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Shah, Wasi Ul Hassan; Hao, Gang; Yan, Hong; Yasmeen, Rizwana; Jie, Yan

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Research paper

The role of energy policy transition, regional energy efficiency, and technological advancement in the improvement of China’s environmental quality

Wasi Ul Hassan Shah a, Gang Hao b, Hong Yan a, Rizwana Yaseen c,*, Yan Jie d

a School of Management, Zhejiang Shuren University, Hangzhou, 310015, China
b Department of Management Sciences, City University of Hong Kong, (H.K), Hong Kong, China
c School of Economics and Management, Panzhihua University, Panzhihua 617000, Sichuan, China
d School of Economics and Management, Tsinghua University

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A B S T R A C T

Energy efficiency and emission reduction are a serious global concern due to rapid economic and infrastructure growth in the twenty-first century. China, the highest energy consumer and carbon emitter, shifted its energy policy in 2011 from security to efficiency and long-term economic growth. Inline, the study employed data envelopment analysis (DEA-SBM) to measure the energy efficiency of Chinese provinces from 2004 to 2017. Mann–Whitney U test was used to explore the statistically significant difference between the energy efficiency level of China for the transit of energy security policy to energy efficiency with emission reduction policy. Further Meta-frontier analysis was employed to gauge the regional heterogeneity in production technology gaps among China’s eastern, central and western regions. In contrast, the Malmquist productivity index measures the technological and energy efficiency change to catch up with the total factor productivity change in all three regions. Our findings show that transaction in energy policy has significant progress. However, the pace to achieve the energy efficiency targets is slow and needs more effort for on-ground implications with advancements in production technologies. Furthermore, a significant technological gap exists between China’s three regions. The Eastern region is more successful in the grasp of the advantage of technological advancement, which improves its energy efficiency level and increases TFP change. Our study suggests that the Chinese government needs to pay more attention to improving the production technologies and energy efficiency levels in central and western regions to fill the gap and come closer to the energy efficiency level of the eastern coastal region, which will ultimately improve the energy efficiency level of the country.

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1. Introduction

China’s GDP has grown with an average of 10 percent and more than 800 million people have been lifted out of poverty since its economic reforms began in 1978. Access to health, education, and other services has also improved significantly over the same period (World Bank, 2022). The share of agriculture in GDP fell from roughly 30% in 1978 to less than 10% in recent years. The industry was the main contributor to China’s GDP till 2012, when the service sector showed growth and overtook manufacturing with a 51% share. The service sector is labour-intensive and less polluting than manufacturing; however, the share of the service sector of China is still less compared to some BRIIS countries (Yang and China’s Progress Towards, 2018). Enormous investment in the manufacturing and construction sectors increases power consumption in most of the country’s urban areas. Since the early 2000s, when China’s economy focused on heavy industries, its rapid economic growth has increased energy consumption. For this reason, the amount of primary energy consumed increased from 412 Mtoe (million tonnes of oil equivalent) in 1981 to 3384.4 Mtoe in 2019.

Excessive energy consumption has been identified as the main reason for carbon emissions in developed and developing countries, which has the ultimate diverse effect on human and animal health, destroys the soil, and contaminates underground water reservoirs (Waheed et al., 2019). The Chinese government took severe measures to reduce emissions and move towards a green economy to counter the environmental concerns. At the United
Nations General Assembly’s 75th session in September 2020, Chinese President Xi Jinping announced that “China will increase its nationally determined contributions by adopting more powerful policies and measures, strive to reach CO₂ emissions peak before 2030 and achieve carbon neutrality before 2060”.

Although the Chinese government emphasizes renewable energy resources, China is still the major consumer of non-renewable resources and the top emitter of CO₂ (Zhao et al., 2020) (see Fig. 1). With the latest technological advancement, power units are becoming more efficient with less consumption of non-renewable resources, producing more power, and decreasing emissions. Many western countries applied these energy or environment efficiency policies to improve environmental quality. Unsurprisingly, the Chinese government also concentrates its efforts on the energy sector to reach its environmental commitments. As with the rest of the economy, this sector has experienced different reforms since 1980. Reducing emissions and improving energy efficiency have been China’s top priorities in recent years.

