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ORIGINAL PAPER

The total-factor energy productivity growth of China's construction industry: evidence from the regional level

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Abstract This study uses the total-factor energy productivity change index (TFEPCH) to investigate the changes in energy productivity of construction industry for 30 provincial regions in China from 2006 to 2015, adopting the improved Luenberger productivity index combined with the directional distance function. In addition to traditional economic output indicator, this study introduces building floor space under construction as a physical output indicator for energy productivity evaluation. The TFEPCH was decomposed into energy technical efficiency change and energy technical progress shift. Results indicate that, first, energy productivity of China's construction industry decreased by 7.1% annually during 2006–2015. Energy technical regress, rather than energy technical efficiency, contributed most to the overall decline in energy productivity of China's construction industry. Second, energy productivity in the central region of China decreased dramatically, by a cumulative sum of approximately 77.1%, since 2006, while energy productivity in the eastern and western regions decreased by over 54.3 and 65.3%, respectively. Only two of the 30 provinces considered—Hebei and Shandong—improved their energy productivity during 2006–2015. The findings presented here provide a basis for decision-making and references for administrative departments to set differentiated energy efficiency goals and develop relevant measures. Additionally, the findings are highly significant for energy and resource allocation of Chinese construction industry in different regions.

Keywords China · Total-factor energy productivity · Construction industry · Energy technical efficiency change · Energy technical change

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1 Introduction

Energy use is the main driver of carbon emission and leads to environmental problems (Zhang and Wang 2017). With the increase in energy consumption, China's CO_2 emission is largest on earth (BP 2017). However, energy efficiency in China remains low relative to that of developed countries, resulted from the restrictions from China's economic development mode these years (Zhang et al. 2017a). The continued increase in energy intensity, accompanied by environmental problems, has created a bottleneck, restricting China's social progress and economic development. Thus, China's energy efficiency issue requires much attention.

The construction industry has become China's pillar industry. China is carrying out urban–rural construction on the largest scale in the world as a result of rapid urbanization, with an average annual construction area of more than 10 billion square meters (m^2) since 2010 (Liang et al. 2014, 2016). In 2015, construction industry added value took up 6.86% of GDP, with an increase of 6.9% over 2014; construction enterprises' profits achieved 650.8 billion yuan, with a growth of 1.57% over the previous year (NBSC 2016). At the same time, the construction industry accounts for the largest share of energy use among Chinese industries. The total energy demand by the construction industry increased 8.9% annually on the average from 2005 to 2014 (NBSC 2016). Moreover, the proportion of building-related energy consumption in national total energy consumption is up to 46% (Cai 2011; Zhao et al. 2017): upstream links to the construction industry include sectors with high volume of energy demand (e.g., the iron and steel sector and cement sector); downstream links to the construction industry include the building sector, the highest energy consumption sector among end-users in addition to industrial and transport sectors. Therefore, improving energy and resource utilization efficiency in construction industry is critical for China to achieve its carbon emissions goals. In this context, the Chinese government has sought to promote green building and industrialized building to reduce energy consumption at the construction stage (Zhao et al. 2016; Liu et al. 2017). The "thirteenth five-year plan (FYP)," released by the Ministry of Housing and Rural–urban Development (MOHURD), emphasizes on improving energy utilization efficiency and optimizing energy structures to effectively curb the increase of building energy use. As for Chinese construction industry, whether these energy policies will in fact improve its regional energy efficiency remains unknown. An effective way to assess energy utilization efficiency in regional construction industry is lacking, limiting the government's ability to evaluate local authorities and set differentiated energy-saving goals. Hence, examining energy utilization efficiency level in Chinese construction industry is imperative, and this can provide guidance for the government in setting differentiated energy-saving goals.

Many scholars used to assess the efficiency level related to energy and environment by data envelopment analysis (DEA) method. Measurement methods they used for energy efficiency evaluation are broadly categorized into two groups: the single-factor energy efficiency (SFEE) approach (e.g., energy intensity indicator) and the total-factor energy efficiency (TFEE) approach. However, energy efficiency values obtained in such studies do not reflect the "separate contribution" of energy as an input in total-factor productivity. The calculated energy efficiency therefore does not correspond to the actual total-factor energy productivity (TFEP) (i.e., dynamic energy efficiency). In measuring and evaluating energy efficiency, previous studies have not considered physical output indicators, which play a role equivalent to that of economic indicators, especially in the construction industry. To date, dynamic energy efficiency in the construction industry has not been researched.

This study seeks to bridge the knowledge gap by offering three main contributions. First, we utilize “physical output”, i.e., floor space under construction by construction enterprises, as an output indicator to establish a set of uniform and rational input and output indicators. Second, we introduce the TFEP change index (TFEPCH), which is the integration of TFEE index and Luenberger productivity index (LPI), to measure changes in TFEP. Third, we measure the “real TFEP” of construction industry in Chinese 30 provinces between 2006 and 2015, adopting improved LPI combined with the directional distance function (DDF).

The rest parts of this study are: the second part is the review on pervious literatures The third part shows method and data used in this paper. The following part is results and discussion. Finally, conclusions and recommendations for policy makers and administrative departments are proposed.

2 Literature review

Selecting an appropriate energy efficiency measurement method is key to the accurate measurement of energy efficiency. Two measurement methods are commonly employed in the existing literature: the single-factor measurement method and the total-factor measurement method (Wu et al. 2017; Zhang et al. 2017b, 2018; Zhu et al. 2018). Single-factor energy efficiency (also called partial factor energy efficiency) is used to measure energy consumed in the production of economic output. The two most commonly used indicators under the single-factor approach are “energy intensity.” Energy intensity represents the energy used when generating each unit of economic output and energy productivity is the energy consumed by a unit of economic output (Patterson 1996; Han et al. 2007; Nel and van Zyl 2010; Hu et al. 2017; Zhu et al. 2018). It is simple and convenient to use the single-factor energy efficiency (SFEE) approach when comparing energy efficiencies of different countries and regions at specific times or over a selected period. It has therefore been widely adopted by many scholars (Liu and Ang 2003; Han et al. 2007; Shi 2007; Liang et al. 2016; Cao et al. 2017) in recent decades. This approach, however, has significant limitations. First, it views energy as the sole input and ignores relationships between energy and other productive factors. It disregards the elasticity of energy and other productive factors, measuring energy efficiency from different angles such as energy macro efficiency, energy efficiency, and physical efficiency. When other factors, such as labor and capital, are taken into account, energy use cannot be adequately evaluated by examining only SFEE or energy productivity. The energy efficiency index may, for example, increase solely because labor has been substituted for energy rather than due to the increase in the technical energy efficiency (Patterson 1996; Zhang et al. 2018; Zhu et al. 2018).

