Nat Hazards (2017) 88:1211–1227
DOI 10.1007/s11069-017-2915-2

ORIGINAL PAPER

Investigating the learning effects of technological advancement on CO_2 emissions: a regional analysis in China

Wei Li[1] · Tao Zhao[1] · Yanan Wang[2] · Fang Guo[1]

Received: 28 July 2016 / Accepted: 7 May 2017 / Published online: 15 May 2017

Abstract Technological advancement plays a crucial role in CO_2 emissions mitigation and has attracted great attention around the world. A multitude of literatures mainly focused on single technological impact on environmental issues at national level, while comprehensive studies concerning technological factors at regional level are rare. This paper employs environmental learning curve model to investigate the learning effects of different technological channels on CO_2 emissions at the national and regional levels using panel data of China's 29 provinces from 1997 to 2014. The technological advancement is disaggregated into indigenous research and development (R&D), foreign technology import and technological revolution. Furthermore, to comprehend the characteristics of various provinces with regard to CO_2 emissions and emission efficiency, China's 29 provinces are divided into four regions according to the features of "CO_2 emissions-efficiency". Empirically results manifest that technical renovation is the paramount driver to mitigate the national CO_2 emissions. The CO_2 learning abilities of indigenous R&D in high emissions regions are greater than those in the low ones, while boosting the investment of foreign technology import in low emission regions has significantly positive impacts on CO_2 emissions, and the technical renovation is effective in abating CO_2 emissions in all regions. The findings not only enrich technology innovation theories, but also deserve special attention from policymakers.

Keywords Technological advancement · Multivariable environmental learning curve · Regional differences · CO_2 emissions

Electronic supplementary material The online version of this article (doi:10.1007/s11069-017-2915-2) contains supplementary material, which is available to authorized users.

✉ Yanan Wang
wyn3615@126.com

1 College of Management and Economics, Tianjin University, Tianjin 300072, China

2 College of Economics and Management, Northwest A&F University, Yangling 712100, China

1 Introduction

The global warming and resource restriction have raised widespread concern in the world. As the country with the largest CO_2 emission globally (Liu et al. 2014), Chinese government has faced enormous pressure of trimming down its emission. To ease the pressure of emission reduction, Chinese government has pledged that by 2030, the CO_2 emissions per unit of GDP would be reduced by 60–65% compared to the level of 2005. In the conference of China–US joint statement on climate change, China also proclaimed that its peak for CO_2 emissions would be reached and the proportion of non-fossil energy in primary energy consumption would increase to 20% by 2030. However, economic development is still the main priority in China. It is widely recognized that controlling CO_2 emissions is especially difficult with the premise of ensuring economic growth (Wang and Li 2016; Zhu et al. 2015; Noailly and Smeets 2015). Under such circumstance, relying on technological advancement is always the pillar of China's climate change mitigation strategy (Yuan et al. 2016). Technological advancement is a primary concern in curbing CO_2 emissions and also plays a crucial role in transforming the Chinese economy toward a low-carbon pathway.

In light of this, there are increasing studies concerning about the effect of technological advancement on CO_2 emissions. After scrutinizing the literature, this study figures out that the role of technological advancement in reducing emissions remains controversial. Some studies reported that the technological advancement played an important role in reducing CO_2 emissions (Wei and Yang 2010; Wang et al. 2012; Yang et al. 2014). Researchers also found that increasing CO_2 emissions are positively associated with technological advancement, which mainly resulted from the existence of rebound effects (Li and Lin 2015; Wang and Lu 2014). However, other researcher stated technological advancement had no significant impact on CO_2 emissions (Hu and Huang 2008; Teng 2012). The influences of technological advancement on environmental issues are complicated and inconsistent because of different factors, models and research samples.

Most studies in this area examined separately the impacts of various technological channels on CO_2 emissions and failed to comprehensively investigate the integrated effect of a variety of channels which together may influence the performance of CO_2 emissions reduction. Thus, as technological advancement impose complicated and changeable influences on CO_2 emissions, a further and detailed exploration of various technological channels for CO_2 emissions reduction in a unified framework is urgently required.

To fill in this research gap, this paper pays special attention to different technological channels influencing CO_2 emissions and considers different technological channels for technology progress in one united framework, which can further compare their relative advantages in abating the CO_2 emissions and avoid the estimation bias caused by omitted variable. In empirical studies, technological advancement can be measured by input indicators [R&D expenditure (Yang et al. 2014; Boeing et al. 2016)] or output indicators [patents (Wang et al. 2012; Wu 2016), literature (Wong et al. 2014)]. But there are some limitations in measuring technological advancement by using output indicators. Taking patents counts, for example, not all innovations are patentable (Albino et al. 2014), and patents counts have no clear interpretation (Pakes 1985). In this sense, this study employs input indicators to measure technological advancement, mainly including indigenous R&D and foreign technology import (Wei and Yang 2010; Teng 2012). Moreover, technical renovation is regarded as another important source of technological advancement (Xu et al. 2013). Considering its significant role in improving environmental performance, it is expected that technical renovation can effectively trim down the CO_2 emissions. However, the impact of technical renovation on CO_2 emissions is still ignored so far. In summary, this study takes into account the role of indigenous R&D, foreign technology import and technical renovation, the main channels of technological advancement, in mitigating the CO_2 emissions.

Furthermore, several econometric energy models have been adopted to estimate the impact of technological advancement on CO_2 emissions, which generally involve building the STIRPAT (stochastic impacts by regression on population, affluence and technology) model (Lin and Xie 2014; Wang and Zhao 2015), the Kaya equation (Wang and Li 2016) and Logarithmic Mean Divisia Index (Ang 2004), etc. Besides the aforementioned models, the environmental learning curve (ELC) model is increasingly applied to estimate the role of technological advancement in curbing CO_2 emissions (Fehr 2003; Sun et al. 2008, 2011; Yu et al. 2011, 2015; Guo et al. 2016). Moreover, ELC model integrates the concept of conventional learning curves and depicts the environmental protection progress along with the development of technology (Yu et al. 2015). This model is thereby more plausible and internally consistent than the intuition of the modeler (Grübler et al. 1999; Yu et al. 2011). More importantly, the strong CO_2 emissions learning ability of technological advancement estimated by ELC model indicates the technologies would effectively curb the emissions, which is crucial for China to achieve the ambitious CO_2 emissions reduction target. Therefore, the ELC model is applied in this paper to address the impacts of different technological channels on CO_2 emissions.