Looking back at China’s energy policy from 1981 to 2020, there have been three major shifts in the policy. China’s attention was directed solely towards improving energy efficiency in its Sixth to ninth Five-Year Plan (1981–2000) to increase the country’s overall energy efficiency. Due to growing concern about the slow depletion of fossil fuels, China’s energy security has been elevated to a priority in each Five-Year Plan since the Tenth (2001). Climate change mitigation has been a major focus of China’s energy policy since 2011 (the 12th and 13th Five-Year Plans). According to this shift in policy since 2011, China’s economy appears to have begun a low-carbon energy transition (Guilhot, 2022).

China’s energy policy was primarily focused on energy security in the tenth (2001–2005) and eleventh Plan (2006–2010). However, the twelfth (2011–2015) and thirteenth Plan (2016–2020) shifted towards a low-carbon energy transition. Examining prior Five-year plan (FYP) accomplishments and targets provides a critical historical context for understanding China’s current efforts to shift its policy to become a green economy. The Chinese government policy of moving towards a green economy is a highly appreciable initiative globally. However, the level of success in this energy efficiency mission is still undiscovered and needs to be explored.

To this end, our study explores the impact of China’s energy policy transition from energy security (2001–2010) to energy efficiency with low carbon emission (2011–2020). By estimating the Chinese provincial-level energy efficiency to investigate the improvement in environmental quality, this study contributes to the existing literature on energy efficiency in many ways. Firstly the application of DEA-SBM gauges the energy efficiency scores of all the 31 provinces and cities of China for an extended period from 2004 to 2017. The study further divides the study period according to 5 years plans and explores the statistically significant difference (through the Mann–Whitney U test) between the average energy efficiency scores in (10th–11th) and (12–13th) five years plans which explain the effect of China’s energy policy shift on EE level and environmental improvement.

Secondly, Meta-frontier analysis measures the production technology gap between the three different regions of mainland China, namely the east region, central region, and western region (see Fig. 2), to explore the regional heterogeneity in production technology and EE. The study also measures the significant statistical difference among the mean technology gap ratio (TGR) scores of all three regions through the Kruskal–Wallis test application. Finally, research also calculates the total factor productivity change over the study period through the Malmquist Productivity index to distinguish whether variation in TFP is due to energy efficiency or technological change.

This article is structured as follows. Section 2 consists of the comprehensive literature of the study. Section 3 presents the detailed methodology employed in the study. Section 4 explains the data sources. Section 5 discusses the Results and Discussions. Section 6 presents the conclusions and puts forward some policy implications.

2. Literature review

Energy efficiency is becoming more essential and critical in terms of sustainable development. Though clean energy is on the rise, fossil fuels like oil and natural gas still account for most global energy consumption, and coal accounts for about half of the world’s power generation (Li et al., 2017). So now it is gaining more attention from the general public, scientists, and governments. Furthermore, it is essential to compare and contrast the energy efficiency of different regions and sectors to detect discrepancies in energy efficiency and offer a quantitative basis for improving efficiency (Song et al., 2015). Patterson (1996) first coined the term “energy efficiency” and provided four measures of how efficiently a given system uses resources. Accurate energy efficiency assessment is critical and necessary. Data envelopment
analysis (DEA), is a well-known method for evaluating energy efficiency and total factor efficiency. Literature advocates that numerous DEA techniques have been employed to measure energy efficiency in different regions and sectors.

