Energy efficiency, carbon emission performance, and technology gaps: Evidence from CDM project investment

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ABSTRACT

Measuring the energy conservation and carbon emission reduction potential proves the fundamental basis for stakeholders in the cooperation over Clean Development Mechanism (CDM) projects. This research adopts the meta-frontier non-radial directional distance function based on the Data Envelopment Analysis (DEA) window analysis to measure the total factor energy efficiency and carbon emission performance of leading countries involved in CDM projects during 1990–2015. This study employs the panel quantile regression to investigate the dynamic impact of CDM projects on different energy efficiency and carbon emission performance of CDM host countries. The results indicate that, first of all, the total factor energy efficiency and carbon emission performance of CDM host countries appear much lower than those of investment countries. Second, the technology gap of energy-use and carbon emissions reduction between CDM host and investment countries is significant. Finally, with the increase of total factor energy efficiency and carbon emission performance in CDM host countries, the impact of CDM projects on their energy efficiency is always negative, and that on their carbon emission performance gradually varies from positive to negative, meaning that CDM projects are not necessarily helpful to improve the energy efficiency and carbon emission performance in host countries.

1. Introduction

The Clean Development Mechanism (CDM) is a flexible compensation mechanism proposed by the Kyoto Protocol. It allows developing countries (i.e., CDM host countries) to sell Certified Emission Reduction (CER) obtained from greenhouse gas mitigation projects to the developed countries referred to as Annex 1 parties (i.e., CDM investment countries) to offset their emission reduction obligation (UNFCCC, 2017). According to the United Nations’ Intergovernmental Panel on Climate Change (IPCC, 2014), the mitigation of climate change is a significant challenge, and CDM projects can promote economic growth and inhibit greenhouse gas emissions growth at the same time. It can enhance the sustainable development of developing countries in a cost-effective way to reduce carbon emissions. Similarly, Huang and Barker (2012) argue that the development of CDM projects has significant positive impact on global carbon emissions reduction, and also helps developing countries to achieve lower-carbon development goal.

CDM projects can be used to improve the lower-carbon technology in developing countries and cut down the emission mitigation costs in developed countries. This is mainly attributed to that the total factor energy efficiency of developed countries is very high (Honma and Hu, 2014), leading to their emissions reduction cost being so high to further improve their energy efficiency and carbon emissions reduction (Apergis et al., 2015). However, the energy consumption and carbon emissions in developing countries are mainly driven by economic growth (Zhang and Da, 2015; Zhang, 2011), and their energy efficiency improvement is always negative, and that on their carbon emission performance gradually varies from positive to negative, meaning that CDM projects are not necessarily helpful to improve the energy efficiency and carbon emission performance in host countries.
2. Related literature review

Up to now, a body of literature has investigated the impact of CDM project on developing countries from various perspectives. This paper reviews the relevant literature from three aspects: the impact of energy conservation and emission reduction potential on CDM project investment, the impact of CDM projects on carbon emission reduction in developing countries, the definitions and the research methods for total factor energy efficiency and total factor carbon emission performance.

First of all, some existing studies have investigated the impact of energy conservation and emission reduction potential on CDM project investment. Some research discovers that higher potentials of energy conservation and carbon emission reduction can attract more CDM project investment (Koo, 2017a, 2017b). For example, more than 83% of the projects in CDM portfolio are located in Asia, and more than 69% of the projects are in China and India alone. This is because China has comparative advantage of lower opportunity cost in energy efficiency projects, while India appears to have comparative advantage in hydro power projects (Rahman and Kirkman, 2015). However, some research holds that the number of CDM projects is very limited in some other developing countries, such as Philippines and Thailand, though their energy efficiency is very low (Zhang et al., 2011). Obviously, it is still a controversial issue whether the CDM project investment is consistent with the energy conservation and emission reduction potential. Thus, this paper further measures the potential of energy conservation and emission reduction in some leading developing countries involved in CDM projects.

Second, a lot of studies have explored the impact of CDM projects on carbon emissions reduction in developing countries, but their viewpoints have not reached a consensus. Some scholars argue that the implementation of CDM projects can effectively mitigate carbon emissions (Zhao et al., 2014; Erickson et al., 2014; Benites-Lazarro and Mello-Thery, 2017). For example, Lim and Lam (2014) claim that the number of registered CDM projects in energy sector is in rising trend and helps in large amount of emission reduction in Malaysia. However, there are also some scholars insisting that the CDM projects should not be helpful to reduce carbon emissions (Zavodov, 2012). For instance, Murata et al. (2016) claim that the co-benefits of CDM projects of reducing air pollutant emissions per avoided carbon emission is shown to be much lower than the values reported in previous studies, and the positive effect of the co-benefits of CDMs is rather limited. Thus, it is still in dispute whether CDM projects are helpful to carbon emissions reduction in developing countries. This may be attributed to the fact that the existing studies just evaluate the average impact or its changing trend of CDM projects on carbon emission reduction. However, they are unable to reflect the dynamic impact of CDM projects on carbon emission reduction of host countries when their low-carbon technologies and emission reduction potentials are different. That is to say, it is worthy to further investigate whether CDM project can always promote the energy efficiency and carbon emission performance in developing countries when they arrive at different levels. In fact, the panel quantile regression employed by this paper can well solve this problem.

