According to the definition of the input distance function, $D_I^t(x^t,y^t)$ must be equal to or greater than one. Let $\ln D_I^t = u_{it}$, then $u_{it} \geq 0$, it represents the technical inefficiency. Shifting $lnD_I^t(x^t,y^t)$ term to the right-hand side of (7), and adding a random noise term, v_{it}, which assumed to be normally distributed, and independent with u_{it}, gives the following regression model:

$$-\ln x_1^t = \alpha_0 + \sum_{k=2}^{K} \alpha_k \ln(\frac{x_k^t}{x_1^t}) + 0.5\sum_{k=2}^{K}\sum_{l=2}^{K} \alpha_{kl} \ln(\frac{x_k^t}{x_1^t}) ln(x_l^t/x_1^t)$$
$$+0.5\sum_{k=2}^{K}\sum_{m=1}^{M} \delta_{km} \, ln(x_k^t/x_1^t)\ln y_m^t + \sum_{m=1}^{M} \beta_m \, lny_m^t$$
$$+0.5\sum_{m=1}^{M}\sum_{m=1}^{M} \beta_{mn} \, lny_m^t lny_n^t + \gamma_0 t \ +0.5\gamma_{00} t^2 \qquad (8)$$
$$+\sum_{k=2}^{K} \eta_k \ln\left(\frac{x_k^t}{x_1^t}\right) t + \sum_{m=1}^{M} \mu_m \, lny_m^t \mathrm{t} + v_{it} - u_{it}$$

Following Battese and Coelli [31], Pantzios et al. [25] model the temporal pattern of technical inefficiency as:

$$u_{it} = \beta(\mathrm{t}) u_i = (\exp[-\xi(t-T)]) u_i \qquad (9)$$

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where ξ is a parameter to be estimated, and $u_i \sim |N(\mu, \sigma_u^2)|$. If its estimated value is negative, technical efficiency tends to improve over time. If $\xi = 0$, then technical efficiency is time-invariant, this means technical efficiency makes no contribution to productivity change.

Following Balk [22] and Fuentes et al. [23], Pantzios et al. [25] illustrates how to use the parameter estimates of the input distance function along with the observed values of input and output to estimate the components of Malmquist productivity index. Specifically, under the translog input distance function specification, the technical efficiency change term, $TCM(y^t, x^t)$ can be expressed as:

$$TCM(y^t, x^t) = \exp\left[\gamma_0 + \gamma_{00}\left(t + \frac{1}{2}\right) + \sum_k^K \eta_k lnx_k^t + \sum_m^M \mu_m lny_m^t\right] \tag{10}$$

The output bias index $OB(y^t, x^{t+1}, y^{t+1})$ can be calculated as:

$$OB(y^t, x^{t+1}, y^{t+1}) = \exp[\sum_m^M \mu_m (lny_m^{t+1} - lny_m^t)] \tag{11}$$

Similarly, input bias index $IB(x^t, y^t, x^{t+1})$ can be given as:

$$IB(x^t, y^t, x^{t+1}) = \exp[\sum_k^M \eta_k (lnx_k^{t+1} - lnx_k^t)] \tag{12}$$

Therefore, the technical change component (2a) of the Malmquist productivity index in (1) can be computed as the product of expressions of (10), (11) and (12).

The technical efficiency change is calculated as the ratio of two successive distance function:

$$TEC_I = \frac{D_I^t(x^t, y^t)}{D_I^{t+1}(x^{t+1}, y^{t+1})} = \exp[lnD_I^t(x^t, y^t) - lnD_I^{t+1}(x^{t+1}, y^{t+1})] \tag{13}$$

Given the stochastic nature of (8), the predicted value of the input distance function is estimated as a conditional expectation:

$$D_I^{i,t}(x^{i,t}, y^{i,t}, t) = E\left[\exp(-u_{i,t})\,|u_{i,t} + v_{i,t}\right]$$

$$= \frac{1 - \Phi\left(\beta(t)\sigma_* - \frac{\mu_i}{\sigma_*}\right)}{1 - \Phi\left(-\frac{\mu_i}{\sigma_*}\right)} \exp(\beta(t)\mu_i + 0.5\beta(t)_{it}^2 \sigma_*^2)$$

where $\mu_i = \frac{(\sum \beta(t)\varepsilon_{it})\sigma_v^2}{(\sigma_v^2 + \sigma_u^2 \sum_t \beta(t)^2)}$, and $\sigma_*^2 = \frac{\sigma_v^2 \sigma_u^2}{(\sigma_v^2 + \sigma_u^2 \sum_t \beta(t)^2)}$.