To eliminate these defects, Hu and Wang first presented the TFEE concept (Hu and Wang 2006). The percentage of target energy input (TEI) on actual energy input (AEI) for a given level of output was defined as TFEE in their study. Employing a data envelopment analysis (DEA) model, they measured TFEE of China’s provinces between 1995 and 2002. Their results showed that SFEE indicator that pervious scholar always used overestimates the contribution of energy owing to the significant substitution effects among those inputs. Following this study, Wei and Shen (2007) provided a vertical comparison and analysis of TFEE of Chinese provinces, using provincial data from 1995 to 2004 (Wei and Shen 2007). Hu and Kao (2007) studied energy-saving among APEC countries by adopting

TFEE method. Following their studies, Zhou and Ang (2008) measured economy-wide energy efficiency performance, using linear programming models. Wang and Wei (2014) studied regional energy efficiency in industrial sector aiming to 30 urban areas in China during 2006–2010. Adopting network DEA, Liu and Wang investigated the efficiency level of energy in Chinese industrial sector (Liu and Wang 2015). Using the World Input–Output Database, Foster-McGregor and Verspagen calculated total-factor productivity (TFP) growth in 40 economies during 1995–2009 and found that the TFP growth in Asian economies has been relatively strong (Foster-Mcgregor and Verspagen 2017). Zhang et al. (2018) used the CDM project evidence and measured the technology gap with DEA.

Within the total-factor framework, two main methods are used to evaluate energy efficiency: one is stochastic frontier analysis (SFA) approach (Liu et al. 2016), and another one is DEA method that is a nonparametric method (Charnes et al. 1981). When evaluating energy efficiency, people need to consider artificial parameters are required in SFA approach, while the assumed functions are not needed in DEA approach (Zhang and Bin 2013; Fernández et al. 2018). The DEA method can overcome the impact on evaluation results due to subjective factors in the SFA method, and therefore the estimation accuracy can be improved. Therefore, DEA is widely popular as a method of evaluating energy efficiency (Zhang and Wei 2015; Qin et al. 2017; Zhang et al. 2018). When comparing the results obtained with DEA methods, the energy utilization efficiency differences can be found between those DMUs. However, efficiency values obtained using DEA software actually pertain to overall technical efficiency, not the real "energy efficiency." Moreover, DEA is a static evaluation method, so evaluations based on it can provide only relative levels of energy efficiency across DMUs but cannot show increases or decreases in energy efficiency between periods. Hence, effective practical recommendations and guidance cannot be proposed based on such methods (Wu et al. 2017; Fernández et al. 2018).

To address the incomparability of energy efficiency levels in different years, Chang and Hu introduced a dynamic method used to measure changes in TFEP at the country level (Chang and Hu 2010). Other scholars have also employed a dynamic method to evaluate changes in energy efficiency (Wang 2011; Yang et al. 2013; Zhang et al. 2014; Fujii et al. 2016; Liang et al. 2016; Fernández et al. 2018; Li and Lin 2018). The energy utilization level of Chinese iron and steel industry and energy consumption in Turkey were measured, respectively, but authors only considered energy-related input indicators, disregarding other input indicators, such as labor and capital (Wei and Shen 2007; Du and Lin 2017). If the adopted methods were used under the TFEE framework, the efficiency measure obtained would be total-factor productivity, not total-factor energy productivity (TFEP). Yang et al. (2013) constructed a total-factor productivity (TFP) index to evaluate changes in TFP in 30 provinces in China during 2006–2015. However, the results that they obtained actually pertained to TFP.

In summary, the main drawbacks of the current literature are as follows: (1) the results obtained do not pertain to actual TFEP. These studies merely took energy as one kind of input among others in the DEA-Malmquist index within the traditional total-factor framework and measured the ability of DMUs to maximize output. They did not differentiate energy from other productive factors, such as labor and capital. Thus, the measures of energy efficiency they obtained could not reveal the "characteristics" of energy, and their results actually pertain to total-factor productivity with three inputs—labor, capital and energy—or, more precisely, total-factor productivity considering energy element input. Such an error leads to an overestimation of energy productivity. (2) These studies mainly considered three key inputs (i.e., labor force, capital, and energy) and only one economic output (e.g., industry value-added or GDP, etc.). None of this research considered physical output, which is just as important as economic output, especially in the construction industry. This is because energy consumption per unit of GDP and energy consumption per unit of floor space are, respectively, macro- and micro-energy intensity indictors that play equivalent roles in evaluating output in construction industry. Failure to consider this output indicator will lead biased measurements of energy efficiency. (3) None of this research focused on dynamic energy efficiency in construction industry. Xue et al. (2015) attempted to study changes in energy utilization efficiency regarding construction industry, but they included merely two energy-related indicators (coal consumption and electricity consumption). They maintained that all regional differences in output in the construction industry were due to differences in energy inputs, ignoring the impact of other inputs on output. As a result, they also failed to obtain the measurement of "total-factor energy productivity."

With this in mind, this study seeks to bridge the gaps by pursuing three main objectives. Specifically, (1) we utilize the "physical output"—floor space under construction—as an output indicator, additional to economic output, and establish a set of uniform and rational input and output indicators. Constructed buildings are the special "product" of the construction industry, and therefore, building floor space plays a role equivalent to that of economic output, one ignored in all other studies. Including floor space as an output can improve the accuracy of measurements of energy productivity in Chinese construction industry. (2) We introduce the TFEPCH index, the integration of TFEE index and LPI, to measure the changes in TFEP of construction industry. This can extend previous related studies, which often focus on other industries, and provide the government with an effective way of assessing energy utilization in the construction industry and encouraging the construction industry in particular regions to reduce energy consumption. (3) We adopt an improved LPI—combined with the DDF—to measure construction industry TFEP rather than TFP, as in most previous literature. This approach captures the "separate contribution" and "dynamic characteristics" of energy within the TFEE framework, which represents actual total-factor energy productivity. Through this approach, evidence needed by the government to set differentiated energy-saving goals can be obtained.

3 Data and methods

3.1 Data description

Determining appropriate input and output indicators and accurately measuring them is vital for measuring energy utilization efficiency in construction industry and calculating the inputs needed to achieve a given energy target. With increasing focus on energy, an economic growth model based on capital, labor and energy has been widely adopted by scholars. Based on previous literatures and the characteristics of Chinese construction industry, we selected suitable indicators regarding input and output. In Table 1, we show the specific description of these indicators.

Table 1 The introduction of indicators regarding input and output

	Variable description	Data source
Input indictor		
Labor force	The number of persons employed in construction at the end of each calendar year denotes the labor input	*China Statistical Yearbook* (NBSC 2016)
Capital	Total assets of construction enterprises represent capital investment in the construction industry, measured in constant prices as a portion of GDP during 2006–2015 (using 2005 as the base year)	*China Statistical Yearbook* (NBSC 2016)
Technical input	Total capacity of machinery and equipment owned (year-end) is represented the technical input	*China Statistical Yearbook* (NBSC 2016)
Energy input	The physical quantity of each kind of energy in each province is converted into SCE, according to the conversion coefficient for each energy type, with the different quantities at the national level, respectively, and then aggregate them together	*China Energy Statistical Yearbook* (NBSC 2016)
Output indicator		
Economic output	Gross output value in construction industry in each province is used as the economic output indicator, measured in constant prices as a portion of GDP during the investigated period, 2006–2015 (using 2005 as the base year)	*China Statistical Yearbook* (NBSC 2016)
Physical output	The floor space of buildings under construction by construction enterprises in each region is the physical output indictor	*China Statistical Yearbook* (NBSC 2016)

3.2 Methods

3.2.1 Luenberger productivity index (LPI)

Chambers et al. (1998) proposed the LPI, and this index is now widely adopted to estimate changes of total-factor productivity of DMUs (i.e., 30 provinces in China) between different time periods. The LPI was more applicable than Malmquist productivity index in some scholars' view because of the flexible characteristics of the DDF (Wang and Wei 2016). The LPI can be used to measure changes in TFP because it is actually a multiple factor productivity index (Chang and Hu 2010).