Third, total factor energy efficiency and total factor carbon emission performance are the key indices influencing efficiency measurement deviation, and have always been calculated by the non-radial directional distance function based on the DEA window analysis to measure the total factor energy efficiency and total factor carbon emission performance under group-frontier and meta-frontier technologies of CDM host and investment countries, and evaluate the technology gap of energy conservation and carbon emissions reduction between the two kinds of countries. For another, this paper adopts panel quantile regression model to explore whether the CDM projects can always have positive impact on various levels of energy efficiency and carbon emission performance in CDM host countries.

The remainder of this paper is organized as follows. Section 2 reviews related literature. Section 3 introduces research methods and data definitions. Section 4 presents empirical results and discussions. Finally, Section 5 concludes the paper and puts forward some policy suggestions.
function not only can both increase desirable outputs and reduce undesirable outputs (Chiu et al., 2013; Barros et al., 2012; Kuosmanen and Johnson, 2017), but also takes into account non-zero slack variables so as to improve the precision of energy measurement with much more actual fitting (Zhou et al., 2012). But it cannot consider the technology gap in various regions, which may lead to measurement bias in cross-regional energy efficiency and carbon emission performance outputs (Zhang et al., 2013; Demchuk and Zelenyuk, 2009). It also cannot compare the energy efficiency of a country during various periods and the energy efficiency of different countries during the same period (Wang et al., 2013; Meng et al., 2014). In fact, these problems can be well solved by the DEA window analysis approach to compute the value of the meta-frontier non-radial directional distance function, which can compare the dynamic efficiency changes in various countries (Zhang et al., 2011) and reduce the measurement deviations by considering the cross-regional technology gaps (Makni et al., 2015; Charnes et al., 1981). Thus, this method is adopted to investigate the dynamic impact of CDM projects on various levels of total factor energy efficiency and carbon emission performance in host countries in this paper.

In summary, following Wang et al. (2016), this paper uses the meta-frontier non-radial directional distance function (DDF) based on the DEA window analysis to measure the total factor energy efficiency and carbon emission performance of the leading countries involved in CDM projects under group-frontier and meta-frontier technologies, respectively. It extends the contribution of existing research in two ways. On the one hand, this paper focuses on sixteen countries involved in CDM project cooperation, including eight CDM host countries and eight investment countries, respectively, and explores their total factor energy efficiency and carbon emission performance. Given that the CDM project investment in developing countries are evenly distributed in terms of the potential of energy conservation and emission reduction; for example, the space for national engagement with the CDM projects is great in India, but the number of CDM projects is limited (Phillips and Newell, 2013); thus this paper chooses to investigate the leading countries involved in CDM projects motivated by rising the importance of the effective investment in CDM projects. On the other hand, in order to solve the problem of neglecting the dynamic impact of CDM projects on different levels of energy efficiency and carbon emission performance in previous literature, this paper employs the panel quantile regression approach to discuss the dynamic impact of CDM projects at various levels of total factor energy efficiency and total factor carbon emission performance in CDM host countries.

3. Methods and data

3.1. Methods

3.1.1. Environmental production technology

This research adopts the non-parametric DEA piecewise-linear production frontier function (Yao et al., 2015) to explore the total factor energy efficiency and carbon emission performance of CDM host and investment countries. Taking the case of eight CDM host countries for example, it corresponds eight Decision Making Units, i.e., 

\[ \sum_{a=1}^{8} a_n y_a \geq y_{a0}, \]

\[ \sum_{a=1}^{8} a_n u_a = u_{a0}, \]

\[ a_n \geq 0, n = 1, 2, ..., 8 \]

(1)

where \( Y_i \) represents the multi-output technology and can both consider the desirable output and undesirable output; \((x, y, u)\) denotes the multi-output production technology and means that \( x \) can produce \( y \) and \( u \); \( y_{a0} \) denotes the DMU currently being evaluated; \( a_n \) is the weight of DMUs; \( x_{mn} \) means the input \( n \) of DMU, \( y_{a} \) and \( u_{a} \) are the desirable and undesirable outputs of DMUs, respectively.

3.1.2. Meta-frontier non-radial DDF based on the DEA window analysis

The DEA window analysis developed by Charnes and Cooper (1985) can be used to explore the efficiency evolution by a sequence of overlapping windows. A DEA window analysis starts from time \( t(1 \leq t \leq T) \), and there are \( N \times W \) (\( n \) is the length and \( W \) is the width of windows) observations in each window. Since this work investigates the energy efficiency and carbon emission performance of sixteen CDM project cooperative countries from 1990 to 2015, thus \( N = 16, W = 26 \). With reference to Halkos and Tzeremes (2009), we adopt a window width of three (i.e., \( W = 3 \)). For example, the first window is formed by the three years of 1990, 1991 and 1992, and the second window is constructed by the following three years of 1991, 1992 and 1993, and so on, until 2015. Thus, there are 24 windows ultimately and each window includes 48 (\( N \times W = 16 \times 3 \)) DMUs. There is only one efficiency value for the years 1990 and 2015, two efficiency values for the years 1991 and 2014, and three efficiency values for other years. The mean value is taken as representative of the energy efficiency and carbon emission performance for each country.