The remaining two components, SEC^t and ME^t can be calculated using estimates of the input-oriented scale efficiency. For the translog input distance function, the scale efficiency of an input-output bundle $(\bar{x}, \bar{y})$ can be estimated as:

$$ISE^t(\bar{x}, \bar{y}) = exp\left[\frac{1}{2\beta}\left(\frac{1 - \varepsilon^t(\bar{x}, \bar{y})}{\varepsilon^t(\bar{x}, \bar{y})}\right)^2\right] \tag{14}$$

where $\beta = \sum_m^M \sum_n^M \beta_{mn}$, and $\varepsilon^t(\bar{x}, \bar{y}) = -\left(\sum_m^M \frac{\partial lnD_I^t(\bar{x}, \bar{y})}{\partial lny_m}\right)^{-1} = (\sum_m^M[\beta_m + \sum_k^K \delta_{km}\, lnx_k + \sum_n^M \beta_{mn}\, lny_n + \mu_m t])^{-1}$, which is the scale elasticity.

According to (2c) and (14), the scale efficiency change can be computed as:

$$SEC_I^t(x^t, y^t, y^{t+1}) = \exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon^t(x^t, y^{t+1})} - 1\right)^2 - \left(\frac{1}{\varepsilon^t(x^t, y^t)} - 1\right)^2\right]\right\} \tag{15}$$

Similarly, based on (2d) and (14), the input-mix effect can be calculated as:

$$ME_I^t(x^t, x^{t+1}, y^{t+1}) = \exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon^t(x^{t+1}, y^{t+1})} - 1\right)^2 - \left(\frac{1}{\varepsilon^t(x^t, y^{t+1})} - 1\right)^2\right]\right\} \tag{16}$$

After computing all parts of the Malmquist productivity index through (10) to (16), Pantzios et al. [25] propose formal procedure to test the statistical significance of various hypotheses on productivity changes. For example, If there is no technical change, then $TC = 1$. A sufficient condition for TC=1 is that the assembling parts, i.e. TCM, OB and IB, are equal to one simultaneously. That means the following parameter restrictions on (10), (11) and (12):

$$\hat{\gamma}_0 = \hat{\gamma}_{00} = \hat{\eta}_k = \hat{\mu}_m = 0 \quad \text{for all k and m} \tag{17}$$

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$$\hat{\mu}_m = 0 \qquad \text{for all m} \tag{18}$$

$$\hat{\eta}_k = 0 \qquad \text{for all k} \tag{19}$$

if the technical inefficiency is time-invariant, then TEC=1. Given (9), TEC=1 implies that $\xi = 0$. Lastly, if the production technology exhibits CRS, then SEC and ME should be equal to one. Pantzios et al. (2011) [25] have shown this implies the following parameter restrictions:

$$\sum_m^M \hat{\beta}_m = -1, \text{ and } \sum_m^M \hat{\delta}_{km} = \sum_m^M \hat{\beta}_{mm} = 0 \tag{20}$$

4. Empirical estimation and decomposition of the total factor energy efficiency in China's industrial sector

4.1 Variables and data

Based on the specification of (8), this section will estimate the total factor energy efficiency of China's industry using the input-output data at sectoral level, and further examine the sources of its growth via the decomposition approach. The standard industrial classification of China has been revised several times since 1994. Considering the availability and continuity of data, this paper selects 30 sub-industries[3] of China's industry as samples. The input-output data of these sub-industries from 2002 to 2014 is employed for the purposes above-mentioned.