2.1. Regional EE and environment improvement

An increasingly important aspect of sustainability and environmental improvement is energy efficiency, which governments worldwide are beginning to recognize (Hanley et al., 2009). Literature proved that many researchers have been interested in energy efficiency evaluation. Hu and Wang (2006) were the first to propose the concept of TFEE (total factor energy efficiency); since then gained widespread acceptance. According to TFEE's explain that a single energy input cannot produce the aggregate output; therefore, it must be combined with other inputs like labour and capital to produce an output. According to the TFEE framework, energy efficiency is the ratio of intended input to actual input required at a given output level. To address the shortcomings of conventional single-factor energy efficiency evaluations, the TFEE concept has major implications for future research. Environmental pollution is becoming more severe as fossil fuels are still the primary source of energy consumption. As a result, many studies have begun to incorporate ecological concerns into energy efficiency assessments (Zhang et al., 2018). It also implies that energy efficiency is a major concern in the integrated growth of the economy, energy, and environment. Carbon emission was used as an undesirable output in many recent studies. For instance, Li and Lin (2015) and Zhang and Choi (2013c) used CO₂ as undesirable output to incorporate the environmental factor in their production model for EE estimation for different cities and provinces of China. Over the period 2000-2009, five major energy-consuming industries in 23 countries of the European Union were evaluated and found that they gradually increased their EE levels (Makridou et al., 2016). Zhao et al. (2019) argue that China's provincial energy efficiency is heavily influenced by the economic and energy consumption structure, urbanization, and technological innovation. Apergis et al. (2015), Zhao et al. (2018), Jebali et al. (2017), and Wu et al. (2017) also incorporate the environmental factor in the estimation of EE in different regions and countries around the globe.

2.2. Production technology heterogeneity and EE

There is a linkage between energy conservation and emissions reduction and the issue of technology gaps. Literature advocates that meta-frontier analysis is consistently used to evaluate technology gaps, as demonstrated by Zhang and Choi (2013a), who differentiate the energy and CO₂ emissions efficiencies in the electricity generation industry of South Korea and China, further gauge the associated technology gaps. Zhang et al. (2014) studied the change in the efficiency of China's fossil fuel power plants. Yao et al. (2015) employed the Meta-frontier analysis to measure the region energy efficiency and technological gaps in China for a specific period. Li and Lin (2015) also research regional technology gaps in China with the application of met-frontier; authors also consider environmental factors incorporating undesirable output carbon emissions. Kounetas (2015) examines Europe's technological gap in environmental efficiency. Wang and Feng (2015a,b) and Lin and Zhao (2016b,a), are some more articles on the technological divide in regional studies.

Wang et al. (2013a), Li and Lin (2015), and Wu et al. (2017) use the DEA approach to assess the energy efficiency of 30 Chinese provinces, and the research indicates that the majority of provinces are inefficient. China's eastern region has the best energy efficiency, whereas western China has the lowest. Efficiency increased in the majority of regions between 2006 and 2010. Yu et al. (2018) proposed a methodology for evaluating energy efficiency considering regional technical heterogeneity and carbon emissions. Between 2007 and 2014, the study evaluated the efficiency.
energy efficiency of 277 cities in China and discovered significant disparities in the energy efficiency of Chinese cities. Sun et al. (2018) examined the heterogeneity and technological gap in energy management across the country and assessed the energy efficiency of 211 cities. Study results illustrate that, on average, the energy efficiency in most cities is low, and a significant difference exists among production technologies of different regions. Data from 26 Chinese prefecture-level towns between 2005 and 2015 was used by Yang and Wei (2019) to calculate the urban total factor EE through DEA game cross-efficiency. While comparing to traditional models, the results show that the energy efficiency level is lower than traditionally computed energy efficiency. Further, it was witnessed that there is no substantial progress in the energy efficiency of urban cities of China. Many studies have been done to compare the energy efficiency of different regions across the globe. For example, Honma and Hu (2008) also used DEA to gauge the energy efficiency in 47 cities and counties of Japan.

2.3. Technological advancement and regional EE

Gang et al. (2003) demonstrate that technological advancement contributed to economic growth by calculating total factor productivity (TFP). Initially, in traditional TFP measures, environmental damage such as carbon emissions was not considered. In the context of climate change, the term “green productivity” refers to the dynamic shifts in carbon emission efficiency that have occurred due to advances in technology. Chiu et al. (2016) Employed the Malmquist Index in G20 countries to evaluate the production-environmental total factor productivity. Results indicate that efficiency level had fallen and still a significant room exists for EE improvement. According to Makridou et al. (2016), the environmental EE and TFP of the five most energy-consuming industries were examined with the application of DEA and the Malmquist index in 23 EU countries. Authors found that EE improved across all study sectors and technical change played an important role in enhancing energy environment TFP. Malmquist index was employed to examine the TFP of environmental regulation in China at the province level by Tang et al. (2017). Research explain that, agglomeration had a positive impact on ecological regulation TFP, further technological advancement also had the utmost effect on environmental regulation TFP. Ma et al. (2017) used the super-efficient DEA model and the Malmquist index to decompose three northeast Chinese provinces’ total factor production efficiency. Their findings indicated that TFP differed from energy and environmental efficiency, with Heilongjiang province having the greatest TFP. Many other studies explore the technological impact of TFP change in different regions and provinces of China (Huang et al., 2017; Woo et al., 2015; Ding et al., 2019). Low-carbon technology innovation directly impacts energy efficiency (Li et al., 2021; Shen et al., 2022).