The DEA window analysis approach is employed to calculate the value of the meta-frontier non-radial directional distance function, because it can consider technology gaps among various groups to reduce measurement deviations (Zhang et al., 2013), such as the technology gaps between CDM host and investment countries. Thus, this paper divides these countries into two groups, i.e., CDM host countries (\( h = 1 \)) and investment countries (\( h = 2 \)) and measures the total factor energy efficiency and carbon emission performance with the meta-frontier non-radial directional distance function computed by DEA window analysis.

According to Battese and Rao (2002) and O’Donnell et al. (2008), and using the case of CDM host countries (i.e., \( h = 1 \) for example), the group-frontier non-radial directional distance function can be expressed as Model. (2):

\[
\overline{D}(x, y, u, g) = \sup \{w^T \theta: (x, y, u) + g \times \text{diag}(\theta) \in I_{g} \}
\]

(2)

where based on Zhang et al. (2013), \( \omega = \left( \begin{array}{cccc} 1 & 1 & 1 & 1 \\ -L & -K & -E & -C \end{array} \right) \) and \( \theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5) \geq 0 \) denote the weight vector of inputs and outputs, the explicit directional vector, and the vector of scaling factors of the three inputs, a desirable output and an undesirable output, respectively, \( I_{g} \) is the multi-output technology of CDM host countries defined by Model. (1). The value of \( \overline{D}(x, y, u, g) \) can be evaluated based on Model. (3).

\[
\overline{D}(x, y, u, g) = \max(\omega_1 \theta_1 + \omega_2 \theta_2 + \omega_3 \theta_3 + \omega_4 \theta_4 + \omega_5 \theta_5)
\]

s.t.

\[
\sum_{a=1}^{24} a_n x_{a0} \leq x_{a0} - \theta_1 y_{a0},
\]

\[
\sum_{a=1}^{24} a_n x_{a0} \leq x_{a0} - \theta_2 y_{a0},
\]

\[
\sum_{a=1}^{24} a_n y_a \geq y_{a0} + \theta_3 y_{a0},
\]

\[
\sum_{a=1}^{24} a_n u_a = u_{a0} - \theta_4 y_{a0},
\]

\[
a_n \geq 0, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5 \geq 0
\]

(3)
where $x_{nt}, \theta_{nt}, x_{nt}, y_{nt}$ and $u_{nt}$ denote the labour input, capital input, energy input, desirable output, and undesirable output of $DMU_{nt}$, respectively; $n_0$ denotes the $DMU$ currently being evaluated; and $a_n$ denotes the weight of $DMU_{nt}$.

According to Yao et al. (2015), meta-frontier technology is defined based on the observations of both groups as shown in Model (4), and $\tilde{I}_{2}$ is the multi-output technology of both CDM host and investment countries. That is to say, $\tilde{I}_{2}$ can take account of both the desirable output (GDP) and the undesirable output (carbon emissions). The value of $\tilde{D}_{mn}^{\tilde{I}_{2}}(x, y, u; g)$ can be computed by using Model. (5) in a DEA window analysis (Chiu, 2012).

$$\tilde{D}_{mn}^{\tilde{I}_{2}}(x, y, u; g) = \sum_{i=1}^{n} \sum_{k=1}^{2} \sum_{l=1}^{2} a_{ni} x_{ni} \leq x_{ni} - \theta_{ni} s_{lni}$$

$$\tilde{D}_{mn}^{\tilde{I}_{2}}(x, y, u; g) = \max_{\alpha \in \alpha_{ni}} (a_{ni} \theta_{ni} + \omega_{ni} \gamma_{ni} + \omega_{ni} \beta_{ni} + a_{ni} \delta_{lni})$$

subject to

where $x_{ni}, x_{ni}, x_{ni}, y_{ni}$ and $u_{ni}$ are the labour input, capital input, energy input, desirable output, and undesirable output of $DMU_{i}$ in group $h$, respectively; $a_n$ indicates the weight of $DMU_{i}$; and $n_0$ means the $DMU$ currently being evaluated.

### 3.1.3. Total factor energy efficiency and carbon emission performance index

Suppose that $\theta^*_n$, $\theta^*_n$, $\theta^*_n$ are the optimal energy consumption reduction, GDP improvement, and carbon emissions reduction, respectively. According to Yao et al. (2015) and Zhang et al. (2013), total factor energy efficiency (TEPI) is defined as the ratio of actual energy efficiency to potential energy efficiency; whereas total factor carbon emission performance index (TCPi) is defined as the ratio of potential target carbon intensity to actual carbon intensity, as shown in Eqs. (6) and (7), respectively.

$$TEPI = \frac{1 - \theta^*_n}{1 + \theta^*_n}$$

$$TCPi = \frac{1 - \theta^*_n}{1 + \theta^*_n}$$

where both TEPI and TCPi range from zero to one; and the higher the value is, the better the energy efficiency and carbon emission performance appear, respectively.

According to O’Donnell et al. (2008) and Zhang et al. (2013), the total factor energy efficiency (carbon emission performance) index under meta-frontier technology can be decomposed into the energy efficiency (carbon emission performance) index under group-frontier technology multiplied by the meta-technology ratio index, as shown in Eqs. (8) and (9), respectively. Specifically, the energy efficiency (carbon emission performance) under group-frontier technology can reflect the relative efficiency of observations under group-frontier technologies. The meta-technology ratio can measure the technology gap between group-frontier and meta-frontier technologies.

$$MTEPi = GTEPi \times MTFRE$$

$$MTCPi = GTCPi \times MTRC$$

where $MTRC(MTRE)$ reflects the technology gap in energy efficiency (carbon emission performance) between group-frontier technology and meta-frontier technology. $MTRE(MTRE)$ is between zero and one, and the higher value corresponds to a smaller technology gap between group-frontier and meta-frontier technologies.