The industrial gross value of above-scale enterprises by industry is used to measure the output. In order to remove the impact of inflation, the industrial gross value for each industry is deflated by the industrial producer price index (2002=100) of that industry. Input variables include labor, capital and energy. The number of employee of above-scale enterprises at the end of each year is used to measure the labor input. The total net fixed asset is used to measure the capital input. The net fixed assets is just a book value, it is unable to reflect the capital stock in production accurately. In order to do that, we use the fixed asset investment price index to adjust the net fixed asset. In China, National Bureau of Statistics classifies the overall price index of fixed asset investment into three categories, i.e. the price indices of construction and installment, purchase of equipment, tool and instrument, and others. We use those three price indices to construct the price index of fixed asset investment for each industry according to the following formula:

$$p_i(t) = w_{ic}(t)p_c(t) + w_{ie}(\mathrm{t})p_e(t) + w_{io}(t)p_o(t)$$

where $p_c(t)$, $p_e(t)$ and $p_o(t)$ denote the price indices of construction and installment, purchase of equipment, tool and instrument, and others, respectively; $w_{ic}(t)$, $w_{ie}(\mathrm{t})$ and $w_{io}(t)$ are the weights of those three price indices, calculated as the ratios of the investments in construction and installment, purchase of equipment, tool and instrument, and other expenses to the total fixed asset investment of each industry, respectively. After constructing the fixed asset investment price index for each industry, we adjust the net fixed asset of each industry with the constructed fixed asset investment price index according to the following formula:

$$K_i^t = K_i^{t_0} + \sum_{t_0+1}^{t} \Delta K_i^t / p_i^t$$

[3] The selected 30 sub-industries include: Coal mining and dressing, Petroleum and natural gas extraction, Ferrous metal mining and dressing, Nonferrous metal mining and dressing, Nonmetal minerals mining and dressing, Agricultural and sideline food processing, Food manufacturing, Beverage manufacturing, Tobacco processing, Textile industry, Timber processing, bamboo, cane, palm fibre and straw product, Furniture manufacturing, Paper making and paper product, Printing and record medium reproduction, Petroleum processing and coking, Raw chemical materials and chemical product, Medical and pharmaceutical product, Chemical fibre industry, Nonmetal minerals product, Smelting and pressing of ferrous metal, Smelting and pressing of nonferrous metal, Metal product, Universe equipment manufacturing, Special purpose equipment, Electric machinery and equipment, Communication and computer and other electronic equipment, Waste resources and materials recovery and processing, Production and supply of electricity and heating power, Production and supply of gas, Production and supply of water.

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where $K_i^{t_0}$ is the net fixed asset of industry i at the end of the year t_0, ΔK_i^t is the increase in the net fixed asset of industry i at the end of year t, which equals the difference between the net fixed asset of two years in succession, p_i^t is the price index of the fixed asset investment of industry i in the year t (2002=100). Finally, we use the amount of the primary energy consumption of each industry to measure its energy input in production. All data of input-output and energy consumption comes from relevant years' *China Industrial Statistics Yearbook* and *China Energy Statistics Yearbook*, the data of the industrial producer price index and the price index of fixed assets investment is from CEIC database. Table 1 presents the summary statistics for related input-output variables.

Table 1. Summary statistics of relevant input-output variables

Variable	Unit	Mean	S.D	Min	Max
Industrial gross output value, Y	billion yuan	1236.90	1630.5	3.21	1255.13
Labor, L	10 thousand	211.25	189.89	1.00	906.59
Fixed asset, K	billion Yuan	446.25	726.85	0.23	605.59
Energy input, E	10 thousand (tce)	7184.74	12573.7	33	69342.42