3. Methodology

DEA is a famous mathematical linear programming technique that is consistently used to evaluate the relative efficiency of homogeneous decision-making units called DMUs. DEA basic model was initially proposed by Charnes et al. (1978) with a constant return to scale (CSR) assumption, later modified by Banker et al. (1984) with a variable return to scale (VSR). As the conventional DEA model cannot incorporate the undesirable output, therefore to resolve the issue Tone (2003) proposed the Slack-based Measure SBM with undesirable output based on his initial research Tone (2001).

3.1. DEA-SBM with undesirable output

We assume that there are n DMUs in total. Input, good outputs, and undesirable outputs are three different elements, which all are denoted by different vectors: \( x \in \mathbb{R}^m, y^g \in \mathbb{R}^l \) and \( y^b \in \mathbb{R}^k \), respectively. In other words, the following is the definition of the set of production possibility P:

\[
P = \{ (x, y^g, y^b) \ | \ x \geq X\lambda, y^g \leq Y^g \lambda, y^b \geq Y^b \lambda, \lambda \geq 0 \}.
\]

When using the intensity vector \( \lambda \in \mathbb{R}^n \), the definition is compatible with the “constant returns to scale assumption”. Even if the model includes bad outputs, it is possible to obtain the efficiency of DMU \( _0 \) \((x_0, y^g_0, y^b_0)\). SBM can be defined as:

\[
[\text{SBM-Undesirable}] \ p^* = \min \left( \frac{1 - \frac{1}{n} \sum_{i=1}^{n} s^i}{1 + \frac{1}{s^1 + s^2} \left( \sum_{r=1}^{s^1} \frac{y^b_r}{y^b_{r0}} + \sum_{r=s^1+1}^{s^2} \frac{y^b_r}{y^b_{r0}} \right)} \right)
\]

Subject to

\[
x_0 = X\lambda + s^r \quad (3)
\]

\[
y^b_0 = Y^b \lambda - s^g \quad (4)
\]

\[
y^g_0 = Y^g \lambda + s^b \quad (5)
\]

\[
s^r \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \quad (6)
\]

These two vectors, \( s^r \in \mathbb{R}^m \) and \( s^b \in \mathbb{R}^k \) represent excessive input and bad output, respectively, while \( s^g \in \mathbb{R}^l \) denotes the lack of good outputs in the first case. This program’s ideal solution is \((\lambda^*, s^r, s^g, s^b)^{\text{T}}\).

RTS features can also be added by adding the following constraint to the [SBM-Undesirable]: than production possibility can be defined as:

\[
L \leq \varepsilon \lambda \leq U \quad (7)
\]

In the first stage of the empirical analysis, we applied SBM-DEA to measure the EE for Chinese provinces for each year (2004–2017).

3.2. DEA-meta frontier model

Efficiency evaluation of DMUs with different groups can be estimated more accurately through Meta-frontier Model. Different groups of DMUs could have different technology; therefore, it is better to compare them in the same group with homogeneous technology levels (Wang et al., 2013b). Meta-frontier ratio (MTR) can calculate technology gaps between different groups. For group I, MTR could be represented as (Wang et al., 2018a; Hang et al., 2015).

\[
TGR = \frac{\text{MEE}}{\text{GEEI}} \quad (8)
\]

where \( \text{GEEI} \) is the energy efficiency of DMU under a particular group, and MEE is the Meta-energy efficiency of DMUs under the technology level of all DMUs included in the evaluation process. A greater TGR indicates that meta-frontier technology is closer to the group frontier technology (Chiu et al., 2012). Considering that TGR’s unity value indicates no technological gap between a group and the Meta frontier, it is widely used to analyse regional differences.