We first define P^t as the production technology of construction industry. We assume that during each period $t(2006{-}2007, 2007{-}2008, 2014{-}2015)$, there are many inputs which are represented as $x^t \in R_+^M$ and can produce many outputs, represented as $y^t \in R_+^S$. Then the production technology, P^t, can be represented as

$$P^t = \{(x^t, y^t) : x^t \text{ can produce } y^t\}. \tag{1}$$

In this study, inputs include the number of person employed in construction, the total assets of construction enterprises, the total capacity of machinery and equipment owned and energy consumption in the construction industry. Outputs are represented by gross output value in the construction industry and building floor space. The calculation of the LPI depends on DDFs (Chambers et al. 1998). The DDF at time t can be represented as:

$$\overrightarrow{F}_t(x^t, y^t; h_x, h_y) = \max\{\beta \in R : (x^t - \beta h_x, y^t + \beta h_y) \in P^t\}. \tag{2}$$

In this equation (h_x, h_y) represented as a nonzero vector in $R_+^M \times R_+^S$. Therefore, when contracting inputs in this function, outputs can be increased at the same time. Given the above definition, only if the point (x^t, y^t) was on the production frontier, $\vec{F}_t(x^t, y^t; h_x, h_y) \geq 0$ and $\vec{F}_t(x^t, y^t; h_x, h_y) = 0$. Thus, the LPI can be represented as follows:

$$L(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{1}{2}\left[(\vec{F}_t(x^t, y^t) - \vec{F}_t(x^{t+1}, y^{t+1})) + (\vec{F}_{t+1}(x^t, y^t) - \vec{F}_{t+1}(x^{t+1}, y^{t+1}))\right]. \tag{3}$$

If the LPI exceeds zero, productivity will increase. If LPI equal to zero, the productivity will remain unchanged. If LPI is less than zero, the productivity will decrease during the time period t to $t+1$.

3.2.2 *The generalized DDF*

The input decreases and output expansions can be measured by DDF in efficiency evaluation, but exact input or output slacks cannot be obtained through this function (Chambers et al. 1998). To address this problem, a generalized DDF combining with a linear programming method was proposed by Färe and Grosskopf. So, the input or output slack adjustments can be acquired when calculating the efficiency (Färe and Grosskopf 2010; Zhang and Chen 2017). We made the following assumptions: in terms of one object in N objects during one period T, there are M inputs and S outputs. x_{ij}^t represents the ith input of the jth object; y_{rj}^t denotes the rth output variable at time t. Therefore, regarding observation o at time t, the input-based DDF functions can be represented as the linear programming problem (Färe and Grosskopf 2010) shown as follows:

$$\vec{F}_t(x^t, y^t) = \max \sum_{i=1}^{M} \varphi_i$$
$$\begin{cases} \text{s.t.} \sum_{j=1}^{N} \lambda_i x_{ij}^t \leq x_{io}^t (1 - \varphi_i) \\ \sum_{j=1}^{N} \lambda_i x_{rj}^t \leq y_{ro}^t \\ i = 1, \ldots, M; \quad j = 1, \ldots, M; \\ \lambda_i \geq 0, \varphi_i \geq 0 \quad r = 1, \ldots, S \end{cases} \tag{4}$$

where λ_i represents the intensity variable. The convex combination of inputs and outputs can be formed by this intensity variable. φ_i represents the contracting amount of the ith input needed to achieve efficiency. Thus, if all redundant variables are zero, then $\varphi_1 = \varphi_2 = \cdots, = \varphi_M = 0$, and DMU o is in the frontier of the production. Obviously, the true slacks are on the basis of the assumption that the returns will keep constant to scale. This illustrates that inputs and outputs efficiency level needed to aggregate technical efficiency.

3.2.3 *The TFEPCH*

The LPI cannot be used to analyze the change in productivity from a separate factor, such as energy, labor or capital, within the total-factor framework (Chang and Hu 2010). This study attempts to use an improved LPI and the TFEPCH index to measure TFEP of Chinese construction industry. The TFEPCH index is in fact a combination of the generalized DDF and TFEE index. Energy efficiency, as defined within the TFEE framework, will be substituted for all the corresponding components in the LPI. In this case, the change in productivity resulted from individual input factors within the TFEE framework can be calculated simultaneously when computing TFP. This paper's purpose is to explore changes in productivity brought about by the "energy element" in the construction industry during the 2006–2015 period within the TFEE framework. The improved LPI satisfies the requirements of the construction industry in this study.

According to the definition (Hu and Wang 2006), TFEE is the percentage of the TEI in the AEI in construction industry, and we know that energy inputs must reduce the total adjustment needed to achieve optimal energy input. If the energy efficiency of one province is inefficient, the energy input need to be adjusted according to the inefficient portion of the energy actually consumed in each province. The redundant energy input and the inefficient portion of output can be obtained according to Eq. (4), and TFEE of DMU i (the given province) at time t is represented as:

$$\mathrm{TFEE}_{(i,t)} = \frac{\mathrm{PE}_{(i,t)}}{\mathrm{AE}_{(i,t)}} = \frac{\mathrm{AE}_{(i,t)} - \mathrm{TE}_{(i,t)}}{\mathrm{AE}_{(i,t)}} \tag{5}$$

where $\mathrm{PE}_{(i,t)}$ represents the target energy input of province i, $\mathrm{AE}_{(i,t)}$ represents the actual energy input of province i, and $\mathrm{TE}_{(i,t)}$ is the total adjustments in the energy input of the construction industry in province i.

We use $\vec{F}_{E_t}(x^t, y^t)$ to represent the distance from provinces at the production frontier (i.e., the optimal energy input) for energy use at time $t(t = 2006, 2007, 2015)$. From Eq. (3), we can see that $\vec{F}_t(x^t, y^t)$ and $\vec{F}_{t+1}(x^{t+1}, y^{t+1})$ actually measure distance within the same time periods, t and $t+1$, while $\vec{F}_t(x^{t+1}, y^{t+1})$ and $\vec{F}_{t+1}(x^t, y^t)$ measure distance in the intertemporal comparison between AEI and TEI during the period from t to $t+1$. Therefore, the percentage of the TEI in the AEI can replace the corresponding components in the input-oriented distance functions, which are shown in the following equation:

$$\mathrm{TFEE}_{(t,t)} = \frac{\mathrm{PE}_t}{\mathrm{AE}_t} = 1 - \overrightarrow{F_{E_t}}(x^t, y^t). \tag{6}$$

We can obtain $\mathrm{TFEE}_{(t+1,t+1)} = \frac{\mathrm{PE}_{t+1}}{\mathrm{AE}_{t+1}} = 1 - \vec{F}_{E_{t+1}}(x^{t+1}, y^{t+1})$, according to formula (6). $\mathrm{TFEE}_{(t,t+1)}$ and $\mathrm{TFEE}_{(t+1,t)}$ can also be obtained. Therefore,

$$\begin{aligned}\mathrm{TFEPCH} = {} & \left[\mathrm{TFEE}_{(t+1,t+1)} - \mathrm{TFEE}_{(t,t)}\right] + \frac{1}{2}\left[\left(\mathrm{TFEE}_{(t+1,t)} - \mathrm{TFEE}_{(t+1,t+1)}\right)\right. \\ & \left. + \left(\mathrm{TFEE}_{(t,t)} - \mathrm{TFEE}_{(t,t+1)}\right)\right] \\ = {} & \frac{1}{2}\left[\left(\mathrm{TFEE}_{(t+1,t+1)} - \mathrm{TFEE}_{(t,t)}\right) + \left(\mathrm{TFEE}_{(t+1,t)} - \mathrm{TFEE}_{(t,t+1)}\right)\right].\end{aligned} \tag{7}$$

The TFEP the construction industry in each province depends on the comparison of the value of TFEPCH and zero. If the TFEPCH is greater than zero, this means the TFEP improves. Similarly, if the TFEPCH is equal to or less than zero, this means TFEP remains unchanged or decreases from the period t to $t + 1$. The linear programming in formula (4) is used to calculate the components in formula (7).