4.2 Empirical results

Having choosing the above-mentioned input-output variables, for the sake of clarity, we write out the following translog input distance function for China's industry:

$$\begin{aligned}\ln D(L,K,E,Y) = {} & \alpha_0 + \alpha_1 lnL + \alpha_2 lnK + \alpha_3 LnE + \frac{1}{2}\alpha_{11}(lnL)^2 + \alpha_{12} lnL * lnK + \alpha_{13} lnL \\ & * lnE + \frac{1}{2}\alpha_{22}(lnK)^2 + \alpha_{23} lnK * lnE + \frac{1}{2}\alpha_{33}(lnE)^2 + \delta_{11} lnL * lnY \\ & + \delta_{21} lnK * lnY + \delta_{31} lnE * lnY + \beta_1 lnY + \frac{1}{2}\beta_{11}(lnY)^2 + \gamma_0 t + \frac{1}{2}\gamma_{00} t^2 \\ & + \eta_1 lnL * t + \eta_2 lnK * t + \eta_3 lnE * t + \mu_1 lnY * t\end{aligned} \quad (21)$$

Since the input distance function is homogeneous of degree one in inputs, dividing the left-hand side and all input variables in the right-hand side of (21) by the quantity of energy input E gives to:

$$\begin{aligned}\ln\left(\frac{D(L,K,E,Y)}{E}\right) & \\ = {} & \alpha_0 + \alpha_1 \ln\left(\frac{L}{E}\right) + \alpha_2 \ln\left(\frac{K}{E}\right) + \frac{1}{2}\alpha_{11}\left(\ln\left(\frac{L}{E}\right)\right)^2 + \alpha_{12}\ln\left(\frac{L}{E}\right) * \ln\left(\frac{K}{E}\right) \\ & + \frac{1}{2}\alpha_{22}\left(\ln\left(\frac{K}{E}\right)\right)^2 + \delta_{11}\ln\left(\frac{L}{E}\right) * lnY + \delta_{21}\ln\left(\frac{K}{E}\right) * lnY + \beta_1 lnY \\ & + \frac{1}{2}\beta_{11}(lnY)^2 + \gamma_0 t + \frac{1}{2}\gamma_{00} t^2 + \eta_1 \ln\left(\frac{L}{E}\right) * t + \eta_2 \ln\left(\frac{K}{E}\right) * t + \mu_1 lnY * t\end{aligned} \quad (22)$$

Let unobservable input distance function value $\ln D(L,K,E,Y) = u_t$, $u_t \geq 0$, rearranging and adding the random error v_t to (22) leads to the following regression model:

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$$-\ln E = \alpha_0 + \alpha_1 \ln\left(\frac{L}{E}\right) + \alpha_2 \ln(\frac{K}{E}) + \frac{1}{2}\alpha_{11}\left(\ln\left(\frac{L}{E}\right)\right)^2 + \alpha_{12}\ln\left(\frac{L}{E}\right) * \ln\left(\frac{K}{E}\right) + \frac{1}{2}\alpha_{22}\left(\ln\left(\frac{K}{E}\right)\right)^2 + \delta_{11}\ln\left(\frac{L}{E}\right) * lnY + \delta_{21}\ln\left(\frac{K}{E}\right) * lnY + \beta_1 lnY + \frac{1}{2}\beta_{11}(lnY)^2 + \gamma_0 t + \frac{1}{2}\gamma_{00}t^2 + \eta_1 \ln\left(\frac{L}{E}\right) * t + \eta_2 \ln\left(\frac{K}{E}\right) * t + \mu_1 lnY * t + v_t - u_t \tag{23}$$

Next, we are applying the input-output data of China's 30 sub-industries to model (23) to measuring and decomposing the total factor energy efficiency in China's industry. Table 2 reports the maximum likelihood parameter estimates of model (23).