Besides, China has a vast territory and exhibits significant regional differences. Previous regional research mainly bases on the classification of geographical location (Wang et al. 2012; Zhang and Zhou 2016). However, there are significant differences among regions in China in terms of CO_2 emissions performance (Wang and Zhao 2015). Hence, to analyze the characteristics of regions with various CO_2 emissions and emission efficiency, this paper divides China into four regions according to the "CO_2 emission-efficiency" features.

The rest sections of this paper are organized as follows. Section 2 presents a literature review; model specification, methodology and data sources are introduced in Sect. 3. Section 4 presents the empirical results and discussions of CO_2 emissions learning curve through technological advancement; main conclusions and policy recommendations of the current research are summarized in Sect. 5.

2 Literature review

This paper constructs the environmental learning curve to identify how different technological channels can influence the regional CO_2 emissions, and further makes a distinction among the four regions. In this section, based on relevant literatures, we analyze the role of indigenous R&D, foreign technology import and technical renovation in CO_2 emissions reduction.

2.1 The role of indigenous R&D in CO_2 emission reduction

Indigenous R&D is recognized as the engine of sustained economic growth in endogenous growth theory (Romer 1990) and is also found to be a vital channel to promote the technology innovation and accumulate absorptive capacity. These capacities are crucial for increasing energy efficiency and curbing CO_2 emissions for a long run (IPCC 2006). Many related papers have been conducted, including those by Ang (2009), Wei and Yang (2010) and Yang et al. (2014). Moreover, previous studies have also reported that finite resources and stringent environmental goals in developing country have facilitated the indigenous R&D investment for energy-saving technologies, which in turn reduced the CO_2 emissions (Teng 2012, Fisher et al. 2004). Additionally, indigenous R&D, which determines the pace and direction of the technology transformation, is used to measure the input of technological innovation. Li and Lin (2016) also confirmed that higher R&D investment in China has resulted in more energy technology patents and thus accelerated the development of energy conservation and low-carbon technology. Consistent with these previous studies, we expect that indigenous R&D could help to reduce CO_2 emissions in China. Thus, we hypothesize:

Hypothesis 1 The indigenous R&D is positively associated with the reduction of CO_2 emissions in China.

2.2 The role of foreign technology import in CO_2 emission reduction

Technological advancement is costly and risky (Boeing et al. 2016). Compared to indigenous R&D, foreign technology import is a relatively low-cost R&D activity (Wei and Yang 2010). Hence, foreign technology import is another key channel for technological advancement. Importing technologies from abroad causes fierce competition to domestic firms and promotes domestic firms' impetus to invest in R&D activities in order to enhance their competitiveness (Boeing et al. 2016). Therefore, importing foreign technology not only accelerates the technological advancement, but also generates a series of beneficial effect, such as vertical linkages (Wei and Yang 2010) and international cooperation (Boeing et al. 2016). Yet, the empirical evidences concerning whether foreign technology import is beneficial to the reduction of CO_2 emission or not are mixed. Wei and Yang (2010) implied that foreign technology import played a crucial role in reducing CO_2 emissions according to a sample of 29 provinces in China, whereas Teng (2012) suggested that foreign technology import has a significant negative influence on energy intensity of the 31 industrial sectors, which in turn may raise CO_2 emission. Besides, Teng (2009) found that the impact of foreign technology import on energy intensity is highly dependent on the technology level of the provinces in China. Following the intuitions derived from the above literatures, we develop the research hypotheses:

Hypothesis 2 The learning ability of foreign technology import in CO_2 emission reduction is modified by regional technological capacity in such a way that greater technological capacity is associated with a higher CO_2 learning ability.

2.3 The role of technical renovation in CO_2 emission reduction

Technical revolution is different from indigenous R&D or foreign technology import. The term "technical revolution" in this paper means that the enterprises implement effective measures to refurbish and retrofit the existing facilities, technological conditions or production services, etc. (SCC 2012). For example, replacing low-efficient coal combustion in industrial and residential heat supply and installing metering equipment for heating energy use (Xu et al. 2013). Thus, the purposes of technical revolution are to eliminate backward production capacity, improve production efficiency, reduce pollutions emission, and ultimately achieve the technological advancement. It implied that technical revolution plays an important role in improving environmental performance. In case of China, technical revolution has become the major initiatives of China's national energy and environment policy. During the 11th FYP period, pushing clean coal power development in both newly built and existing fleets mainly relies on the technical revolution (Yuan et al. 2016). In 2014, the Action Plan on Energy Saving and Emissions Reduction Upgrading & Retrofitting in Coal Power Plants (2014–2020) was issued by National Development and Reform Commission (Yuan et al. 2016). The Action Plan aims to build a clean and high efficient coal power sector through technical revolution in China. Thus, it is necessary to know whether technical revolution can cut down the CO_2 emissions in China. However, only a few environmental literatures have taken into account the role of technical revolution (Rodney and Phil 2009; Xu et al. 2013). Thus, this study will place particular emphasis on the role of technical revolution in mitigating CO_2 emissions.

Hypothesis 3 Boosting the investment of the Technical revolution is beneficial to curb the CO_2 emissions in China.

3 Data and methodology

3.1 Multivariable ELC model

The original learning curve model was firstly proposed by Wright (1936) to depict the time savings (or cost reduction) accompanying the increasing output of aircraft manufacturing. The learning curve model reveals the gradual manufacturing cost decline with repeating production process or increasing output in the enterprises. It also reflects that enterprises succeeded in reducing the manufacturing cost with the experience accumulation or technological advancement. Later, learning curve has been extended to not only manufacturing industry, but also engineering technology innovation, products research and development and other industries (Fehr 2003; Sun et al. 2011). Recently, borrowing from learning curve, "environmental learning curve" has been proposed. Previous related studies have employed the ELC to explore the energy, water consumption and SO_2 emissions (Sun et al. 2008, 2011; Yu et al. 2011). The ELC model introduces a concept of "environmental learning" that reflects environmental improvements (i.e., CO_2 emissions abatement) through the economic development and technological advancement (Fehr 2003). However, previous studies in this area only considered the per capita GDP factor (Sun et al. 2008, 2011) and technological factors were ignored. Therefore, the environmental learning by technological advancement needs to be further explored.