### 3.1.4. Panel quantile regression approach

To explore the dynamic impact of CDM projects on the total factor energy efficiency and total factor carbon emission performance of CDM host countries when they vary from low to high, the panel quantile regression approach is employed. It can reflect the relationship between independent and dependent variables at various quantiles and the relevant coefficients can be evaluated more accurately than using traditional regression techniques, which tend to assess the mean effect and may fail to detect significant relationship (Binder and Coad, 2011). In this paper, Certified Emission Reduction (CER) obtained from CDM projects in host countries is defined as the independent variable, while the total factor energy efficiency and total factor carbon emission performance under meta-frontier technology in host countries are the dependent variables, respectively. Taking the total factor energy efficiency for an example, the conditional quantile function for any quantile $\tau (\tau \in (0, 1))$ can be expressed as Eq. (10).

$$Q_{ln(MTEPi)}(\tau|x_{ni}, \xi, ln(x_{nt})) = a_n + \xi + \beta_n ln x_{nt}$$

where $MTEPi$ denotes the total factor energy efficiency under meta-frontier technology of CDM host countries during different periods; $a_n$ indicates the fixed effect; and $x_{nt}$ means the CERs in CDM host countries.

Meanwhile, the coefficient $\beta_n$ at quantile $\tau$ can be obtained by Eq. (11).

$$\min_{(a, \beta, \gamma)} \sum_{k=1}^{K} \sum_{i=1}^{N} u_i \rho_{ki} (ln(MTEPi))_h - \beta_n ln x_{nt} - a_n$$

where $\rho_{ki}$ means the weight that controls the relative influence of the $k$ quantiles $\{l, ..., n\}; \rho_{ki}$ denotes the quantile loss function; $n$ indicates the numbered CDM host countries; and $x_{nt}$ represents the CERs of host countries.

Similarly, taking CERs and total factor carbon emission performance of host countries as the independent and dependent variables, respectively, we can obtain their results of panel quantile regression.

### 3.2. Data definitions

This research adopts the annual data during 1990–2015 for all the necessary variables concerned to measure the total factor energy efficiency and carbon emission performance of CDM host and investment countries. Specifically, the three input factors are labour, capital, and energy, which can be represented by labour force, capital stock and primary energy consumption, respectively. Meanwhile, we choose gross domestic product (GDP) and carbon emissions as the desirable and undesirable outputs, respectively. Specifically, the data of labour force and GDP are derived from the World Development Indicators database (World Bank, 2017), and the data of primary energy consumption (quoted in million tonnes oil equivalent) and carbon emissions (quoted in million tonnes carbon dioxide) are extracted from BP (2017). To eliminate the influence of price, capital stock and GDP are measured in the purchasing power parity term (constant 2010, US$). Because the capital stock cannot be directly obtained from any statistical yearbooks, according to Hu and Kao (2007) and Zhang et al. (2011), we use the perpetual inventory method to calculate the capital stock, as shown in Eq. (12).
derived from the World Development Indicators database (World Bank, 2017); and $\delta$ denotes the depreciation rate of capital stock, and is set to 6% based on published data (Hu and Wang, 2006; Wu, 2004). Besides, the capital stock per worker in 1990 can be obtained from the databases in Penn World Table 5.6. Thus, the capital stock in 1990 can be evaluated by knowing the capital stock per worker and multiplied by the size of labour, namely, $K_{1990} = L^*c$. Hence, based on Eq. (12), we can get the capital stock in 1991. Furthermore, we can calculate the annual capital stock of CDM project cooperation countries from 1990 to 2015.

4. Empirical results and analyses

4.1. Total factor energy efficiency and carbon emission performance under the group-frontier and meta-frontier technologies

According to Models (2) and (3), and Eq. (6), the total factor energy efficiency of CDM host and investment countries under group-frontier technology can be obtained, and that under meta-frontier technology can be derived from Models (4) and (5), and Eq. (6). The results can be found in Fig. 1 and Table 1. Meanwhile, their total factor carbon emission performance under group-frontier technology can be obtained from Models (2) and (3), and Eq. (7), and that under meta-frontier technology can be derived from Models (4) and (5), and Eq. (7). The results are shown in Fig. 2 and Table 2. Based on the results, some main findings are described below.