From Eq. (7), we know that the TFEPCH index is an aggregate index equal to average value of TFEP in construction industry. However, if we rely exclusively on this index, we cannot identify the driving force behind the changes in energy productivity. Therefore, it is necessary to more specifically decompose TFEPCH. The TFEPCH can be broken down into two parts: energy technical efficiency change (EFFCH) and energy technical progress shift (ETECHCH) (Wang and Wei 2016). The EFFCH is used to measure changes in relative energy efficiency, while the ETECHCH is utilized to measure shifts in the frontier. The formulas for EFFCH and ETECHCH are as follows:

$$\mathrm{EFFCH} = \mathrm{TFEE}_{(t+1,t+1)} - \mathrm{TFEE}_{(t,t)} \tag{8}$$

$$\mathrm{ETECHCH} = \frac{1}{2}\left[\left(\mathrm{TFEE}_{(t+1,t)} - \mathrm{TFEE}_{(t+1,t+1)}\right) + \left(\mathrm{TFEE}_{(t,t)} - \mathrm{TFEE}_{(t,t+1)}\right)\right]. \qquad (9))$$

4 Results and discussion

4.1 Measurement results

The DEA measurement software—MaxDEA5—is adopted to measure the total adjustment and projection of energy consumption, based on formula (4). Then, the TFEE index in the construction industry in each province in China can be obtained using formula (5). The TFEPCH index can be obtained according to formulas (6) and (7). The calculated results are shown as follows.

4.1.1 Changes in TFEP of China's construction industry

Table 2 lists the TFEPCH values for Chinese construction industry by provincial region in China from 2006 to 2015.

Figures 1 and 2 show TFEPCH in the construction industry of three major regions (the eastern, central and western region) during each period and cumulative energy productivity changes in the three regions in each year.

4.1.2 The components of changes in TFEP in China's construction industry

The TFEPCH index can be broken down to its two primary components—the EFFCH and the ETECHCH, using Eqs. (8) and (9)). Energy technical efficiency change is actually the change in the relative efficiency of energy input in each region, as shown in Table 3. The ETECHCH indicates the technology changes in energy utilization during one period, showing movements of the production frontier within the total-factor framework. Table 4 shows the ETECHCH in the construction industry in China by region during 2006–2015.

The change in the average EFFCH and the average energy technical change in three major regions and at the national level are shown in Figs. 3 and 4.

4.2 Analysis and discussion

To address the geographical disparity and challenges, to conduct regional analysis is critical. In the light of the rules of economic development and geographical division,

Table 2 TFEPCH for Chinese construction industry by provincial region from 2006 to 2015

Province	06–07	07–08	08–09	09–10	10–11	11–12	12–13	13–14	14–15	Average	Cumulative
BJ	− 0.042	− 0.070	− 0.240	− 0.101	0.043	0.055	0.157	0.021	0.047	− 0.014	− 0.130
TJ	− 0.158	− 0.687	− 0.126	− 0.120	− 0.093	− 0.048	− 0.011	− 0.014	− 0.066	− 0.147	− 1.323
HB	− 0.021	− 0.028	− 0.030	− 0.105	− 0.084	− 0.022	0.444	0.050	− 0.145	0.007	0.059
SX	− 0.008	− 0.098	− 0.122	− 0.060	− 0.074	− 0.033	− 0.037	0.079	− 0.036	− 0.043	− 0.389
IM	− 0.027	− 0.093	− 0.041	− 0.146	− 0.025	− 0.012	0.000	0.002	0.046	− 0.033	− 0.296
LN	− 0.109	− 0.037	− 0.098	− 0.127	− 0.118	− 0.100	− 0.380	− 0.023	0.025	− 0.108	− 0.968
JL	− 0.011	0.562	− 0.100	− 0.154	− 0.080	− 0.077	− 0.298	0.009	− 0.039	− 0.021	− 0.189
HLJ	0.022	− 0.053	− 0.200	− 0.327	− 0.347	− 0.095	− 0.093	− 0.034	− 0.021	− 0.128	− 1.149
SH	− 0.032	− 0.048	− 0.659	0.553	0.016	− 0.007	− 0.002	0.029	− 0.056	− 0.023	− 0.206
JS	− 0.058	− 0.005	− 0.058	− 0.097	− 0.131	− 0.112	− 0.111	− 0.046	0.093	− 0.058	− 0.526
ZJ	− 0.073	− 0.077	− 0.109	− 0.169	− 0.078	− 0.008	− 0.117	− 0.029	− 0.014	− 0.075	− 0.673
AH	− 0.068	− 0.105	− 0.040	− 0.133	− 0.139	− 0.095	− 0.161	− 0.033	− 0.049	− 0.092	− 0.824
FJ	− 0.062	− 0.373	− 0.024	− 0.062	− 0.072	− 0.071	− 0.049	− 0.042	− 0.007	− 0.085	− 0.762
JX	− 0.041	− 0.153	− 0.172	− 0.155	− 0.201	− 0.079	− 0.159	− 0.050	− 0.170	− 0.131	− 1.180
SD	− 0.006	0.002	− 0.045	− 0.008	− 0.029	0.051	0.322	− 0.030	0.020	0.031	0.276
HN	− 0.025	0.001	− 0.240	− 0.315	− 0.152	− 0.081	− 0.045	− 0.147	− 0.201	− 0.134	− 1.205
Hb	− 0.050	0.002	− 0.142	− 0.253	− 0.060	0.008	− 0.066	− 0.041	− 0.026	− 0.070	− 0.627
Hn	− 0.024	− 0.095	− 0.048	− 0.209	0.237	− 0.598	0.311	− 0.108	− 0.070	− 0.067	− 0.604
GD	− 0.057	− 0.007	− 0.011	− 0.522	− 0.016	− 0.023	0.013	− 0.025	0.000	− 0.072	− 0.647
GX	0.033	0.297	− 0.138	− 0.016	− 0.165	− 0.015	− 0.033	− 0.096	− 0.150	− 0.032	− 0.284
HAI	− 0.104	0.011	− 0.271	− 0.242	− 0.165	− 0.135	− 0.149	− 0.189	− 0.093	− 0.149	− 1.337
CQ	− 0.055	− 0.140	0.049	− 0.145	− 0.144	− 0.020	− 0.076	− 0.045	0.014	− 0.062	− 0.562
SC	− 0.150	0.084	− 0.132	− 0.339	− 0.092	− 0.053	0.027	− 0.070	− 0.027	− 0.083	− 0.751
GZ	0.088	− 0.188	− 0.070	− 0.021	0.045	− 0.084	− 0.182	− 0.113	0.041	− 0.054	− 0.484
YN	− 0.010	− 0.106	− 0.034	− 0.051	− 0.120	0.025	0.016	− 0.059	− 0.025	− 0.040	− 0.364