3.3. DEA-malmquist index model

A DMU’s Malmquist productivity index can be used to track changes in efficiency over time. This index is based on the premise...
that a production function exists for each period, reflecting the current technological state. To determine this boundary, we use the DEA models. According to Färe et al. (1992) a given DMU (DMU₀) can be characterized by the fluctuation in productivity between periods t and t + 1 (9).

\[ M₀ = \frac{D₀^{t+1} (x₀^{t+1}, y₀^{t+1})}{D₀^t (x₀^t, y₀^t)} \left[ \frac{D₀^{t+1} (x₀^{t+1}, y₀^{t+1})}{D₀^t (x₀^t, y₀^t)} - \frac{D₀^{t+1} (x₀^{t+1}, y₀^{t+1})}{D₀^t (x₀^{t+1}, y₀^{t+1})} \right]^{1/2} \]  

(9)

- Where: \( D₀^t (x₀^t, y₀^t) \) refers to the DMU₀’s technical efficiency measurement in time period t.
- \( D₀^{t+1} (x₀^{t+1}, y₀^{t+1}) \) refers to the DMU₀’s technical efficiency measurement in time period t + 1.
- \( D₀^t (x₀^t, y₀^t) \) represent the shift pf technical efficiency from t to t + 1.
- \( D₀^{t+1} (x₀^{t+1}, y₀^{t+1}) \) refer to the technical efficiency of given DMU₀ gauged through relieving the data of given DMU from t + 1 with those from period t.

Between periods t and t + 1, the first term of Eq. (9), without parenthesis, describes the shift in DMU₀’s technical efficiency. The second term of Eq. (9), between square brackets, explains how that same DMU’s technological boundary has shifted. An index greater than 1 implies that DMU₀ has been more productive than the first period. One of the two possible explanations for a rise in production is that the DMU altered its methods to become more efficient (change in efficiency) (technological change). We applied the DEA Malmquist index to measure the effect of technological improvement for a reduction in emissions and a rise in EE in Chinese provinces over the period.

3.4. Mann whitney U test and Kruskal–Wallis test

The Mann Whitney U test proposed by Wilcoxon (1945) is a famous non-parametric test for comparing the outcomes of two independent groups. Two samples are tested to see if they are from the same population using the Mann Whitney U test, also known as the Mann Whitney Wilcoxon test or the Wilcoxon Rank Sum Test (i.e., the two populations have the same shape). The medians of the two populations are compared in this test. Parametric testing compares the means (H₀: 1 = 2) of two groups of independent individuals (H₁: 1 ≠ 2). However, if the independent groups are more than two Kruskal–Wallis test is applied to measure the statistically significant difference. We used the Mann–Whitney test to measure the statistically significant difference among the mean energy efficiency scores of two time periods, 2004–2010 and 2011–2017. Therefore, our null and alternative hypothesis are as follow:

H₀: The distribution of Avg.EE is the same across categories of two time periods.
H₁: The distribution of Avg.EE is not the same across categories of two time periods.

Kruskal Wallis test was employed to assess whether the TGR in the east, centre, and west differ significantly. Our null and alternatives hypothesis are as follows:

H₀: The distribution of average TGR is the same across three different regions.
H₁: The distribution of average TGR is not the same across three different regions.

4. Data sources

This study divides China’s 31 provinces and cities into three distinct regions (see Table A.1). Scholars have employed a variety of input–output indicators in their energy efficiency estimates, but they all have a few common indicators (Li and Lin, 2015; Zhang and Choi, 2013b; Wang et al., 2012). After considering previous research experience and data availability, the following input and output variables are chosen (see Table 1). Data is collected from China’s and the regional Statistical Yearbooks for 2004–2017.