The ELC model is commonly estimated by Alchian multilog model, Cobb–Douglas multiplicative exponential model and Womer's variable production rate model (Badiru 1992). Due to the feature of flexibility and concise structure, Cobb–Douglas model has been multiply utilized (Rubin et al. 2004). The standard Cobb–Douglas model can be expressed as Eq. (1).

$$C = A\prod_{i=1}^{n}(x_i)^{-b_i}\varepsilon \tag{1}$$

where C denotes the environmental cost; A indicates the initial environmental cost with fixed value which is determined by the development of society and economy. b_i represents the learning coefficient of the ith factor, which can be estimated by regression; x_i stands for the ith learning factor; and ε is the error term.

Similar to the ELC, the CO_2 emissions learning curve reflects that enterprises (i.e., industries or regions) succeed in reducing CO_2 emissions through experience accumulation and technological advancement. The CO_2 emissions learning by technolocal advancement implies the technology transformation from carbon-intensive technologies towa low-carbon ones, which is important to curb the CO_2 emissions in China for a long run.

Above all, this paper explores the CO_2 emissions learning by technological advancement in China, and three different technological channels are adopted to construct the process of technological advancement, including indigenous R&D activity, foreign technology import and technical renovation. To avoid omitted variable bias, GDP per capita is also included in the present study due to its important role in influencing CO_2 emissions and technological advancement. By applying the natural logarithms of Eq. (1) to both sides, an extended ELC was proposed.

$$\ln \mathrm{CE}_{i,t} = A_0 - b_{1i}\ln Y_{i,t} - b_{2i}\ln \mathrm{RD}_{i,t-1} - b_{3i}\ln \mathrm{FT}_{i,t-1} - b_{4i}\ln \mathrm{TR}_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where i is the ith region, and t is the tth year; CE represents CO_2 emissions, A_0 denotes the initial CO_2 emissions which are determined by the development of society and economy. Y stands for GDP per capita computed as GDP divided by population at the end of the year t. RD, FT and TR indicate the knowledge stock of indigenous R&D, foreign technology import and technical renovation, respectively. Further,RD, FT and TR variables are lagged by one year to allow their impacts on CO_2 emissions to be sluggish. b_{1i}, b_{2i}, b_{3i} and b_{4i} indicate the learning coefficient of the RD, FT and TR, respectively. Taking the learning coefficient of indigenous R&D, for example, the larger value of b_{2i} implies the stronger CO_2 learning ability of indigenous R&D in the ith region, while the impact on CO_2 emissions reduction associated with indigenous R&D is also greater. Additionally, if $b_{2i} > 0$, it denotes that there exists reverse changes in the relationship between indigenous R&D and CO_2 emissions. That is, if indigenous R&D increases, then CO_2 emissions decrease. If $b_{2i} < 0$, the CO_2 emissions change in the same direction as indigenous R&D. The specific descriptions of the variables are shown in Table 1.

4 Methodology

To avoid the pseudo-regression issue caused by nonstationary panel data, four panel unit root tests are employed, including Levin, Lin and Chu (LLC) (Levin et al. 2002), Im, Pesaran and Shin (IPS) (Im et al. 2003) Fisher-ADF and Fisher-PP tests (Maddala and Wu

Table 1 Description of variables used in the analysis for the period 1997–2014

Variable	Definition	Unit of measurement
CE	Energy-related CO_2 emissions	10^4 ton
Y	GDP divided by population at the end of the year	10^8 RMB in constant 1997 price
RD	Knowledge stock of indigenous R&D computed by perpetual inventory method	10^8 RMB
FT	Knowledge stock of foreign technology import computed by perpetual inventory method	10^8 RMB
TR	Knowledge stock of technical renovation computed by perpetual inventory method	10^8 RMB

1999). Table 2 summarizes the statistics at the national and regional levels. As shown, the series are nonstationary in levels but stationary in first differences, which indicates that the series are first-order integrated series. Further, Pedroni (1999) and Kao (1999) cointegration test are adopted to test the long-run equilibrium among variables. In accordance with the descriptive evidence in Table 3, the null of no cointegration is rejected in our sample.

Five regression methods are used after building the national-level and regional-level CO_2 learning curve. These methods contribute to gain more reliable regression results, including fixed effects (FE), linear regression with Newey–West standard errors (N–W), feasible generalized least squares (FGLS), linear regression with panel corrected standard errors (PCSE) and linear regression with Driscoll–Kraay standard errors (DK) estimation. To select the appropriate regression methods for different regions, four statistic tests are carried out in this study. The robust Hausman test is firstly adopted to choose between the

Table 2 Results of panel unit root tests

Region	Variable	Difference order	LLC test	IPS test	Fisher-ADF test	Fisher-PP test
National	lnCE	1	−10.665***	−10.489***	212.648***	485.658***
	lnY	1	−2.563***	−2.650***	80.176***	67.143***
	lnRD	1	−21.142***	−17.656***	352.859***	794.997***
	lnFT	1	−13.721***	−140.734***	198.351***	719.677***
	lnTR	1	−13.686***	−140.660***	197.678***	719.716***
H–H region	lnCE	1	−1.784**	−2.178**	21.965**	18.908*
	lnY	1	−3.087***	−2.427***	24.193**	18.721*
	lnRD	1	−6.669***	−5.719***	53.352***	68.417***
	lnFT	1	−72.739***	−64.166***	110.524***	110.524***
	lnTR	1	−72.711***	−64.141***	110.524***	110.524***
H–L region	lnCE	1	−5.312***	−5.247***	54.679***	58.475***
	lnY	1	−4.544***	−3.173***	41.898***	46.613***
	lnRD	1	−6.830***	−7.825***	79.916***	78.824***
	lnFT	1	−83.980***	−74.082***	147.365***	147.365***
	lnTR	1	−83.930***	−74.037***	147.365***	147.365***
H–L region	lnCE	1	−6.249***	−5.334***	60.491***	79.410***
	lnY	1	−3.339***	−2.465***	32.891***	29.013***
	lnRD	1	−10.115***	−9.060***	100.203***	146.925***
	lnFT	1	−89.114***	−78.610***	165.786***	165.786***
	lnTR	1	−89.073***	−78.574***	165.786***	165.786***
L–L region	lnCE	1	−7.811***	−7.566***	69.437***	54.718***
	lnY	1	−1.430***	−1.216**	15.859*	11.971**
	lnRD	1	−10.510***	−9.171***	81.547***	81.677***
	lnFT	1	40.241*	−5.679***	48.995***	110.524***
	lnTR	1	−7.811***	−7.566***	69.437***	54.718***