Table 2 continued

Province	06–07	07–08	08–09	09–10	10–11	11–12	12–13	13–14	14–15	Average	Cumulative
SAX	0.306	− 0.654	0.160	− 0.274	− 0.026	− 0.066	− 0.087	− 0.083	0.083	− 0.071	− 0.642
GS	− 0.033	− 0.018	− 0.001	− 0.065	− 0.071	− 0.050	− 0.019	− 0.093	0.094	− 0.028	− 0.256
QH	0.007	− 0.274	− 0.060	− 0.153	− 0.163	− 0.061	− 0.073	− 0.037	− 0.079	− 0.099	− 0.894
NX	− 0.151	− 0.618	− 0.143	− 0.162	− 0.114	− 0.034	− 0.047	− 0.007	0.061	− 0.135	− 1.217
XJ	− 0.001	− 0.057	− 0.138	− 0.080	− 0.203	− 0.177	− 0.406	0.042	− 0.050	− 0.119	− 1.068
Average	− 0.031	− 0.101	− 0.109	− 0.135	− 0.087	− 0.067	− 0.044	− 0.039	− 0.027	− 0.071	− 0.641

Notes: the abbreviations for the provinces in China are as follows: BJ (Beijing), TJ(Tianjin), HB(Hebei), SX(Shanxi), IM(Inner Mongolia), LN(Liaoning), JL(Jilin), HLJ(Heilongjiang), SH(Shanghai), JS(Jiangsu), ZJ(Zhejiang), AH(Anhui), FJ(Fujian), JX(Jiangxi), SD(Shandong), HN(Henan), Hb(Hubei), Hn(Hunan), GD(Guangdong), GX(Guangxi), HAI(Hainan), CQ(Chongqing), SC(Sichuan), GZ(Guizhou), YN(Yunnan), SAX(Shaanxi), GS(Gansu), QH(Qinghai), NX(Ningxia), XJ(Xinjiang)

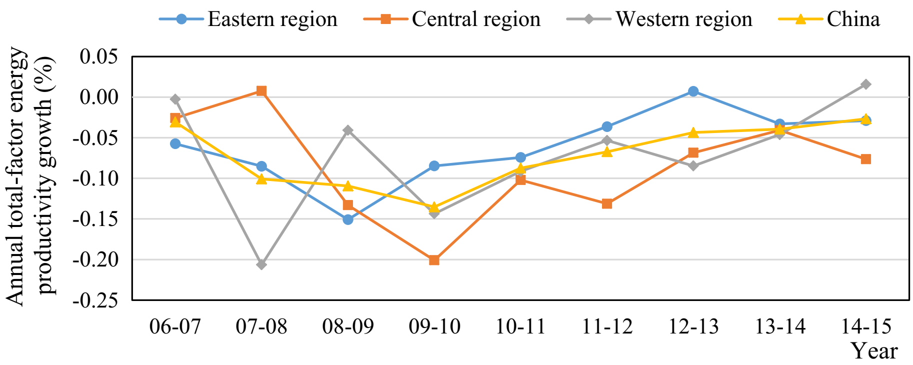

Fig. 1 Annual TFEP growth in three regions and at national level

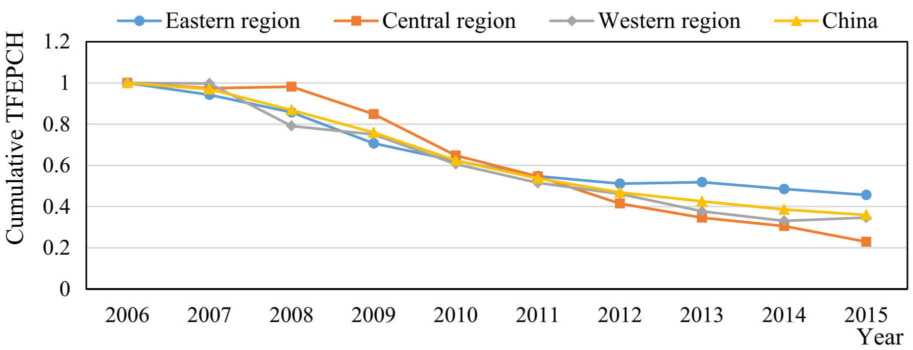

Fig. 2 Cumulative energy productivity changes in three regions and at national level in China

Chinese 30 provincial regions are categorized into three major regions.[1] Considering the above results, several findings are obtained.

4.2.1 Analysis on the TFEP changes from three main regions

According to the above results, three major regions experienced negative growth of energy productivity in the construction industry almost over all periods during 2006–2015. In fact, TFEPCH was positive only in the eastern region during 2012–2013 and the central region during 2007–2008. With the rapid growth of urbanization process in China, higher construction standards and building quality are required to achieve green construction and energy-saving buildings. More construction quantities would increase for this purpose, which would lead to more energy consumption in the construction process. Besides, the environmental protection requirements, such as noise control, dust control and building wastes disposal, are even stricter in the new urbanization context in China. These measures would also result in higher energy consumption. These can be served as the explanations for energy productivity decrease in China's construction industry.

[1] We categorize the 30 provinces into three groups. The eastern region includes 11 provinces: LN, HB, SD, JS, ZJ, FJ, GD, BJ, TJ, SH, HAI. The central region contains eight provinces: JL, HLJ, SX, HN, AH, JX, Hu, Hb. The western region contains 11 provinces: IM, XJ, GS, SAX, NX, SC, CQ, GZ, YN, GX, QH.

Table 3 EFFCH in construction industry in China by province from 2006 to 2015

Province	06–07	07–08	08–09	09–10	10–11	11–12	12–13	13–14	14–15	Average
BJ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
TJ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	− 0.176	− 0.020
HB	0.236	− 0.153	0.122	− 0.060	0.064	0.457	0.003	0.002	− 0.270	0.045
SX	0.197	− 0.027	0.126	− 0.051	− 0.080	− 0.001	0.047	− 0.008	0.000	0.023
IM	0.342	− 0.310	0.033	− 0.084	− 0.013	0.062	− 0.037	0.029	− 0.003	0.002
LN	− 0.034	0.118	0.161	0.000	0.000	0.000	0.000	− 0.091	− 0.184	− 0.003
JL	0.618	0.000	0.000	0.000	0.000	− 0.137	− 0.160	0.297	− 0.199	0.047
HLJ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	− 0.020	− 0.002
SH	0.000	0.000	0.000	0.000	− 0.347	− 0.104	− 0.061	0.512	0.000	0.000
JS	0.045	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005
ZJ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AH	− 0.005	− 0.017	0.044	0.000	− 0.024	0.033	0.028	0.003	0.079	0.016
FJ	0.112	− 0.380	0.040	0.067	− 0.010	− 0.037	0.053	0.037	0.049	− 0.008
JX	0.000	− 0.025	− 0.013	0.025	0.009	− 0.020	− 0.012	− 0.012	0.046	0.000
SD	0.034	0.016	0.057	− 0.004	0.000	0.373	− 0.009	− 0.002	− 0.088	0.042
HN	0.068	0.038	− 0.038	− 0.089	− 0.034	− 0.010	0.023	0.023	− 0.006	− 0.003
Hb	0.108	0.081	0.209	− 0.261	− 0.037	0.077	0.364	0.000	0.000	0.060
Hn	0.022	− 0.070	0.024	− 0.100	0.613	0.000	0.000	0.000	− 0.398	0.010
GD	− 0.050	0.069	0.202	− 0.438	− 0.008	0.207	− 0.144	− 0.001	0.051	− 0.013
GX	0.129	0.188	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.035
HAI	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CQ	− 0.003	− 0.006	0.140	0.135	− 0.117	− 0.024	0.043	0.203	0.000	0.041
SC	− 0.117	0.169	0.039	− 0.209	− 0.092	− 0.079	0.106	0.172	0.009	0.000
GZ	0.068	− 0.132	0.011	0.194	0.023	− 0.020	− 0.071	− 0.011	0.017	0.009