5. Results & discussion

5.1. SBM–DEA findings

Figs. 3 and A.1 show the energy efficiency levels for 31 Chinese provinces from 2004 to 2017 with the application of the DEA–SBM model with undesirable outputs. The figures show that, compared to other Chinese provinces, the average EE of Beijing, Shanghai, and Tibet is 1 which indicates that these provinces or cities have successfully implemented the policy of sustainable growth with less carbon emission. Beijing and Shanghai have relatively advanced economies and advanced CO₂ emission technologies and management systems; moreover, it was witnessed that Tibet has improved its economic growth with less emissions, which improved its energy efficiency level. Results indicate that most Chinese provinces in central and western regions are inefficient as their EE scores are less than 0.44, which indicates that these provinces or cities still have the potential for 56 percent improvement in their energy efficiency level. Our research results are aligned with Li and Lin (2015), who estimated the EE of 30 Chinese provinces from 1997 to 2011 and found that the average EE scores of the cities and provinces in the east are higher than in other parts of the country. Our study proves that although central and western provinces have improved their technologies to achieve sustainable economic growth with the least carbon emissions, they are still behind eastern coastal cities. When looking at the three regions for average EE (see Table A.2, Fig. 4), the east has the highest energy efficiency (0.667), followed by the west (0.465), and the centre has the lowest (0.428). This ranking agrees with the research by Hu and Wang (2006); however, their results showed that the West had the worst energy efficiency as compared to the east or centre region of China. The differences between our findings are due to variation in the EE over time, as his sample data was for the period 1997–2008.

Fig. 5 shows a continuous decline in energy efficiency from 2004 to 2010 during China’s energy security policy. However, in the transition of energy policy towards energy efficiency with low emission for 2011–2017, there is a gradual and slow rise in EE, which shows improvement in energy efficiency, but the pace is slow in EE level improvement. Further to strengthen the results, the independent sample Mann–Whitney U test shows a significant statistical difference among the Avg. EE between 2004–2010 and 2011–2017 reject the Null hypothesis (see Fig. 6).

The government took serious initiatives to reduce emissions and move towards renewable resources. For example, since the early 2000s, China has become the world’s largest manufacturer of solar panels and wind turbines thanks to investments, subsidies, and favourable feed-in tariffs for power (Wang et al., 2018b). Substantial investments have been made in renewable energy
generation (Sandalow, 2018). Our study shows that the energy efficiency policy (2011) with the least emissions has shown considerable improvement with a gradual increase in EE. However, this progress in transition cannot be considered sustainable because the provincial and city level governments are reluctant to impose strict laws on the massive production, which is a big source of revenue generation and a big cause of emissions.

5.2. Meta-frontier findings

As China has a diverse production technology in different provinces, evaluating accurate energy efficiency is tricky. While measuring the EE, we use the DEA Meta-frontier to explore the regional heterogeneity of the production technology gap across three different regions of China. Table 2 displays the MEE, GEE, and TGR related to the group frontier, meta-frontier, and technology gap ratio. In Table 2, for example, in Anhui province, located in the central region, under the group frontier, the average energy efficiency is 0.787. This suggests that Anhui has a 21.3 percent potential for energy saving and GDP growth if the technology in the central region is used as a reference technology. When referring to the meta-frontier, Anhui’s average energy efficiency is 0.391 with a 60.9 percent increase potential, a significantly higher than the group frontier. Further, the technology gap ratio is 0.528, far away from 1, which shows the gap in EE between the region and nationwide. When referring to the meta-frontier, Anhui’s average energy efficiency is 0.391 with a 60.9 percent increase potential, a significantly higher than the group frontier. Further, the technology gap ratio is 0.528, far away from 1, which shows the gap in EE between the region and nationwide. The majority of provinces in China are in a similar situation to Anhui in that energy efficiency is lower at the meta-frontier than at the group frontier. This is because all samples define the meta-frontier. Thus, the meta-frontier calculation assumes the highest technical level countrywide, whereas the group frontier contains only the best technological level inside the region. Eastern provinces such as Beijing, Guangdong, Hainan, and Shanghai exhibited extraordinary energy efficiency inside and across groups and meta-frontiers. This demonstrates that these provinces or cities exemplify the most acceptable energy efficiency practices in the region and the country.