1. The total factor energy efficiency of CDM host countries is much lower than that of CDM investment countries, and in particular, the total factor energy efficiency of China is much lower than the average level of that in host countries. As shown in Table 1, the average GTEPI value of CDM host countries is 0.6980. This suggests that the energy consumption per unit of GDP of host countries can be reduced by 30.2% on average during 1990–2015 when they operate on the optimal technology of developing countries. In contrast, their average MTEPI value is 0.3842, suggesting that the average energy consumption per unit of GDP of host countries can be reduced by 61.58% with the optimal technology of developed countries. This indicates that the energy use technology of CDM host countries is too low, and especially, that of China and India is the lowest among countries concerned, which is mainly due to the fact that their coal consumption shares are substantial in their primary energy consumption structure. For example, according to BP (2017), coal consumption accounted for 61.83% and 56.91% of total primary energy consumption in China and India in 2016, respectively, which are much higher than the global average level (i.e., 29.75%). Similarly, Pang et al. (2015) argue that the total factor energy efficiency of China and India is very low. Particularly, from Fig. 1(a), we learn that the energy efficiency of China gradually increased after 2007, implying that China has made significant efforts to improve energy efficiency in the past years. For example, Chinese government issued an energy conservation and emissions reduction work-plan in 2007. It claimed that the emissions per ten thousand Yuan GDP should be reduced from 1.22 t of coal equivalent (tce) in 2005 to below 1 tce by 2010 with a decrease of about 20%. China finally achieved a reduction of 19.2% during this period. Meanwhile, China’s central government launched a series of ambitious policies to promote energy...
conservation and emissions reduction, such as integrating the use of legal, economic, technological, and administrative means on ten major energy conservation projects, thousands of enterprises taking energy conservation actions, the energy conservation project benefiting the people, the elimination of outdated production capacity, the energy-saving renovation of the construction industry, and contract energy management measures etc. Influenced by these policies, the production comprehensive energy consumption of some primary enterprises has decreased significantly. However, the total factor energy efficiency of developed countries appears far higher as can be seen from Fig. 1 and Table 1, which is mainly due to their high proportion of tertiary industries and lower energy intensity of industrial structure with increasing adoption of high-technologies. Similarly, Honma and Hu (2014) claim that the energy efficiency of developed countries, such as UK and Japan, is all at high levels.

(2) The total factor carbon emission performance of CDM host countries is much lower than that of CDM investment countries, and in particular, the total factor carbon emission performance of China is much lower than the average level of that in host countries. Specifically, the mean GTCEPI and MTCPI of CDM host countries on the whole are 0.6652 and 0.3582, respectively, while the mean GTCEPI and MTCPI of China are 0.2803 and 0.1533, respectively; and their corresponding carbon emissions reduction performances of the sixteen CDM host and investment countries are 9.123 billion tonnes of carbon equivalent in 2016, accounting for 27.28% of global carbon emissions with the first in the world (BP, 2017). However, its carbon emissions reduction technology is still relatively lower than the optimal technology in developed countries. In fact, according to Gaast et al. (2009), CDM projects can be used to improve technology transfer in accordance with the development priorities of host countries, and achieve more carbon emission reduction in a cost effective way. Actually, incentives and subsidies can promote the development of CDM projects (Sawhney and Rahul, 2014). Thus, Chinese government can develop more effective incentives to attract CDM projects with greater technological innovation (Zhang and Yan, 2015). The total factor carbon emission performances of investment countries are all high under both group-frontier and meta-frontier technologies as shown in Fig. 2 and Table 2, and the results are consistent with that of Lu et al. (2013). This is mainly attributed to the fact that their proportions of coal consumption are relatively lower in their primary energy consumption structure. Based on BP (2017), the average coal consumption proportion of the eight developed countries concerned was 10.05% in 2016, which is much lower than the global average level (i.e., 28.11%). Meanwhile, their average clean energy consumption proportion is 50.33%, which is much higher than the global average level (i.e., 38.61%).

(3) There is significant difference in the energy conservation and emissions reduction potentials of the sixteen CDM host and investment countries. Specifically, from Tables 1 and 2, we can learn that, when the eight CDM host countries operate on the optimal technology of developed countries, the energy consumption per unit of GDP of China, India, Mexico, Thailand, Chile, Philippines, Colombia and Peru can be reduced by 84.48%, 80.14%, 65.07%, 75.82%, 57.15%, 61.98%, 44.46% and 44.34%, respectively. The results indicate

Table 1
Total factor energy efficiency under group-frontier and meta-frontier technologies.

<table>
<thead>
<tr>
<th>Country group</th>
<th>GTEPI</th>
<th>MTEPI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. dev</td>
</tr>
<tr>
<td>CDM host countries</td>
<td></td>
<td></td>
</tr>
<tr>
<td>China</td>
<td>0.2803</td>
<td>0.1533</td>
</tr>
<tr>
<td>India</td>
<td>0.3586</td>
<td>0.1780</td>
</tr>
<tr>
<td>Mexico</td>
<td>0.8473</td>
<td>0.1236</td>
</tr>
<tr>
<td>Thailand</td>
<td>0.5035</td>
<td>0.2266</td>
</tr>
<tr>
<td>Chile</td>
<td>0.9928</td>
<td>0.0181</td>
</tr>
<tr>
<td>Philippines</td>
<td>0.6722</td>
<td>0.1496</td>
</tr>
<tr>
<td>Colombia</td>
<td>0.9842</td>
<td>0.0246</td>
</tr>
<tr>
<td>Peru</td>
<td>0.9540</td>
<td>0.0550</td>
</tr>
<tr>
<td>Host countries</td>
<td>0.6980</td>
<td>0.3029</td>
</tr>
<tr>
<td>CDM investment countries</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UK</td>
<td>0.8679</td>
<td>0.1552</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.9853</td>
<td>0.0234</td>
</tr>
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<td>Netherlands</td>
<td>0.5077</td>
<td>0.1571</td>
</tr>
<tr>
<td>Japan</td>
<td>0.4847</td>
<td>0.1213</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.6620</td>
<td>0.2720</td>
</tr>
<tr>
<td>USA</td>
<td>0.4047</td>
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<td>Spain</td>
<td>0.5154</td>
<td>0.1551</td>
</tr>
<tr>
<td>Italy</td>
<td>0.8009</td>
<td>0.1821</td>
</tr>
<tr>
<td>Investment countries</td>
<td>0.6536</td>
<td>0.2638</td>
</tr>
</tbody>
</table>

GTEPI and MTEPI represent the total factor energy efficiency under group-frontier and meta-frontier technologies, respectively.