Table 3 continued

Province	06–07	07–08	08–09	09–10	10–11	11–12	12–13	13–14	14–15	Average
YN	0.228	− 0.209	0.139	0.025	− 0.035	0.217	− 0.049	0.028	0.020	0.041
SAX	0.501	− 0.353	0.290	0.102	0.000	− 0.368	0.049	0.214	0.028	0.052
GS	0.118	− 0.120	0.104	0.080	− 0.082	0.220	0.065	− 0.006	0.076	0.051
QH	0.007	0.067	0.030	0.000	− 0.157	0.047	0.068	0.041	0.000	0.012
NX	0.000	0.000	0.000	0.000	− 0.313	0.313	− 0.210	0.210	− 0.103	− 0.011
XJ	0.084	0.342	0.000	0.000	− 0.024	0.024	0.000	0.000	0.000	0.047
Average	0.090	− 0.024	0.057	− 0.022	− 0.022	0.041	0.003	0.055	− 0.036	0.016

Table 4 Energy technical changes of Chinese construction industry by province from 2006 to 2015

Province	06–07	07–08	08–09	09–10	10–11	11–12	12–13	13–14	14–15	Average
BJ	− 0.042	− 0.070	− 0.240	− 0.101	0.043	0.055	0.157	0.021	0.047	− 0.014
TJ	− 0.158	− 0.687	− 0.126	− 0.120	− 0.093	− 0.048	− 0.011	− 0.014	0.109	− 0.128
HB	− 0.258	0.125	− 0.152	− 0.044	− 0.148	− 0.479	0.441	0.048	0.126	− 0.038
SX	− 0.205	− 0.071	− 0.248	− 0.009	0.006	− 0.032	− 0.084	0.087	− 0.036	− 0.066
IM	− 0.369	0.216	− 0.074	− 0.062	− 0.012	− 0.074	0.037	− 0.026	0.049	− 0.035
LN	− 0.076	− 0.155	− 0.258	− 0.127	− 0.118	− 0.100	− 0.380	0.068	0.209	− 0.104
JL	− 0.629	0.562	− 0.100	− 0.154	− 0.080	0.059	− 0.138	− 0.288	0.159	− 0.068
HLJ	0.022	− 0.053	− 0.200	− 0.327	− 0.347	− 0.095	− 0.093	− 0.034	− 0.002	− 0.126
SH	− 0.032	− 0.048	− 0.659	0.553	0.363	0.097	0.060	− 0.483	− 0.056	− 0.023
JS	− 0.103	− 0.005	− 0.058	− 0.097	− 0.131	− 0.112	− 0.111	− 0.046	0.093	− 0.063
ZJ	− 0.073	− 0.077	− 0.109	− 0.169	− 0.078	− 0.008	− 0.117	− 0.029	− 0.014	− 0.075
AH	− 0.063	− 0.089	− 0.084	− 0.133	− 0.115	− 0.128	− 0.188	− 0.036	− 0.128	− 0.107
FJ	− 0.174	0.006	− 0.064	− 0.129	− 0.062	− 0.034	− 0.102	− 0.079	− 0.056	− 0.077
JX	− 0.041	− 0.128	− 0.159	− 0.180	− 0.211	− 0.058	− 0.147	− 0.038	− 0.216	− 0.131
SD	− 0.040	− 0.014	− 0.102	− 0.004	− 0.028	− 0.322	0.331	− 0.028	0.108	− 0.011
HN	− 0.093	− 0.037	− 0.202	− 0.226	− 0.118	− 0.072	− 0.068	− 0.171	− 0.195	− 0.131
Hb	− 0.158	− 0.080	− 0.351	0.008	− 0.023	− 0.069	− 0.430	− 0.041	− 0.026	− 0.130
Hn	− 0.046	− 0.025	− 0.073	− 0.109	− 0.377	− 0.598	0.311	− 0.108	0.328	− 0.077
GD	− 0.007	− 0.075	− 0.212	− 0.084	− 0.008	− 0.230	0.157	− 0.024	− 0.051	− 0.059
GX	− 0.096	0.109	− 0.138	− 0.016	− 0.165	− 0.015	− 0.033	− 0.096	− 0.150	− 0.067
HAI	− 0.104	0.011	− 0.271	− 0.242	− 0.165	− 0.135	− 0.149	− 0.189	− 0.093	− 0.149
CQ	− 0.052	− 0.134	− 0.091	− 0.279	− 0.027	0.004	− 0.120	− 0.248	0.014	− 0.104
SC	− 0.032	− 0.085	− 0.171	− 0.130	0.000	0.027	− 0.078	− 0.242	− 0.036	− 0.083
GZ	0.020	− 0.056	− 0.081	− 0.215	0.021	− 0.064	− 0.111	− 0.102	0.024	− 0.063

Table 4 continued

Province	06–07	07–08	08–09	09–10	10–11	11–12	12–13	13–14	14–15	Average
YN	− 0.238	0.103	− 0.173	− 0.077	− 0.085	− 0.192	0.065	− 0.087	− 0.045	− 0.081
SAX	− 0.195	− 0.301	− 0.130	− 0.377	− 0.026	0.302	− 0.136	− 0.297	0.055	− 0.123
GS	− 0.152	0.102	− 0.105	− 0.144	0.011	− 0.270	− 0.084	− 0.088	0.018	− 0.079
QH	− 0.001	− 0.342	− 0.090	− 0.153	− 0.007	− 0.109	− 0.142	− 0.078	− 0.079	− 0.111
NX	− 0.151	− 0.618	− 0.143	− 0.162	0.198	− 0.347	0.162	− 0.216	0.163	− 0.124
XJ	− 0.084	− 0.398	− 0.138	− 0.080	− 0.179	− 0.202	− 0.406	0.042	− 0.050	− 0.166
Average	− 0.121	− 0.077	− 0.167	− 0.113	− 0.065	− 0.108	− 0.047	− 0.094	0.009	− 0.087

