



Carbon emissions trading policy, carbon finance, and carbon emissions reduction: evidence from a quasi-natural experiment in China

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Abstract

The purpose of this paper is to explore whether the implementation of carbon emissions trading policy (CETP) promotes carbon finance, proxied by investment and financing facilitating carbon emissions reduction (IFCER), and reduces carbon emissions. Evidence shows that first, CETP is effective in stimulating IFCER and reducing carbon emissions. Second, the effects of CETP persist over time. Third, the effects of CETP taking effect in pilot regions can spill over to non-pilot regions nearby. Fourth, the effect is more pronounced in eastern and wealthy regions. Finally, R&D and industrial upgrading have a mediating effect linking CETP to IFCER and carbon emissions.

Keywords Carbon emissions trading policy · Investment and financing facilitating carbon emissions reduction · Carbon emissions reduction · Carbon finance

JEL Classification G10 · O13 · Q50

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1 Introduction

Carbon finance, emerging as an important engine for green economic development, is essential in financing renewable and green energy projects to reduce carbon emissions and their negative health impacts, develop climate resilient infrastructure for cities, and ensure environmental sustainability (Labatt and White 2007; Taghizadeh-Hesary and Yoshino 2019). It also refers to financial activities facilitating carbon emissions reduction (CER), such as investment and financing facilitating CER (IFCER) and carbon emissions trading (CET) (Borghesi et al. 2015).¹ To ensure stable operations of carbon markets, the Kyoto Protocol to the United Nations Framework Convention on Climate Change entered into force on December 11, 1997.² Since then, regional carbon markets have operated and CET has become an ongoing and vital environmental issue in major economies (Kemp and Pontoglio 2011).

Through government policies, CET legalizes emissions and issues emissions permits to firms by making the permits tradable as commodities, which controls carbon dioxide (CO₂) emissions to maintain sustainable development (Coase 1960; Dales 1968; Cropper and Oates 1992). Many studies (e.g., Jefferson et al. 2013; Borghesi et al. 2015) also note that carbon emissions trading policy (CETP) can effectively reduce carbon emissions and the associated emissions reduction costs. However, most of the research focuses on the CERP effect on carbon emissions, while little attention has been paid to the effect on carbon finance. Motivated by this possible insufficiency, the purpose of this paper is to study the effect of CETP on carbon finance or, specifically, IFCER in China, in addition to the effect on carbon emissions, measured by carbon emissions intensity (CEI).

Unlike traditional financial activities, carbon finance promotes trading of carbon emissions rights and derivatives that change cost structures of firms with carbon footprints, encouraging them to reduce greenhouse gas emissions (Li and Liu 2011). CETP explicitly helps establish effective carbon trading markets and solve problems associated with carbon emissions allowance reallocation, the measurement of CET, carbon reporting, carbon credit verification, and CER regulations (Peng et al. 2018; Zhou and Li 2019).³ CETP is considered a low-cost and sustainable environmental measure that could not only control the quantity of carbon emissions, but also incentivize firms to develop new technologies to further reduce carbon emissions (Requate and Unold 2003).

There are two popular viewpoints on the effects of an environmental measure like CETP considered important for both environmental protection and economic development (Dales 1968). One viewpoint focusing on compliance costs suggests

¹ All abbreviations are recorded in “Appendix 1” of this paper.

² The Kyoto Protocol is an international environmental treaty with the goal of stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. Industrialized countries and economies were committed to limiting and reducing greenhouse gases emissions in accordance with agreed individual targets.