The lag lengths are selected using SIC. Newey–West automatic bandwidth selection and Bartlett kernel

* Rejection of the null hypothesis at the 10% significance level

** Rejection of the null hypothesis at the 5% significance level

*** Rejection of the null hypothesis at the 1% significance level

Table 3 Results of Pedroni and Kao panel cointegration tests

Statistics	National	H–H region	H–L region	L–H region	L–L region
Panel v	−3.053	0.564	−0.790	−1.794	−1.262
Panel rho	3.628	0.883	1.309	1.865	1.217
Panel pp	0.500	−0.048	−0.174	0.306	−0.282
Panel ADF	−3.818***	−1.068***	0.012**	−1.535***	−0.843***
Group rho	4.753	2.000	2.343	3.296	2.338
Group pp	−0.219	−0.030	0.286	1.844**	0.362*
Group ADF	−3.144***	−1.272***	0.638**	−0.025***	−0.763***
Kao-ADF	−3.758***	−3.371***	−1.685**	−3.003***	−1.919***

The lag lengths are selected using SIC. Newey–West automatic bandwidth selection and Bartlett kernel. The null hypothesis is of no cointegration

* Rejection of the null hypothesis at the 10% significance level

** Rejection of the null hypothesis at the 5% significance level

*** Rejection of the null hypothesis at the 1% significance level

Table 4 Results of Robust Hausman test

Statistics	National	H–H region	H–L region	L–H region	L–L region
F stat	52.041***	13.063**	25.961***	27.187***	18.738***

** Rejection of the null hypothesis at the 5% significance level

*** Rejection of the null hypothesis at the 1% significance level

fixed and random effects models. The results are summarized in Table 4. As we can see, all the statistics reject the null hypothesis, suggesting that the fixed effects model is more suitable in both national and regional levels. In addition, modified Wald test (Greene 2000), Wooldridge test (Wooldridge 2002) and cross-sectional dependence test (Pesaran 2004) are conducted to detect the heteroskedasticity, autocorrelation and cross-sectional dependence in FE models. As shown in Table 5, the three statistics are all significant at national-level. There exist heteroskedasticity, autocorrelation and cross-sectional dependence among H–H region, H–L region and L–H region, whereas heteroskedasticity and autocorrelation in L–H region are significant in spite of insignificant cross-sectional dependence. From the above analysis, the estimation results of FE models could possibly be biased. To solve these issues, N–W, FGLS and PCSE are used to obtain the more reliable results. N–W estimation could deal with the heteroskedasticity, autocorrelation without consideration of cross-sectional dependence (Newey and West 1987). Additionally, FGLS and PCSE estimation are carried out to overcome cross-sectional correlation. The FGLS estimation could be against the disadvantage of inaccurate standards errors and will be suitable when the cross-sectional dimension N is smaller than the time dimension T (Beck and Katz 1995). Nevertheless, in the finite sample, PCSE estimation is poor when the N is rather large compared to the T (Hoechle 2007). Hence, DK estimation is implemented to overcome the bias results by modifying the standard nonparametric time series covariance matrix estimator (Driscoll and Kraay 1998).

In summary, this paper estimates the empirical models (model 4, 6 and 10) by DK estimation to solve heteroskedasticity, autocorrelation and cross-sectional dependence

Table 5 Results of group-wise heteroskedasticity, autocorrelation and cross-sectional dependence test

Statistics	National	H–H region	H–L region	L–H region	L–L region
Wald stat	8959.443***	1698.626***	2102.187***	1206.684***	3433.994***
F stat	30.270***	466.290***	2.889*	42.217***	18.964**
CD stat	10.112***	3.891***	2.235**	1.029	1.960**

* Rejection of the null hypothesis at the 10% significance level

** Rejection of the null hypothesis at the 5% significance level

*** Rejection of the null hypothesis at the 1% significance level

issues, and focuses on N–W estimation for L–H regions (model 8) to address the heteroskedasticity, autocorrelation problems in this region.

4.1 The division of the provinces in China

To further investigate the CO_2 emissions learning curve in regions with different CO_2 emissions and efficiency, this paper selects the average amount of CO_2 emissions as emission targets and CO_2 intensity as emission efficiency indicators, and the 29 provinces in China are divided into four regions using the method proposed by Shao et al. (2014). The four regions are high emission–high efficiency region (H–H), high emission–low efficiency region (H–L), low emission–high efficiency region (L–H) and low emission–low efficiency region (L–L). The results are shown in Table 6 and Fig. 1.

4.2 Data source and description

This paper includes annual data of China's 29 provinces covering the period from 1997 to 2014. Hong Kong, Macao, Taiwan and Tibet are not included because of lack of data, and Chongqing is merged in Sichuan province to ensure the consistency of data. The provincial data of CO_2 emissions are computed according to the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2006). The calculation is based on the final energy consumption provided by the China Energy Statistical Yearbook (NBSC 1997–2014b). Three types of fossil fuels (raw coal, crude oil and natural gas) are included.

GDP per capita is computed as GDP divided by population at the end of year, the panel data of GDP (in 1997 constant price, Yuan) and population are collected from the China Statistical Yearbook (NBSC 1997–2014a)

The R&D expenditure has invariably influences on CO_2 emissions, so the knowledge stock of R&D expenditures is more appropriate chosen as a factor in our paper than R&D expenditure flow. The knowledge stock of R&D expenditures is computed using the

Table 6 "Emission-efficiency" type of provinces in China

Regions	Provinces
H–H region	Hubei, Shandong, Sichuan, Zhejiang, Jiangsu, Guangdong
H–L region	Anhui, Shaanxi, Heilongjiang, Henan, Hebei, Liaoning, Inner Mongolia, Shanxi
L–H region	Beijing, Guangxi, Fujian, Shanghai, Hainan, Jiangxi, Tianjin, Yunnan, Hunan
L–L region	Qinghai, Ningxia, Gansu, Xinjiang, Jilin, Guizhou