Fig. 7 & Table A.3 shows the average technology gap ratio in the east, central, and western regions from 2004 to 2017. The energy technology gap ratio in the east is much larger than in the west and central areas; the east’s technology gap ratio remains over 0.95 throughout the sample period. As a result, the eastern provinces have the most advanced energy use technologies. Our results align with Wang et al. (2013a), who argue that most provinces in the east have high energy efficiency and advanced production technologies. The east is the pioneer and early adopter of energy technology reform, and as a result, it has the most advanced energy technology and management systems in the country. This is supported by the fact that provinces in the east do well under group and meta-frontiers outlined before. The west technology gap ratio (0.58) lags behind the east, but it is superior to the central (0.496). It is recommended that the central region continue to update and import energy technology from the east and encourage the development of energy management staff and planning systems. Otherwise, conserving energy and reducing consumption in the central region will become increasingly difficult.

The non-parametric Kruskal–Wallis test assessed whether the TGR in the east, centre, and west differ significantly. We assume that the east, central, and west have the same TGR. The Kruskal–Wallis shows that both p-values are less than the significance level of 0.05. As a result, the null hypothesis that the three regions have the same across is rejected, implying that the east, centre, and west have significantly different TGR (see Fig. 8).
5.3. DEA-malmquist productivity findings

Employing the Malmquist productivity index specified in Eq. (9), we evaluate the change in the energy productivity of different cities, provinces, and regions. Results in Table 3 show that the Malmquist indices’ average value (2004–2017) is 1.009, indicating 0.9 percent energy productivity growth over the period. Further decomposing the Malmquist index into technical efficiency and technology progress, we found that MI changes are mainly due to changes in technological advancement. The mean value of technical change is 1.029, which shows a 2.9 percent increase in technology advancement, while the mean efficiency change EC value is 0.983, which shows a 1.7 percent decline in the efficiency change. These results conclude that although energy productivity in China had improved over the period but mainly due to technological advancement, average energy efficiency has declined, which signals the inefficiency in the production process and growth in energy consumption and carbon emissions. We compare the regional Malmquist energy productivity index in China’s eastern, central, and western areas between 2004 and 2017. This is favourable for understanding the energy efficiency and technology level in different country regions and formulating appropriate energy consumption and emission reduction policies. During the period 2004–2017 Malmquist index of the eastern region illustrated the growth with MI score of 1.048, while a declining trend was noticed in western and central regions with mean MI scores of 0.982 and 0.997, respectively. The central and east regions witness high growth in technology, with an average TC 1.064 and 1.029, respectively, while technology in...
Fig. 6. Mann–Whitney U Test (Mean ranking).

Fig. 7. Technology gap ratio in the east, central and west.

Fig. 8. Kruskal–Wallis test (mean ranking).
attracting global attention to severe environmental concerns. In consumption of non-renewable resources increased dramatically, resources. The targets were not fully achieved in the two FYPs, but consumption of non-renewable resources increased dramatically, attracting global attention to severe environmental concerns. In

6. Conclusion

The Chinese government’s core objective of the Tenth and Eleventh FVPs from 2001 to 2010 was to reduce the consumption of fossil fuels and move towards nuclear power and renewable resources. The targets were not fully achieved in the two FYPs, but consumption of non-renewable resources increased dramatically, attracting global attention to severe environmental concerns. In 2011 China moved towards an energy efficiency policy with emission reduction. The level of success in this mission of energy efficiency during the transition in energy policy is the main objective of our current study. Moreover, regional heterogeneity in production technology gaps among China’s eastern, central and western regions can affect national energy efficiency. Therefore, estimation of production technology gaps can further explain the success level of regional efforts towards energy efficiency with the least carbon emission. Finally, technological advancement and technical efficiency are the two main components of total factor productivity change, which catch-up the change in growth or decline in TFP from t to t + 1. Therefore, change in TFP can explain the year to year change in three different country regions, distinguishing the factors of energy productivity growth.