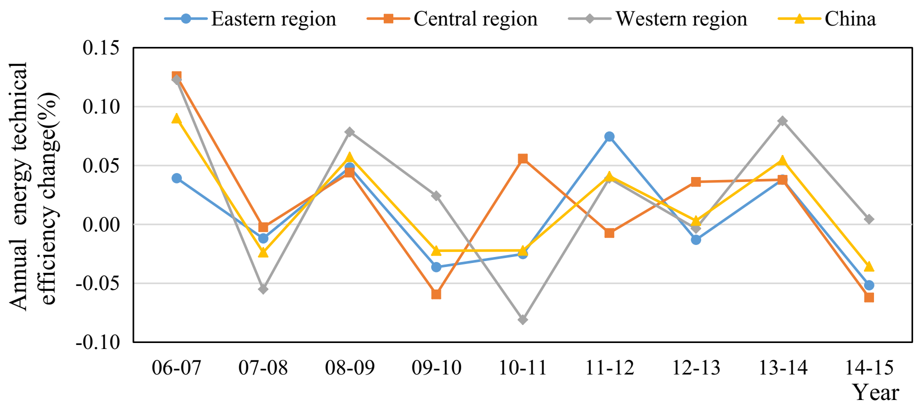

Fig. 3 Average energy technical efficiency changes in three major areas and at the national level

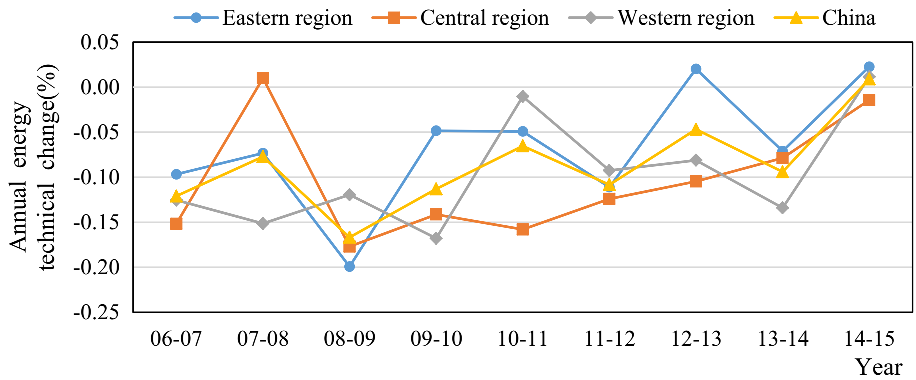

Fig. 4 Average energy technical changes in three major areas and at the national level

From Table 2 we can see, average TFEP of China's construction industry decreased by 7.1% annually since 2006 and decreased especially sharply from 2009 to 2010 (13.5%). By contrast, according to the traditional energy productivity index, energy productivity in the construction industry in China increased by 4.05% annually during 2006–2015, as calculated using data from uniform data sources: Chinese energy statistics and statistics yearbook (NBSC 2016). This indicates that the energy productivity changes were overestimated using conventional energy productivity index, because only energy was considered as the input. The significant substitution effects of other inputs can be served as the explanation of this phenomenon. This finding conforms to that of Chang and Hu (2010).

As Fig. 2 shows, the cumulative changes in energy productivity in the three main regions were negative over the period (the initial TFEP was assumed to equal to unity in 2006). This result conforms to the changing trend in energy productivity, seen in Fig. 1. Energy productivity in the central region decreased dramatically, by a cumulative 77.1% since 2006, while energy productivity in the eastern and western regions decreased by over 54.3 and 65.3%, respectively. From Fig. 2, we also know that the economic growth and energy productivity growth in eastern region were both the highest compared to the other two regions, a finding that conforms with those of other studies (Chang and Hu 2010;

Wang et al. 2013; Zhang et al. 2016). This can be attributed to the regional disparities in China. In line with other scholars' study results, the economy and technology are the major drivers influencing energy productivity (Chang, 2015; Wu et al. 2012). As the pioneer of "Reform and Open Policy," eastern region has developed firstly and therefore become the manufacturing center of China and the advanced economic development regions (Liang et al. 2016). The gross output of construction industry, the building floor space, and energy productivity growth in eastern region were highest among three regions, whereas these indicators in western region were the lowest, and the technological level was lower in central and western regions. The eastern region has the highest level of per capita income and the highest level of energy productivity growth, while the western region has the lowest level of per capita income and energy productivity growth. The convergence of energy productivity of China construction industry cannot be represented with the results, suggesting that regions with relatively lower economic growth cannot catch up to developed regions (Hu and Wang 2006).

4.2.2 Analysis on the TFEP changes at the provincial level

Changes in energy productivity in different provinces varied widely due to the disparities of different provinces, with only two provinces showing positive growth in energy productivity. As shown in Table 2, only Hebei and Shandong improved their energy productivity during the reference period. Energy productivity in Shandong increased by a cumulative 27.6% since 2006, while the annual growth rate in Hebei was 0.7%. Regional disparities such as the economic development modes, the technological development levels, and the industry structures are large in China's different province, and therefore energy productivity levels in the construction industry in different provinces are also discrepant. As shown in Tables 3 and 4, the average energy technical efficiency in the construction industries of Shandong and Hebei increased by 4.5 and 4.2%, respectively. They were ranked 6th and 7th in China and were the only two provinces in the eastern area whose average EFFCH ranked above that of China as a whole. The energy consumption in construction industry in Shandong exhibited a downward trend during the reference period and reached a low point of 4.43 Mtce in 2013 (NBSC 2016). During the 12th FYP period, Shandong developed green building pilots, enhanced energy conservation and emissions reduction in construction industry. Apart from that, many large-scale construction enterprises in Shandong increased their investment in science and technology during the eleventh FYP period. Similarly, energy consumption in the construction industry in Hebei saw a significant decline, from 4.06 Mtce to 2.95 Mtce, from 2012 to 2015, although the figure increased during the 11th FYP period. This is due to Hebei's policy of promoting green and low-carbon techniques and transformation from an extensive-oriented to an intensive-oriented construction industry during the 12th FYP period. However, eight regions (Hainan, Tianjin, Ningxia, Henan, Jiangxi, Heilongjiang, and Xinjiang) saw dramatic declines of more than 10% in their energy productivity since 2006.

These findings conform to those of some existing related studies. For example, Yang found that strategies regarding regional development in China directly drive the widening spatial development gap (Yang 2002; Zhang and Hao 2015). Zhang et al. argued that industrial structure adjustment can be served as an important policy tool for local governments in achieving low-carbon development and energy productivity growth (Zhang et al. 2016). Additionally, Yan et al. (2017) proposed that adjusting the structure of cross-industrial linkages in the construction industry can improve energy efficiency, while Chen et al. (2012) and Wang et al. (2016) claimed that the shift of industry structure can greatly impact energy efficiency.

4.2.3 Analysis on the EFFCH

In the following section, we intend to explore the driving forces behind energy productivity of Chinese construction industry. The TFEPCH can be decomposed into two primary components, EFFCH and ETECHCH, based on the results shown in Sect. 4.1.2. And therefore several findings are obtained as follows.

Regions differed with respect to shift in energy technical efficiency, but the overall trend was positive. In Table 3 and Fig. 3, we observe that the average EFFCH was highest (2.4%) in the western area throughout the period, while the figure in central and eastern areas was 1.9 and 0.7%, respectively. This finding conforms to those of related studies, and the reasons can be attributed to the regional disparity in China. The eastern region emphasizes the adoption of environmentally friendly energy technologies and reform of traditional production and consumption patterns, while inland regions with less economic development attach importance to the efficient use and conservation of energy.