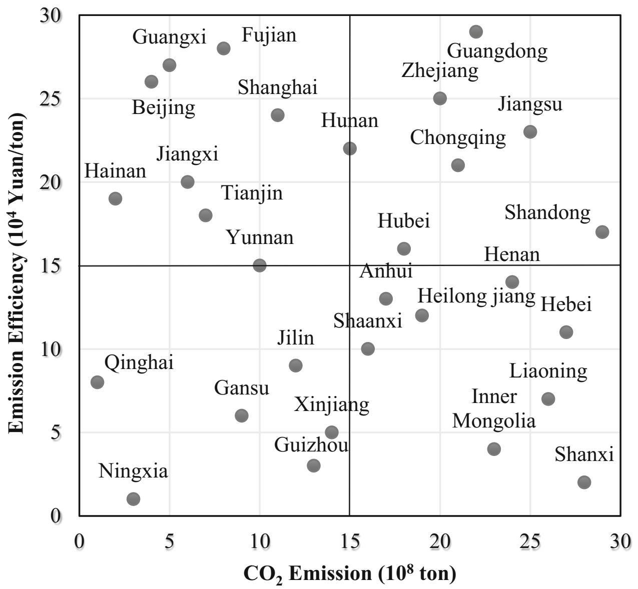

Fig. 1 Histogram of average CO_2 emission and emission efficiency in China from 1997 to 2014

perpetual inventory method as $K_{i,t} = I_{i,t} + (1 - \delta)K_{i,t-1}$ where δ represents the knowledge stocks depreciation rate and is assumed by 15% as same as the previous literature (Hall and Mairesse 1995). Expenditures of indigenous R&D, foreign technology import and technical renovation are collected from China Statistical Yearbook on Science and Technology (NBSC 1997–2014a).

The distribution of CO_2 emission and emission efficiency in different regions during 1997–2014 is illustrated in Fig. 2. As shown, all emission regions show an ascending trend in CO_2 emissions with different change rates. The average annual growth rate of CO_2 emission in L–L region (7.56%) is the highest, following by H–H (7.46%), H–L (6.86%), L–H region (6.03%). In 2014, CO_2 emission of L–L, H–H, H–L and L–H region has been raised by 237.24, 230.52, 202.63 and 163.99%, respectively. Nevertheless, there is an obvious upward trend in emission efficiency of four regions during 1997 and 2014 except L–L region. The emission efficiency in L–L region slightly increases with an average growth rate of 2.24% and aggregate growth rate of 43.17%. Conversely, the emission efficiency of the H–H region is 4.40% with a total rapid increase of 104.37%, while that in H–L and L–H region are 4.27 and 4.31%, respectively, growing by 101.04 and 101.61% in all.

5 Empirical results and discussion

In current study, CO_2 emissions learning curve is adopted to explore the role of three different technological factors in CO_2 emissions reduction with a consideration of regional differences. The results are shown in Table 7. Additional results based on alternative regression methods (i.e., FGLS/ PCSE method) are present in supplementary materials

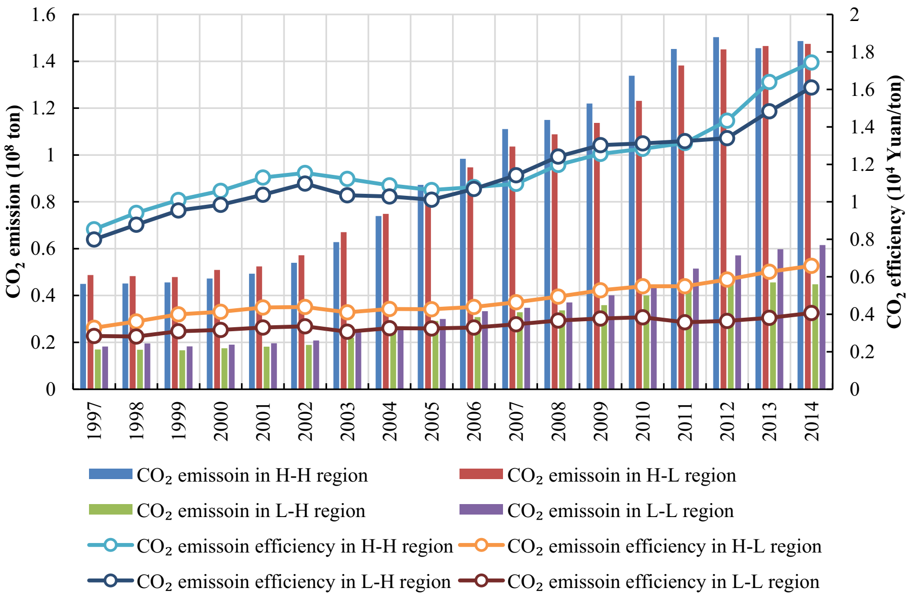

Fig. 2 CO_2 emissions and emission efficiency of different regions in China from 1997 to 2014

Tables S1-S5. For the ease of interpretation, the analysis of technological factors is discussed separately.

5.1 Impact analysis of indigenous R&D

The estimation results for the whole country are clearly shown in Table 7. From model 2, it can be seen that indigenous R&D has no significant impact on CO_2 emissions, indicating the poor CO_2 learning ability for indigenous R&D and insufficient environmental conscious across the country, which is inconsistent with Hypothesis 1.

Table 7 shows the results of the H–H, H–L, L–H and L–L region, respectively. As shown, the learning coefficients of indigenous R&D in the four regions are apparently different. Indigenous R&D in H–H and H–L region has negatively influences on the CO_2 emissions. On the contrary, the elasticity of indigenous R&D in L–L region is −0.346. This means that the CO_2 learning ability in L–L region is rather weak. Furthermore, the learning coefficient of the indigenous R&D in L–H region is insignificant at the 5% level, indicating that L–H region cannot benefit from indigenous R&D. In sum, this study finds an interesting phenomenon that the CO_2 learning ability in regions with higher emissions is much better than the lower ones.