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*In fact, the GTEPI and GTCEPI of China in 1990 should not be at a higher level in Figs. 1(a) and 2(a), because China’s energy intensity and carbon intensity were higher than those of other developing countries. For example, the energy intensity and carbon intensity of China were 0.8214 and 2.2970 in 1990, respectively, while those of the rest seven developing countries were 0.2032 and 0.5424 on average, respectively. However, the results in Figs. 1(a) and 2(a) show that the GTEPI and GTCEPI of China in 1990 were both high. This was caused by the measurement bias, because the results of 1990 were only calculated by one window. As the number of DEA windows increases, the GTEPI and GTCEPI saw a decline in 1991, and then they changed stably at the relatively lower level.*
that, comparatively, the energy conservation and carbon emission reduction potential of Colombia and Peru appears relatively lower, but that of China and India proves far higher. Meanwhile, based on UNFCCC (2017), the proportions of global registered CDM projects of Colombia, Peru, China and India are 0.82%, 0.78%, 48.40% and 21.17%, respectively. This may be due to that the higher potentials of energy conservation and carbon emission reduction these CDM host countries have, the more CDM projects they tend to register.

Similarly, given the optimal technology of developed countries, the

![Fig. 2. The changing trends of GTCPI and MTCPI values for both CDM host and investment countries. GTCPI and MTCPI denote the total factor carbon emission performance under group-frontier and meta-frontier technologies, respectively.](image-url)
energy consumption per unit of GDP of UK, Switzerland, Netherlands, Japan, Sweden, USA, Spain and Italy can be reduced by 12.71%, 3.26%, 48.87%, 51.9%, 33.77%, 59.52%, 48.9% and 19.71% during 1990–2015, respectively; and their corresponding carbon emissions reduction can be improved by 10.18%, 1.54%, 54.17%, 58.52%, 10.25%, 56.59%, 54.66% and 29.22%, respectively (see Tables 1 and 2). Comparatively, the energy conservation and emission reduction potentials of UK and Switzerland appear relatively lower, while they contribute to 24.08% and 16% of global CDM projects (UNFCCC, 2017). In particular, it is worth noting that although the potential of energy conservation and emission reduction of a few developed countries is higher than that of developing countries, a number of studies show that the costs of energy conservation and emission reduction in developing countries are lower than developed countries (Almeida and Ferreira, 2017; Wu et al., 2016). Under this circumstance, it is helpful for developed countries to invest in CDM projects in developing countries overall, because this way can help those developed countries to achieve their greenhouse gas emission reduction targets in a cost-effective way.

4.2. Analyses of the technology gap between CDM host and investment countries

According to Eqs. (8) and (9), the meta-technology ratio of the energy efficiency and carbon emission performance in CDM host and investment countries, namely, the technology gaps of energy efficiency and carbon emission performance between group-frontier and meta-frontier technologies, can be obtained (see Table 3 and Fig. 3).

We find that the technology gaps of energy-use and carbon emission reduction between CDM host and investment countries are significant. Specifically, the mean MTRE and MTRC of host countries are 0.5957 and 0.5878, respectively (see Table 3), indicating that the energy efficiency and carbon emission performance can, on average, be improved by 40.43% and 41.22% during 1990–2015 when host countries overcome their technological limitations and regulations, respectively. This may be driven by the fact that economic growth promotes the energy consumption and carbon emissions in developing countries (Zhang, 2011), and their coal-fired power plants play the dominant role in the power industry (Zhang and Sun, 2016). However, their low-carbon technology and clean energy consumption structure are both at a relatively lower level. In fact, CDM projects can effectively promote carbon emissions reduction (Rive and Aunan, 2010), and especially CDM is partly towards large scale projects with high emission reductions (Koo, 2017a, 2017b).

However, the mean values of MTRE and MTRC of CDM investment countries are very close to 1 (see Table 3). They stay at a relatively stable level during 1990–2015 (see Fig. 3(a) and (b)), which implies that their technologies of energy-use and carbon emission reduction are close to the optimal technology of developed countries.

4.3. The dynamic impact of CDM projects on energy efficiency and carbon emission performance of host countries

According to UNFCCC (2017), the CERs provided by CDM projects in host countries mainly began from 2007. Thus, we employ the panel quantile regression approach to investigate the dynamic impact of CERs on the energy efficiency and carbon emission performance of host countries during 2007–2015.