Energy technical efficiency in Chinese construction industry increased by approximately 1.6% annually, which means that the gap in energy technical efficiency among China's all regions has gradually narrowed since 2006. This is attributed to the research on the technology regarding energy conservation and emissions reduction in China during the eleventh and twelfth FYP periods. The government has encouraged advanced and mature energy-saving emissions reduction technologies to reduce the use of building materials with high carbon emissions and gradually increased the proportion of high-strength and high-performance building materials. In addition, according to the report on the 11th and 12th FYP for the construction industry, the government has implemented energy-saving and emissions reduction technology integration pilot projects, such as green construction demonstration projects, and established the green labeling system in the housing system. Additionally, the state has introduced a series of specific policies (e.g., differential electricity price policies) in some high energy-consuming industries, like cement, iron and steel, and electrolytic aluminum, among others (Zhang et al. 2015; Zhang and Peng 2017). Such measures could reduce unit energy consumption in the production of building materials, effectively promoting energy conservation and improving the energy utilization efficiency level.

4.2.4 Analysis on the ETECHCH

From the perspective of the national level, the overall ETECHCH of Chinese construction industry declined throughout the whole period, and the decline in energy technology improvement was the main cause of the decline in energy productivity. As demonstrated in Table 4 and Fig. 4, the average energy technical change at the national level is − 0.087, which shows that energy utilization technology in China's construction industry declined dramatically, by 8.7% annually, throughout the 2006–2015 period. The explanations are that the construction industry was still labor-intensive and that construction enterprises were small in scale; construction methods were backward, the degree of industrial modernization was low, and technological innovation capabilities were insufficient. In addition, the market was homogeneous and characterized by excessive competition. The proportion of clean energy consumption (e.g., electricity) was still low, and low-efficiency energy sources (e.g., coal) continued to grow in China from 2006 to 2015 (NBSC 2016).

If looking into from the perspective of three main region groups, the average ETECHCH across the three regions showed a downward trend and then increased gradually, with some fluctuations during 11th FYP period. This probably was due to new goals regarding saving energy and reducing emissions, proposed during twelfth FYP period, motivating enterprises to focus more on scientific and technological innovation and improve their management models. At the same time, the government provided a strong policy environment, encouraging improvements in energy technology. ETECHCH in eastern and western regions exceeded zero at the end of the 12th FYP period as a result of green and energy-saving techniques developed during the 12th FYP period.

At the provincial level, we can observe that no region exhibits nonnegative ETECHCH throughout the 2006–2015 period, showing that the energy technology frontier in all the provinces of China regressed during the research period. ETECHCH decreased most rapidly—by more than 10% annually—in more than ten provinces, including Xinjiang, Hainan, Henan, Jiangxi, and Tianjin. Moreover, average ETECHCH in Heilongjiang was − 12.6%, while the annual average ETECHCH in Liaoning and Jilin was − 10.4 and − 6.8% annually on average, respectively. This phenomenon can be attributed to the regional unique characteristics. Heilongjiang, Jilin, and Liaoning are all China's oldest industrial bases. The technological regression in construction industry and inefficient energy usage are the main reasons leading to the negative average ETECHCH in these three provinces.

In summary, during 2006–2015, energy productivity in China dropped by a cumulative 64.1%, and the average annual rate dropped 7.1% since 2006. However, energy technical regress—rather than changes in energy technical efficiency—contributed most to the overall decline in TFEP in China's construction industry. The above analytical results reveal significant regional disparity of the energy productivity in China. Developed eastern region suffered the slowest drop in the energy productivity, while central and western regions witnessed faster decline in the energy productivity. On the whole, China suffers from great imbalance of regional economy and energy productivity, although benefiting to its fast growth of economy.

4.3 Policy implications

Based on the above results obtained in this study, this section proposes and discusses measures to increase energy productivity of China's construction industry and overcome the negative impacts generated from the decrease of it and regional imbalance.

1. Promoting technology and process innovations. Technology innovation and transfer is the foundation. Sustainable and clean construction technologies and processes are the foundation to achieve energy-saving and emission mitigation for the construction industry. Compared with the eastern regions of China, the western and central regions in China lack enough funds to implement the new and innovative technologies and processes. Therefore, the Chinese government is supposed to set special funds to enhance the technologies and process innovations, especially for regions that consume large volume of energy but produce low outputs, such as the central and western regions.
2. Developing alternative renewable energy sources: renewable energy sources can be promoted to developed, especially the cleaner energy sources, such as solar power, wind power, and hydropower. These green energy sources can be used substitute the traditional fossil fuels for adjusting the energy structure of the western and central

regions. This can significantly improve the energy utilization efficiency of Chinese construction industry.

3. Establishing flexible energy consumption and emission reduction policies. The government is supposed to design flexible and distinct energy consumption and emission reduction policies to accommodate the varied and specific characteristics of different regions. The energy-saving and emission mitigation measures should be implemented for achieving clean and environmental-friendly production especially for those old processed plants in less developed regions.
4. Enhancing the inter-region cooperation. Cooperative efforts should be initiated and strengthened at the inter-region level to make common progress and narrow regional differences. The western region should learn advanced and energy-saving technologies from the eastern and central regions and develop low-energy consumption industries to continuously improve their energy utilization level.

5 Conclusions

To investigate real "TFEP" in the construction industry in China, we used the TFEPCH index and adopted an improved LPI combined with a generalized DDF within the TFEE framework. Additionally, we added a physical output indicator to more conventional output indicators. We then measured and analyzed the TFEP of Chinese construction industry in 30 provinces during 2006–2015. The main conclusions and contributions are as follows.

First, at the national level, average TFEPCH in China's construction industry decreased by 7.1% annually since 2006, with the steepest decline (13.5%) occurring in the 2009–2010 period. EFFCH increased by approximately 1.6% annually, while average ETECHCH declined dramatically, by 8.7% annually, throughout the 2006–2015 period. Energy technical regress—rather than changes in energy technical efficiency—contributed most to the overall decline in energy productivity in China's construction industry.

Second, three regions experienced nearly negative growth of energy productivity in construction industry nearly all over the period during 2006–2015. Average TFEPCH at regional level and the national level were negative, illustrating that energy productivity decreased annually throughout the 11th and 12th FYP period. The central area's energy productivity dramatically decreased by a cumulative 77.1% since 2006, while the decrease in the eastern and western areas was over 54.3 and 65.3%, respectively. Average EFFCH in the western region was the largest (2.4%) throughout the period, followed by central region (1.9%), while the figure for eastern region was lowest (0.7%).

Third, at the provincial level, only two of 30 provinces (Hebei and Shandong) improved their energy productivity during the reference period. Conversely, eight regions (Hainan, Tianjin, Ningxia, Henan, Jiangxi, Heilongjiang, and Xinjiang) saw a dramatic decline, of more than 10%, in their energy productivity since 2006. For ETECHCH, no region exhibited nonnegative ETECHCH throughout the 2006–2015 period, illustrating that the energy usage technology frontier in all provinces in China regressed during the referenced period.

Finally, energy productivity of Chinese construction industry was measured, and the "best practice" provinces and those lagging behind with regard to TFEPCH in the construction industry were identified. These findings provide a basis for decision-making and a reference for administrative departments in setting differentiated energy efficiency goals and developing relevant measures. Such measurements are vital to energy and resource allocation in the construction industry in China's various regions. At last, policy implications are proposed, such as promoting technology and process innovation, developing alternative renewable energy sources, establishing flexible energy consumption and emission reduction policies and enhancing the inter-region cooperation.

As for future work, much remains to be done. For example, we can continue to investigate TFEE in Chinese construction industry with respect to undesirable output. Additionally, we can explore sources of inequality and discrepancies among regions.

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