The possible reason is that high emission pressure may motivate indigenous R&D to invest in the low-carbon technology, and then may promote the technological progress away from carbon-intensive technologies toward carbon-free technologies. For example, renewable energy technologies are better developed in the regions with higher CO_2 emissions. According to the data from Collection of China Electric Power Statistics, the cumulative installed capacity of photovoltaic power in H–H region accounts for 48% of the total capacity in China by the end of 2013. Moreover, the wind power capacity in H–L region increased much more quickly, such as Inner Mongolia; the cumulative installation

Table 7 Panel estimation results for CO_2 emissions of different regions in China during 1997–2014

Variable	National		H–H region		H–L region.		L–H region		L–L region	
	FE(1)	DK(2)	FE(3)	DK(4)	FE(5)	DK(6)	FE(7)	N–W(8)	FE(9)	DK(10)
lnY	0.969***	0.326***	0.682***	0.412***	1.456***	0.838***	1.274***	0.283***	−0.033	0.652***
	(0.063)	(0.064)	(0.147)	(0.110)	(0.093)	(0.031)	(0.108)	(0.054)	(0.173)	(0.056)
lnRD	−215.113	0.050	−582.185	0.357***	219.781	0.345***	−306.993	0.024	101.840	−0.346**
	(161.838)	(0.033)	(369.791)	(0.035)	(244.144)	(0.086)	(255.073)	(0.033)	(407.677)	(0.087)
lnFT	215.046	0.090***	582.232	−0.005	−220.037	−0.522***	306.846	0.169***	−101.629	0.356***
	(161.839)	(0.019)	(369.802)	(0.126)	(244.146)	(0.083)	(255.072)	(0.041)	(407.671)	(0.059)
lnTR	−0.559***	0.337***	0.289	0.285***	−2.378***	0.125*	−1.394***	0.191***	2.891***	0.186**
	(0.215)	(0.026)	(0.490)	(0.065)	(0.336)	(0.075)	(0.347)	(0.038)	(0.589)	(0.067)
Cons	565.395	6.529***	1372.460	4.887***	−510.859	8.137***	764.9907	6.474***	−329.273	8.581***
	(417.659)	(0.190)	(867.135)	(0.558)	(588.305)	(0.136)	(625.815)	(0.121)	(1318.940)	(0.494)
R^2	0.895	0.699	0.912	0.778	0.940	0.721	0.897	–	89.250	89.460
Observations	522	522	108	108	144	144	162	162	108	108

* Rejection of the null hypothesis at the 10% significance level

** Rejection of the null hypothesis at the 5% significance level

*** Rejection of the null hypothesis at the 1% significance level of wind power sharply increased from 157 to 22,312 MW during the period of 2006 to 2014. However, due to the increasing demand of energy consumption in China, only regions with high emissions can benefit from the indigenous R&D, which raises the concern that the CO_2 leaning abilities in L–L and L–H region need to be further improved by increasing emissions reduction pressure. Particularly, the L–L region is rich in renewable energy resources, such as solar PV power, and the development potential of renewables technology in this area is tremendous. But the weak learning capacity of indigenous R&D has severely impeded the development of renewables technologies. Meanwhile, most of the provinces in L–L region are inland provinces and in the advanced situation for foreign trade with Central Asia energy-rich countries. Thus, importing foreign technology from abroad and enhancing the international cooperation may make up the poor indigenous R&D capacity.

5.2 Impact analysis of the foreign technology import

The estimated results of the impacts of foreign technology import on CO_2 emissions for the whole country are presented in Table 7. The learning coefficient of foreign technology import for the whole country is greater than zero. Boosting the investment in foreign technology import will lead to CO_2 emissions reduction over the period, which enhances the confidence of the government in mitigating the emissions through foreign technology import. This finding is consistent with that of Wei and Yang (2010).

The learning abilities of foreign technology import on emissions abatement also differ among the four regions. With the exception of H–H region, all influences of foreign technology import on emissions are statistically significant at 1% level. Learning coefficient of foreign technology import in H–L regional is less than zero ($b_{31} = -0.522$), which means raising the investment in foreign technology will lead to the increase in the CO_2 emissions. Conversely, foreign technology import for the L–H and L–L region makes an achievement about declining the CO_2 emissions during the research period. A 1% increase in foreign technology import will decrease the emissions of L–H and L–L region by 0.169 and 0.356%, respectively. From the discussions above, we can conclude that the CO_2 learning abilities in L–H and L–L region are stronger than that in H–H and H–L region.

This finding does not conform to Hypothesis 2, as L–L region with poor technological capacity has a relatively stronger CO_2 learning ability. Although unexpectedly, the possible reason for such finding may be that the expenditures of foreign technology import in H–L and L–L region are spatially more concentrated. Data show that approximately 74.0% expenditure for importing the foreign technology is concentrated on 50% provinces of the L–L region. Similarly, 75.3% of that is concentrated on 44% provinces of L–H region. Nevertheless, H–H and H–L regions are more evenly distributed across provinces. A higher degree of spatial concentration of expenditure will have better technology capabilities, which benefit the technology transfer and absorbing knowledge from abroad (Zhang and Zhou 2016), and this is essential for China to improve energy efficiency and reduce the emissions. This raises the concern that the CO_2 emissions gap between low emissions regions (L–H and L–L region) with high CO_2 learning ability and high emissions regions (H–H and H–L region) with low CO_2 learning ability may be broadened. Meanwhile, the H–H and H–L region still face limitations with regard to low-carbon technology transfer and absorbing knowledge from abroad. Hence, there is a great need to strengthen technology capabilities in these regions through concentrated for investment of foreign technology import. Finally, these regions should seek to import low-carbon and energy-saving technologies due to its energy-guzzling industrial structure.

5.3 Impact analysis of the technical revolution

The results from Table 7 strongly suggest that technical renovation is the effective measure for abating CO_2 emissions both in the national and regional levels, which is consistent with Hypothesis 3. The technical revolution is the dominant contributor to the CO_2 emissions reduction in the national level. Furthermore, technical renovation in H–H region has theoretical maximum CO_2 learning ability ($b_{41} = 0.285$), followed by L–H region ($b_{43} = 0.191$), L–L region ($b_{44} = 0.186$) and H–L region ($b_{42} = 0.125$). This indicates that throughout the entire period of 1997–2014, emission reduction in H–H region is most effective in the technical revolution.

Our finding implies that the more investment of technical renovation will result in lower CO_2 emissions, and the reasons mainly lie in the following aspects. Firstly, the main purpose of technical renovation is to improve the energy efficiency by refurbishing and retrofitting low-efficient equipment, which can directly cut down the CO_2 emissions. Secondly, the renovation relies less on the technology capabilities, i.e., high human capital and economics base, to adopt and absorb the new technologies (Xu et al. 2013). Thus, technical renovation can reduce investment risk and increase the efficiency in a short term that enables the enterprises to more effectively assimilate low-carbon technology. Finally, due to indispensable role of coal power, clean and efficient coal power development through technical renovation has been the priority of Chinese government. The government has implemented a series of measures concerning energy efficiency retrofitting in traditional coal-fired generating units (Yuan et al. 2016). Nevertheless, technical renovation tends to achieve high energy efficient by implementing the mature and efficient technologies, but cannot promote the development of new renewables technologies. Hence, apart from the technical renovation, it is crucial to emphasis on the investment of indigenous R&D and foreign technology import to accelerate the renewables technologies and achieve the CO_2 emissions reduction target for a long run.