Table 2. The ML parameter estimates of model (23)

Parameter	Estimate	SE	Parameter	Estimate	SE
α_0	-1.8469	(0.5350) **	γ_0	-0.3459	(0.0241) ***
α_1	-2.6861	(0.1543) ***	γ_{00}	-0.0035	(0.0005) ***
α_2	1.7406	(0.1578) ***	η_1	-0.0454	(0.0047) ***
α_{11}	-0.0358	(0.0261)	η_2	0.0390	(0.0053) ***
α_{12}	0.1006	(0.0604) *	μ_1	0.0292	(0.0028) ***
α_{22}	-0.0077	(0.0433)	σ^2	0.7836	(0.0779) ***
δ_{11}	0.2782	(0.0174) ***	γ	0.9946	(0.0991) ***
δ_{21}	-0.2408	(0.0230) ***	μ	1.7656	(0.1468) ***
β_1	1.3131	(0.1246) ***	ξ	-0.0088	(0.0014) ***
β_{11}	-0.0072	(0.0085)	ln(θ)	402.63	

note：*, ** and *** denote the statistical significances at the level of 10%, 5% and 1% , respectively.

We notice that the estimated coefficients are statistically significant except the estimated coefficients for the terms of the squared ln(L/E), squared ln(K/E) and squared ln(Y). The estimated value of ξ is negative, and statistically significant at the 1% level, this provides evidence that the level of the energy efficiency in China's industry is improving over time, it can be confirmed by the results of the decomposition later. The estimated values for σ^2 and γ are significant statistically at the 1% level, in addition, the estimated value of parameter γ, the ratio of the inefficiency term variance σ_u^2 to the overall variance σ^2, is 0.99, which implies that almost all deviations from the input set frontier in China's industry can be attributed to the inefficiency.

Figure 3 displays the average score of the total factor energy efficiency for every sub-industries during the period 2002 to 2014. It shows that most sub-industries have a poor performance in energy efficiency. However, there is a significant variation among sub-industries. Some industries perform excellently in terms of energy efficiency, including waste resources and materials recovery and processing, production and supply of electricity and heating power with the energy efficiency scores averaged greater than 0.9. Instead, some others (for instance, coal mining and dressing, petroleum and natural gas extraction, ferrous metal mining and dressing, and production and supply of water) are underperforming with the energy efficiency scores between 0.4 and 0.6. What worth noticing is that the average energy efficiency score of the production and supply of electricity and heating power is high up to 0.98. Because of its large share of national capital and the nature of monopoly, the production and supply of electricity and heating power has been for a long time regarded as an inefficient sector. Actually, China's power sector has been devoted to improving energy efficiency and reducing emissions through innovation and new technology promotion in past decade. For instance, the widespread of ultra-supercritical pulverized coal and circulating fluidized bed boiler

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technologies has dramatically increased the efficiency of China's fleet of coal-fired power plants. The coal consumption for every kilowatt-hour has dropped to roughly 315 grams of coal in 2015 from around 370 grams in 2005, broadly having reached the average level of the developed countries. Our estimate of energy efficiency for that sector is consistent with this situation.