To this end, firstly, we employed the DEA-SBM model to measure the energy efficiency of China’s 31 cities and provinces from 2004 to 2017. We found that the average efficiency level gradually decreased during the period of the energy security policy, but a slow and fluctuating rise in EE level was noticed after the transition towards the policy of energy efficiency (2011), with less carbon emission and sustainable economic development. The Mann–Whitney U test further strengthens our findings and proves that the distribution of average EE scores across the two-time durations of before and after energy policy transition are statistically and significantly different. EE of Beijing, Shanghai, and Tibet is 1, indicating that these provinces or cities had successfully implemented sustainable growth policies with less carbon emission. Beijing and Shanghai have relatively advanced economies and advanced CO₂ emission reduction technologies and management systems.
Moreover, it was witnessed that Tibet has improved its economic growth with fewer emissions which improved its energy efficiency level. Results indicate that the eastern coastal region is most efficient among all three regions, while most of the Chinese provinces in central and western regions are inefficient as their EE scores are less than 0.44, which indicates that these provinces or cities still have a potential of 56 percent improvement in its energy efficiency level. The policy of EE With the least emissions has shown considerable improvement with a gradual increase in EE level. However, this progress in transition cannot be considered sustainable because the provincial and city level governments are reluctant to impose strict laws on the massive production, which is a big source of revenue generation and a big cause of emissions. It is suggested that the Central Chinese government pay considerable attention to the policy implementation in the central and western regions to improve the regional energy efficiency gaps.

Secondly, with the application of DEA-Meta frontier analysis and the Kruskal–Wallis test, we found that production technology gaps in three different regions are enormous. TGR variations shows that the eastern coastal region is closer to the Meta frontier, indicating that central and western regions are far behind the east and have considerable production technology gaps. This proves that the government is not entirely successful in implementing the policy to improve energy efficiency nationwide. Therefore it is advised to the central and western provinces to shrink the production technology gap with the eastern region to get the entire gains of the national EE policy. Therefore it is advised to the central and western provinces to shrink the production technology gap with the eastern region to get the entire gains of the national EE policy. Elaborating the regional results, we found that the east has TFP growth while the centre and west have declined. Technological progress was witnessed in the eastern region, improving overall TFP growth. Although the centre and west are technologically inferior to the east, they improved their technology over time, but the decline in TFP is primarily due to technical inefficiency. Therefore, our study concludes with two main policy implications. Firstly, central and western regions need to improve their technologies, resulting in less energy consumption and emission. Secondly, the inefficiencies in management need to be enhanced to implement the national energy policy. Data availability is a limitation of the study, and further latest data could give more insights into EE and energy productivity growth in Chinese Provinces. Moreover, a sectoral analysis of China's agriculture, industry and service sectors could be an innovative study, giving brief results on energy inefficiency and productivity decline over the period.

<table>
<thead>
<tr>
<th>Table A.1</th>
<th>Regional distribution of cities and provinces in China.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>East</td>
</tr>
<tr>
<td>Beijing</td>
<td>Anhui</td>
</tr>
<tr>
<td>Fujian</td>
<td>Henan</td>
</tr>
<tr>
<td>Guangdong</td>
<td>Heilongjiang</td>
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<td>Tianjin</td>
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<td>Zhejiang</td>
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<td>Chongqing</td>
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</table>

CRediT authorship contribution statement

Wasi Ul Hassan Shah: Conceptualization, Methodology, Formal analysis, Writing – original draft. Gang Hao: Validation, Supervision. Hong Yan: Validation, Supervision. Rizwana Yasmeen: Data curation, Writing – review. Yan Jie: Data curation, Writing – review.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix

See Tables A.1–A.3.
Table A.2
EE of all three regions over the period 2004–2017.

<table>
<thead>
<tr>
<th>Year</th>
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<th>Central</th>
<th>West</th>
</tr>
</thead>
<tbody>
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<td>0.593</td>
<td>0.537</td>
</tr>
<tr>
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<tr>
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<tr>
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<tr>
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<tr>
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<tr>
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<tr>
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<tr>
<td>2013</td>
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<tr>
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<tr>
<td>2015</td>
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<tr>
<td>2016</td>
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<tr>
<td>2017</td>
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<td>0.378</td>
<td>0.460</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.667</td>
<td>0.428</td>
<td>0.465</td>
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Table A.3
TGR in all three regions over the period 2004–2017.

<table>
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<th>Central</th>
<th>West</th>
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</thead>
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<tr>
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<tr>
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<td>0.537</td>
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<tr>
<td>2010</td>
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<tr>
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<tr>
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<tr>
<td>2017</td>
<td>0.998</td>
<td>0.411</td>
<td>0.585</td>
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References