6 Conclusion and policy implications

This paper establishes an environmental learning curve model to explore the impact of technological advancement on CO_2 emission in China from 1997 to 2014 by using a panel data of 29 provinces, with a particular emphasis on different technological channels and regional differences. There are three technological channels including indigenous R&D activity, foreign technology import and technical renovation. Furthermore, China's 29 provinces are decomposed into high emission–high efficiency region (H–H), high emission–low efficiency region (H–L), low emission–high efficiency region (L–H) and low emission–low efficiency region (L–L). The empirical results of this study are as follows:

(1) Technological progress accompanied by the indigenous R&D has environmental learning effect on CO_2 emission in H–H and H–L region, while the increase in indigenous R&D leads to the raise of CO_2 emission in L–L region. In terms of L–H region, it has no significant impact on CO_2 emissions.

(2) The environmental learning effects by the foreign technology import are different among the different regions. Only L–H region and L–L region have a negative learning effect on reducing CO_2 emission. However, the learning effect of foreign technological import on CO_2 emission is not obvious in H–H region, while the learning ability in H–L region is weak.

(3) The technical renovation in all regions has positive impact on curbing the CO_2 emissions. The environmental learning ability in H–H region is the largest, followed by L–H region, L–L region and H–L region.

These results not only contribute to enrich the technology innovation theory, but also proposing specific policies for improving the environmental performance in China, which are summarized as follows:

Firstly, the results suggest that different regions should take differentiated investment strategy and policy measures to curb CO_2 emissions according to local conditions. Firstly, CO_2 emission learning abilities of indigenous R&D in high emissions regions are stronger than the low ones, which imply that high pressure of emissions reduction may arouse the environmental consciousness and facilitate the indigenous R&D in low-carbon technologies. However, high emissions regions still remain high emissions and it suggests that the indigenous R&D's learning abilities in these regions should continually be improved in order to transform their emissions-efficiency performance to L–H regions. Indigenous R&D is the source of the creation of new clean technology and mainly relies on the enterprises. Therefore, in order to encourage them to invest in low-carbon technologies, China should promulgate more stringent CO_2 emissions and efficiency policies to provide incentives for enterprises to be involved in low-carbon technology innovation. In addition, designing proper subsidies for firms will be another effective incentive policy and can ensure compensation for their investment in clean technologies.

Secondly, the CO_2 emission learning effects of foreign technology import depend on the concentrated degree of the local expenditure. The results suggest that H–H and H–L region should import foreign technology more spatially concentrative, and focus on low-carbon and energy-saving technologies due to its energy-intensive industrial structure. Meanwhile, L–H and L–L region should seek to import foreign technology to further reduce emissions. Furthermore, the government should insist on strengthening competitiveness in energy-intensive industries and, emphasizing on cultivating technology capabilities, especially for L–L region, to adopt and absorb advanced foreign technologies.

Thirdly, the excellent learning ability of technical renovation implies that it will effectively reduce the CO_2 emission and improve energy efficiency in China. Thus, it calls for striving to lessen CO_2 emissions through technical renovation. In particular, the resource-dependent provinces are located in H–L regions, such as Shanxi and Inner Mongolia, which are rich in resources of coal and major energy exporter through coal power generation. Thus, the Chinese government should particularly emphasis on the technical revolution in coal power of H–L region. Besides, the haze smog frequently occurred in China during recently years. The government should also be cautious of the strict pollution control standard in the heavy industry and implement the electricity substitution projects.

Acknowledgements The authors would like to thank the anonymous referees for their helpful suggestions and corrections on the earlier draft of our paper. This study is funded by the Social Science major projects of Chinese Ministry of Education (15JZD021), the Ministry of Education of Humanities and Social Science Research Fund Plan (15YJA790091), Research Start-up Funds of Northwest A&F University (2452016161), Basic Service Funds of Northwest A&F University (2017RWYB06) and Social Science major projects of Tianjin Municipal Education Commission (2016JWZD04). In addition, the authors want to thank Dr. Juan Wang, Dr. Zengming Liu and Dr. Junna Yan for their comments and suggestions. The authors also express their gratitude to Dr. Shuang Jiang, Dr. Jingxiang Yang and postgraduate Yu Liu for providing with their linguistic supports.

References

Albino V, Ardito L, Dangelico RM, Messeni PA (2014) Understanding the development trends of low-carbon energy technologies: a patent analysis. Appl Energy 135:836–854

Ang BW (2004) Decomposition analysis for policymaking in energy: Which is the preferred method? Energy Policy 32(9):1131–1139

Ang JB (2009) CO_2 emissions, research and technology transfer in China. Ecol Econ 68(10):2658–2665

Badiru AB (1992) Computational survey of univariate and multivariate learning curve models. IEEE Trans Eng Manag 39(2):176–188

Beck N, Katz JN (1995) What to do (and not to do) with time-series cross-section data. Am Polit Sci Rev 89(3):634–647

Boeing P, Mueller E, Sandner P (2016) China' s R&D explosion—analyzing productivity effects across ownership types and over time. Res Policy 45(3):159–176

Driscoll JC, Kraay AC (1998) Consistent covariance matrix estimation with spatially dependent panel data. Rev Econ Stat 80(4):549–560

Fehr M (2003) Environmental management by the learning curve. Waste Manag 23(5):397–402

Fisher VK, Jefferson GH, Liu H (2004) What is driving China's decline in energy intensity? Resour Energy Econ 26(1):77–97

Greene WH (2000) Econometric analysis, 4th edn. Prentice-Hall, Upper Saddle River

Grübler A, Nakićenović N, Victor DG (1999) Dynamics of energy technologies and global change. Energy Policy 27(5):247–280

Guo F, Zhao T, Wang Y, Wang Y (2016) Estimating the abatement potential of provincial carbon intensity based on the environmental learning curve model in China. Nat Hazards 84(1):685–705

Hall B, Mairesse J (1995) Exploring the relationship between R&D and productivity in French manufacturing firms. J Econom 65(1):263–293

Hoechle D (2007) Robust standard errors for panel regressions with cross-sectional dependence. Stata J 7(3):281–312