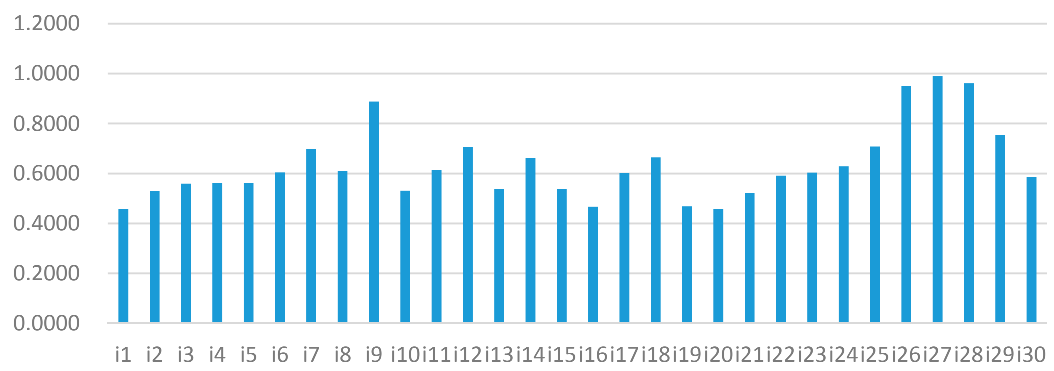

Figure 3 the average level of energy efficiency of different sub-industries

Note: the symbols i1 to i30 correspond to following sub-industries, respectively: (i1) coal mining and dressing; (i2) petroleum and natural gas extraction; (i3) ferrous metal mining and dressing; (i4) nonferrous metal mining and dressing; (i5) nonmetal minerals mining and dressing; (i6) agricultural and sideline food processing; (i7) food manufacturing; (i8) beverage manufacturing; (i9) tobacco processing; (i10) textile industry; (i11) timber processing, bamboo, cane, palm fibre and straw product; (i12) furniture manufacturing; (i13) paper making and paper product; (i14) printing and record medium reproduction; (i15) petroleum processing and coking; (i16) raw chemical materials and chemical product; (i17) medical and pharmaceutical product; (i18) chemical fibre industry; (i19) nonmetal minerals product; (i20) smelting and pressing of ferrous metal; (i21) smelting and pressing of nonferrous metal; (i22) metal product; (i23) universe equipment manufacturing; (i24) special purpose equipment; (i25) electric machinery and equipment; (i26) communication and computer and other electronic equipment; (i27) waste resources and materials recovery and processing; (i28) production and supply of electricity and heating power; (i29) production and supply of gas; (i30) production and supply of water.

Table 3 reports the Malmquist total factor energy efficiency index (MTFEEI) and the sources of its growth in China's industry. According to these estimates, the Malmquist total factor energy efficiency index grows at an annually averaged rate of 3.36% from 2002 to 2014, which indicates during this period the energy efficiency of China's industry has been increasing. In terms of the sources of TFP growth, technical change (TC) and technical efficiency change (TEC) make positive contributions to the growth of the total factor energy efficiency. Albeit the growth rate of technical change is negative at the beginning, but the yearly averaged rate of growth of TC is as high as 2.49% during the period 2002 to 2014. Meanwhile, the average annual growth rate of technical efficiency is 1.31%. These figures illustrate that the technical change and technical efficiency's increase have played crucial role in improving energy efficiency. On the other hand, scale efficiency change is found to be a negative force, the scale efficiency associated with output in two successive years is declining at an annually averaged rate of 4.22%. This implies that China's industry is moving away the technically optimal scale in terms of output. The input-mix effect (ME) is the most important source of total factor energy efficiency growth during the period examined. The average value of the input-mix effect indicates the scale efficiency associated with the input combinations used in two successive years increases at an annual rate of 3.95%. However, the input-mix effect is not strong enough to offset the negative effect of the scale efficiency changes on total factor energy efficiency. Hence, the overall scale effect, that is, the combined effect of radial scale efficiency changes and scale efficiency changes associated with temporal changes in the input mix decreases the total factor energy efficiency by 0.27%.

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Table 3. Malmquist energy efficiency index and its decomposition

	TC	TEC	SEC	ME	TFP
2002-2003	0.9917	1.0135	0.9515	1.0519	1.0059
2003-2004	1.0107	1.0134	0.9455	1.0630	1.0295
2004-2005	1.0198	1.0132	0.9627	1.0284	1.0230
2005-2006	1.0124	1.0142	0.9780	1.0411	1.0453
2006-2007	1.0263	1.0131	0.9642	1.0255	1.0281
2007-2008	1.0384	1.0129	0.9513	1.0206	1.0212
2008-2009	1.0202	1.0128	0.9611	1.0415	1.0342
2009-2010	1.0306	1.0125	0.9506	1.0323	1.0239
2010-2011	1.0309	1.0137	0.9617	1.0590	1.0643
2011-2012	1.0368	1.0126	0.9559	1.0440	1.0477
2012-2013	1.0380	1.0125	0.9642	1.0247	1.0383
2013-2014	1.0426	1.0124	0.9469	1.0427	1.0421
Mean	1.0249	1.0131	0.9578	1.0395	1.0336
Annual growth rate (%)	2.49	1.31	-4.22	3.95	3.36