4.3.1. The results of panel unit root and panel cointegration tests

The independent variable is \( \ln x \) and the dependent variables are \( \ln \text{METE} \) and \( \ln \text{MTCP} \), and their descriptive statistics are shown in Table 4. Then, we test whether the variables \( \ln \text{METE} \), \( \ln \text{MTCP} \) and \( \ln x \) during 2007–2015 are stationary before developing the panel quantile regression model. Specifically, we adopt three panel unit root tests: the LLC test, the Fisher-ADF test and the Fisher-PP test, and get the results shown in Table 5. We find that the results of \( \Delta \ln \text{METE} \), \( \Delta \ln \text{MTCP} \) and \( \Delta \ln x \), respectively, all reject the unit root null hypothesis at the 1% level, indicating that they are all stationary. Furthermore, we adopt both the Pedroni residual cointegration test and Kao residual co-integration test to explore whether there is a long-run relationship between dependent and independent variables, and the results are presented in Table 6. It can be found that all the results reject the null hypothesis at the 10% level. Thus, we can say that there is a long-run relationship between the independent variable of CERS and the dependent variables of energy efficiency and carbon emission performance during 2007–2015.

4.3.2. Results of the dynamic impact of CDM projects

Based on Eqs. (10) and (11), we get the quantile regression results of the impact of CERs on the total factor energy efficiency and carbon emission performance of CDM host countries, as shown in Fig. 4 and Table 7. We find that:

As the quantiles become higher, which means the increase of total factor energy efficiency and total factor carbon emission performance of CDM host countries, the impact of CDM projects on the energy efficiency is negative on the whole, but that on the carbon emission performance gradually changes from positive to negative. Specifically, as shown in Fig. 4, the CDM projects do not help to improve energy efficiency, which is consistent with the existing literature (Zavodov, 2012). However, the impact of CDM project is positive when the total factor carbon emission performance is low. This may be due to the fact that their carbon emission reduction potentials are great at this time, so increasing CDM projects investment can significantly promote their carbon emission performance. For example, we can learn that the carbon emission performance of CDM host countries, and, especially that of China, appears relatively lower as shown in Fig. 2. To be similar, Zhao et al. (2014) investigate the impact of CDM on renewable energy source in China, and claim that CDM is one of the most significant factors in promoting the development of wind power in China.

However, more investment of CDM projects may result in negative impact when the carbon emission performance of CDM host countries becomes higher. This may be caused by the fact that when the carbon emission reduction potential becomes lower, and more costs may be needed to achieve equal carbon emission reduction. With the improvement of low-carbon technology in developing countries in future, as stated by Hieronymi and Schüller (2015), CDM projects have negative impact on renewable energy investment, which can further influence carbon emissions reduction.

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In fact, the results of the T test of independent sample show that the \( P \) values of F test and T test are both 0.000, indicating that the difference is statistically significant at the 1% level.

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In fact, we conduct the panel quantile regression at 99 quantiles from 0.01 to 0.99 with the step length 0.01, and find that the impact of CDM projects on carbon emission performance changes from positive to negative at the relatively lower quantile of 0.28.
Furthermore, the impact of CDM projects on the energy efficiency and carbon emission performance becomes stronger as the quantiles approach to the higher levels. Specifically, we can learn from Table 7 that, in terms of the results of quantiles 0.10 through 0.99, the impact on energy efficiency ranges from $-0.0556$ to $-0.2093$, and that on carbon emissions ranges from $-0.0763$ to $-0.1974$.

Table 4
Descriptive statistics of the variables of CDM host countries.

<table>
<thead>
<tr>
<th>Variable</th>
<th>ln MTEP</th>
<th>ln MTCPI</th>
<th>ln x</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>$-1.0618$</td>
<td>$-0.9262$</td>
<td>$15.0853$</td>
</tr>
<tr>
<td>Median</td>
<td>$-1.0152$</td>
<td>$-0.8468$</td>
<td>$14.8780$</td>
</tr>
<tr>
<td>Maximum</td>
<td>$0.0000$</td>
<td>$0.0000$</td>
<td>$19.4249$</td>
</tr>
<tr>
<td>Minimum</td>
<td>$1.8401$</td>
<td>$1.9031$</td>
<td>$10.2089$</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>$0.5011$</td>
<td>$0.5678$</td>
<td>$2.5451$</td>
</tr>
<tr>
<td>Skewness</td>
<td>$0.0805$</td>
<td>$-0.2345$</td>
<td>$-0.0190$</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>$2.1117$</td>
<td>$1.9875$</td>
<td>$2.0776$</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>$2.4450$</td>
<td>$3.7352$</td>
<td>$2.5565$</td>
</tr>
</tbody>
</table>

Table 5
Results of panel unit root tests.$^a$

<table>
<thead>
<tr>
<th>Variable</th>
<th>LLC test</th>
<th>ADF-Fisher test</th>
<th>PP-Fisher test</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln MTEP</td>
<td>$0.4956$ (0.68)</td>
<td>$12.4197$ (0.71)</td>
<td>$10.8638$ (0.81)</td>
</tr>
<tr>
<td>$\Delta$ ln MTEP</td>
<td>$4.3622$ (0.00)</td>
<td>$35.1140$ (0.00)</td>
<td>$39.0687$ (0.00)</td>
</tr>
<tr>
<td>ln MTCPI</td>
<td>$0.5288$ (0.70)</td>
<td>$11.2828$ (0.79)</td>
<td>$10.1541$ (0.85)</td>
</tr>
<tr>
<td>$\Delta$ ln MTCPI</td>
<td>$6.8121$ (0.00)</td>
<td>$60.8960$ (0.00)</td>
<td>$61.7355$ (0.00)</td>
</tr>
<tr>
<td>ln x</td>
<td>$1.5408$ (0.93)</td>
<td>$4.5212$ (0.99)</td>
<td>$4.3067$ (0.99)</td>
</tr>
<tr>
<td>$\Delta$ ln x</td>
<td>$6.8398$ (0.00)</td>
<td>$61.7525$ (0.00)</td>
<td>$65.3535$ (0.00)</td>
</tr>
</tbody>
</table>

$^a$ LLC test is the panel unit root test of Levin et al. (2002), Fisher-ADF test and Fisher-PP test are the Maddala and Wu (1999) Fisher-ADF and Fisher-PP panel unit root tests, respectively. The P-values of corresponding statistics are reported in parentheses.