Hu C, Huang X (2008) Characteristics of carbon emission in china and analysis on its cause. China Popul Resour Environ 18(3):38–42 **(in Chinese)**

Im KS, Pesaran MH, Shin Y (2003) Testing for unit roots in heterogeneous panels. J Econom 115(1):53–74

Intergovernmental Panel on Climate Change (IPCC) (2006) IPCC Guidelines for National Greenhouse Gas Inventory. Intergovernmental Panel on Climate Change (IPCC), Japan

Kao C (1999) Spurious regression and residual-based tests for cointegration in panel data. J Econom 90(1):1–44

Levin A, Lin C, James CC (2002) Unit root tests in panel data, asymptotic and finite-sample properties. J Econom 108(1):1–24

Li K, Lin B (2015) Heterogeneity in rebound effects: estimated results and impact of China's fossil-fuel subsidies. Appl Energy 149:148–160

Li K, Lin B (2016) Impact of energy technology patents in China: evidence from a panel cointegration and error correction model. Energy Policy 89:214–223

Lin BQ, Xie CP (2014) Reduction potential of CO_2 emissions in China's transport industry. Renew Sustain Energy Rev 33:689–700

Liu LC, Liang QM, Wang Q (2014) Accounting for China's regional carbon emissions in 2002 and 2007: production-based versus consumption-based principles. J Clean Prod 103:384–392

Maddala GS, Wu S (1999) A comparative study of unit root tests with panel data and a new simple test. Oxf Bull Econ Stat 61(S1):631–652

National Bureau of Statistics of China (1997–2014a) China Statistical Yearbook. China Statistics Press, Beijing

National Bureau of Statistics of China (1997–2014b) China Statistical Yearbook. China Statistics Press, Beijing

Newey WK, West KD (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrics 55(3):703–708

Noailly J, Smeets R (2015) Directing technical change from fossil-fuel to renewable energy innovation: an application using firm-level patent data. J Environ Econ Manag 72:15–37

Pakes A (1985) On patents, R&D, and the stock market rate of return. J Polit Econ 93(2):390–409

Pedroni P (1999) Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxf Bull Econ Stat 61(S1):653–670

Pesaran MH (2004) General diagnostic tests for cross section dependence in panels. CESifo working paper Series No. 1229

Rodney G, Phil D (2009) Evaluating options for US coal fired power plants in the face of uncertainties and greenhouse gas caps: the economics of refurbishing, retrofitting, and repowering. Energy Procedia 1(1):4347–4354
Romer PM (1990) Endogenous technological change. J Polit Econ 98(5):71–102
Rubin ES, Taylor MR, Yeh S, Hounshell DA (2004) Learning curves for environmental technology and their importance for climate policy analysis. Energy 29(9–10):1551–1559
Shao C, Guan Y, Wan Z et al (2014) Performance and decomposition analyses of carbon emissions from industrial energy consumption in Tianjin, China. J Clean Prod 64(2):590–601
State Council of China (SCC) (2012) Guidance of the State Council on promoting enterprise technical revolution. http,//www.gov.cn/zwgk/2012-09/10/content_2221011.htm. Accessed 10 Sep 2012
Sun GN, Li Q, Han YF (2008) The reduction potential and environmental learning curves of China's regional SO_2 emissions. Environ Sci 10(5):59–63 **(in Chinese)**
Sun GN, Li J, Han YF (2011) Theoretical and practical significance to establish environment learning curve. J Hebei North Univ 27(2):51–56 **(in Chinese)**
Teng YH (2009) Own R&D, technology purchased and energy intensity in China's industrial sector—an empirical analysis based on panel data models of 31 industries. Collect Essays Finance Econ 2(143):1–6 **(in Chinese)**
Teng YH (2012) Indigenous R&D, Technology imports and energy consumption intensity, evidence from industrial sectors in china. Energy Procedia 16:2019–2026
Wang JJ, Li L (2016) Sustainable energy development scenario forecasting and energy saving policy analysis of China. Renew Sustain Energy Rev 58:718–724
Wang Z, Lu M (2014) An empirical study of direct rebound effect for road freight transport in China. Appl Energy 133(6):274–281
Wang Y, Zhao T (2015) Impacts of energy-related CO_2, emissions, evidence from under developed, developing and highly developed regions in China. Ecol Indic 50:186–195
Wang Z, Yang Z, Zhang Y et al (2012) Energy technology patents-CO_2, emissions nexus: an empirical analysis from China. Energy Policy 42(2):248–260
Wei WX, Yang F (2010) Impact of technology advance on carbon dioxide emission in China. Stat Res 27(7):36–44 **(in Chinese)**
Wong CY, Fatimah MZ, Keng ZX (2014) Examining the patterns of innovation in low carbon energy science and technology: publications and patents of Asian emerging economies. Energy Policy 73(5):789–802
Wooldridge JM (2002) Econometric analysis of cross section and panel data. The MIT Press, Cambridge
Wright TP (1936) Factors affecting the cost of airplanes. J Aeronaut Sci 3(4):122–128
Wu CC (2016) Constructing a weighted keyword-based patent network approach to identify technological trends and evolution in a field of green energy: a case of biofuels. Qual Quant 50(1):213–235
Xu P, Xu T, Shen P (2013) Energy and behavioral impacts of integrative retrofits for residential buildings: What is at stake for building energy policy reforms in northern China? Energy Policy 52(1):667–676
Yang Y, Cai W, Wang C (2014) Industrial CO_2 intensity, indigenous innovation and R&D spillovers in China's provinces. Appl Energy 131:117–127
Yu CF, van Sark WGJHM, Alsema EA (2011) Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. Renew Sustain Energy Rev 15(1):324–337
Yu S, Zhang J, Zheng S (2015) Provincial carbon intensity abatement potential estimation in China: a PSO–GA-optimized multi-factor environmental learning curve method. Energy Policy 77:46–55
Yuan J, Na C, Lei Q et al (2016) Coal use for power generation in China. Resour Conserv Recycl. doi:10.1016/j.resconrec.2016.03.021
Zhang CG, Zhou XX (2016) Does foreign direct investment lead to lower CO_2 emissions? Evidence from a regional analysis in China. Renew Sustain Energy Rev 58:943–951
Zhu BZ, Wang KF, Chevallier J et al (2015) Can China achieve its carbon intensity target by 2020 while sustaining economic growth? Ecol Econ 119:209–216