Three hypotheses relating to model specification are examined using LR test. Table 4 reports the results. First, if the technical inefficiency is not present in sample data, then $\gamma = \mu = \xi = 0$. The null hypothesis that $\gamma = \mu = \xi = 0$ is rejected at the 1% level of significance, indicating that the technical inefficiency is present in the data. This finding is consistent with the statistical significance of the γ-parameter in Table 2. Next, if technical efficiency is time-invariant, then $\xi=0$. The null hypothesis that $\xi=0$ is rejected at the 1% level of statistical significance, which illustrating the technical inefficiency is time-variant. In fact, as shown in Table 3, the technical efficiency has been increasing over time. Finally, the hypothesis that there is no technical change, i.e. TC=1 is also rejected at the 1% level of significance, this means that the technical change is present. This finding is also depicted by the statistically significant, negative estimates of parameters γ_0 and γ_{00} in Table 2.

Table 4. hypothesis tests

Hypothesis	LR-test	Critical value
No technical inefficiency	27.6	$\chi^2_{0.99}(4)$ =13.27
No technical change effect	31.2	$\chi^2_{0.99}(6)$ =16.81
Time-invariant technical inefficiency	9.92	$\chi^2_{0.99}(1)$ =6.64

5. Conclusions

Based on the input-oriented distance function framework, this paper estimates and decomposes the total factor energy efficiency of China's industry using parametric techniques. The results show that the total factor energy efficiency has been increasing at an annually averaged rate of 3.36% during the period 2002-2014. The technical change, technical efficiency change and input-mix effect are key sources of the total factor energy efficiency, the yearly averaged growth rates of these three factors are 2.49%, 1.31% and 3.95%, respectively. That is, the input-mix effect, measuring the scale efficiency associated with input mix, is the largest contributor to the energy efficiency improvement. Our results also indicate the scale efficiency change associated with output exerts a negative impact on the growth of energy efficiency, its annual growth rate averages of -4.22%. The overall scale effect, i.e. the combined effect of the scale efficiency change and input-mix effect on energy efficiency is -0.27%, this implies the overall scale efficiency of China's industry is deteriorating during the period examined.

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Since scale efficiency is the main factor refraining the total factor energy efficiency from increasing, China should put more attention to improving the scale efficiency of China's industry. Currently China is facing serious overcapacity problem, which is rooted in the intrinsic motivations of both enterprises and governments to expand investment and production. To promote local economy and tax revenues, the governments at all levels are willing to provide a variety of preferential policies for enterprises' investment, on the other hand, enterprises have incentives to expand investment and capacity in order to enjoy governments' favorable conditions in land use, bank credit and tax deductions etc. As a result, many enterprises blindly expand the scale of production, and their production capacity far exceeds the market demand for their products. The overcapacity means that many productive resources do not contribute to the increase in society's welfare. This necessarily leads to the deterioration in scale efficiency.

The key to improve the scale efficiency lies in getting rid of the intrinsic motivation of enterprises and governments to expand blindly investment and output. Enterprise should make their investment and production decisions based on the price signals. Therefore, it is necessary to get the prices right in order to let price mechanism allocate resources. China have to further push the market-oriented reform in some crucial areas, such as interest rates and electricity price, and establish an effective tax and fees system for the environment and resources to reflect the social costs of environmental resources utilization. This can help to curb the blind investment and excessive expansion, and improve the scale efficiency of the enterprises.

China's industry also needs to accelerate the pace of technological progress and technical efficiency change. Despite both the technical change and technical efficiency change are growing during the period examined, but at a relatively low rate. The historical experience suggests China has to promote indigenous innovations through increasing R&D investment and establishing an effective mechanism, while learning and imitating the advanced foreign technologies. In addition, China should continue to transform and upgrade its traditional manufacturing through modern information technologies and other best applicable technologies. This will help China use its huge potentials of energy conservation.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "X.X. and Y.Y. conceived and designed the experiments; X.X. performed the experiments; X.X. and Y.Y. analyzed the data; W.W. contributed reagents/materials/analysis tools; Y.Y. wrote the paper." Authorship must be limited to those who have contributed substantially to the work reported.

Conflicts of Interest: The authors declare no conflict of interest.

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