Table 6
Results of panel co-integration test.$^a$

<table>
<thead>
<tr>
<th>Statistics</th>
<th>lnMTEP ↔ ln x</th>
<th>lnMTCPI ↔ ln x</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Pedroni residual co-integration test</td>
<td>$-0.4133$ (0.66)</td>
<td>$-0.1320$ (0.04)</td>
</tr>
<tr>
<td>Panel rho-Statistic</td>
<td>$-0.2364$ (0.40)</td>
<td>$-0.1107$ (0.54)</td>
</tr>
<tr>
<td>Panel PP-Statistic</td>
<td>$-0.7160$ (0.79)</td>
<td>$0.8328$ (0.20)</td>
</tr>
<tr>
<td>Panel ADF-Statistic</td>
<td>$1.4629$ (0.92)</td>
<td>$1.4504$ (0.92)</td>
</tr>
<tr>
<td>Group rho-Statistic</td>
<td>$-0.1320$ (0.04)</td>
<td>$-0.8328$ (0.20)</td>
</tr>
<tr>
<td>Group PP-Statistic</td>
<td>$-0.1320$ (0.04)</td>
<td>$-0.8328$ (0.20)</td>
</tr>
<tr>
<td>Group ADF-Statistic</td>
<td>$0.1107$ (0.54)</td>
<td>$2.5109$ (0.00)</td>
</tr>
<tr>
<td>Panel B: Kao residual co-integration test</td>
<td>$0.6060$ (0.07)</td>
<td></td>
</tr>
<tr>
<td>ADF</td>
<td>$-2.2717$ (0.01)</td>
<td></td>
</tr>
</tbody>
</table>

$^a$ The P-values of corresponding statistics are reported in parentheses; Pedroni residual co-integration test and Kao residual co-integration test are two kinds of panel co-integration test, respectively; $\text{lnMTEP} \leftrightarrow \text{ln x}$ denotes the co-integration relationship between $\text{lnMTEP}$ and $\text{ln x}$; $\text{lnMTCPI} \leftrightarrow \text{ln x}$ indicates the co-integration relationship between $\text{lnMTCPI}$ and $\text{ln x}$.

Furthermore, the impact of CDM projects on the energy efficiency and carbon emission performance becomes stronger as the quantiles approach to the higher levels. Specifically, we can learn from Table 7 that, in terms of the results of quantiles 0.10 through 0.99, the impact on energy efficiency ranges from $-0.0556$ to $-0.2093$, and that on carbon emissions ranges from $-0.0763$ to $-0.1974$. The detailed results can be obtained upon request from authors.

$^a$ Table 7 only presents the results of 11 quantiles and some results in Table 7 are not statistically significant, such as quantiles 0.1 and 0.2, but we actually conduct 99 quantiles and most of them are statistically significant.
carbon emission performance varies from 0.0092 to −0.1090. To facilitate comparisons, we also estimate the static results of OLS regression as shown in Table 8. We can learn that the impact of CDM projects on energy efficiency and carbon emission performance is negative on average, which is similar to the dynamic results of quantile regression overall but is unable to reflect the dynamic details.

5. Conclusions and policy suggestions

Using the meta-frontier non-radial directional distance function based on the DEA window analysis, this paper measures the total factor energy efficiency and total factor carbon emission performance of sixteen CDM host and investment countries under group-frontier and meta-frontier technologies, respectively. It also investigates the dynamic impact of CDM projects on the energy efficiency and carbon emission performance of host countries. According to the results above, some main conclusions are soundly drawn as follows:

1. The total factor energy efficiency of CDM host countries is much lower than that of CDM investment countries during the sample period, and in particular, the total factor energy efficiency of China is much lower than the average level of that in host countries. The energy consumption per unit of GDP in host countries and China can be reduced by 30.2% (61.58%) and 71.97% (81.89%) on average during 1990–2015 when they operate with the optimal technology of developing (developed) countries, respectively.

2. The total factor carbon emission performance of CDM host countries is much lower than that of CDM investment countries, and in particular, the total factor carbon emission performance of China is much lower than the average level of that in host countries. Carbon emissions reduction of host countries and China can be improved by 33.48% (64.18%) and 75.46% (84.48%) on average from 1990 to 2015, respectively, given that they operate with the optimal technology of developing (developed) countries.

3. As the total factor energy efficiency and total factor carbon emission performance of CDM host countries increase, the impact of CDM projects on the energy efficiency is negative all the time, but that on the carbon emission performance gradually changes from positive to negative. Put another way, the implementation of CDM projects is not necessarily conducive to the improvement of carbon emission performance in host countries, when their carbon emission performance stays at a relatively higher level.

Based on these conclusions, we also try to propose two main suggestions for both CDM host and investment countries. (1) The carbon emission reduction potentials in China and India are much higher than...
to developing countries through the CDM. Appl. Energy 86, 230–236.