³ Because of negative externality of environmental pollution caused by carbon emissions, it is necessary to regulate the rights to pollute to achieve sustainable economic development (Coase 1960; Wanley and Whitehead 1994; Levinson 1996; Li et al. 2014).

that an environmental measure inevitably raises production costs of firms, which decreases their production efficiency and competitiveness (Brännlund et al. 1995; Levinson 1996). The other viewpoint argues that an environmental measure can stimulate technological innovations due to a compensation effect (Magat 1978; Porter and Van der Linde 1995). Compensation for innovations can even lower production costs under environmental regulations, enhancing both economic growth and environmental protection (Porter and Van der Linde 1995).⁴

In fact, the two schools of thought above do not necessarily contradict to each other. According to the first school of thought, CETP limits the greenhouse gas emissions by firms, inevitably increasing their production costs in the first place. However, if funding is easily accessible and CETP generates extra opportunities, governments and firms may increase IFCER to finance research and development (R&D) and improve green production efficiency (Zhang et al. 2020a; b; Zhang et al. 2021). In addition, regional governments often engage in industrial upgrading. Firms are encouraged to either consume less energy or shift from sectors dominated by high energy-consuming industries to sectors dominated by low energy-consuming and low emissions industries in order to develop their low-carbon economies. The positive feedback, thanks to R&D and industrial upgrading, further benefits firms and the economy, which is in line with the second school of thought. So, can CETP promote carbon finance or IFCER in China? If yes, how CETP operates and what economic mechanisms are at work? We shall study these issues later in this paper.

The reason why we choose the sample in China is that it is not only the largest developing country, but also the largest energy consumer and CO₂ emitter in the world. On the one hand, according to the BP Statistical Review of World Energy 2017,⁵ total carbon emissions in China reached 9.12 billion tons in 2016, accounting for 27.3% of global carbon emissions. China plans to reduce carbon emissions by 2–3 billion tons by 2030 (Zhang 2016), dominating total CER of all European countries. Thus, whether China achieves CER will significantly impact global climate change (Wang and Wang 2017; Zhou and Li 2019). In light of the importance of China's carbon markets, their prosperity plausibly plays an essential role in the success of carbon trading worldwide. Moreover, we use a sample consisting of 30 regions (22 provinces, 4 direct-controlled municipalities, and 4 autonomous regions) in China from 2004 to 2019 that exhibit a great deal of economic diversity. Given the diversity, China's results may provide insights into CETP and the associated consequences over various stages of economic development. Thus, China offers a perfect and comprehensive platform to study carbon finance.

On the other hand, existing research on CER mainly examines issues in European carbon markets (e.g., Daskalakis 2018; Koch and Mama 2019; Herweg 2020). Although there is limited research on similar issues in China, in reality, abundant

⁴ Appropriate environmental measures can encourage firms to advance their technologies and optimize the allocation of resources, increasing the productivity of firms (Porter and van der Linde 1995; Berman and Bui 2001; Antweiler et al. 2001; Brunnermeier and Cohen 2003; Pargal and Wheeler 1996).

⁵ Please see "<https://www.connaissancedesenergies.org/sites/default/files/pdf-actualites/bp-statistical-review-of-world-energy-2017-full-report.pdf>".

attractive investment opportunities and government subsidies for CET prevail in China (Linnenluecke et al. 2016; Liobikienė and Butkus 2017). This study may not only provide practitioners with potentially profitable opportunities, but also help policy makers in other emerging markets identify their possible opportunities and obstacles when implementing the likes of CETP.

Primarily employing the difference-in-difference (DID) model, we assess the effects of CETP on IFCER and CEI in China. Our empirical evidence shows, first, that CETP is significantly and positively (negatively) associated with IFCER (CEI). The effects are robust to numerous tests adopting alternative proxies for major variables, changing the sample interval, using the alternative PSM-DID (propensity-score-matching-difference-in-difference) method, applying randomly selected samples and placebo tests. It definitely suggests that CETP encourages (reduces) IFCER (CEI) in China.

Second, the effects of CETP on IFCER and CEI are persistent for up to six years. Third, CETP can differently impact IFCER across regions. Specifically, CETP significantly promotes IFCER in wealthy regions and eastern regions, but has no significant effect on IFCER in central and western regions. Finally, CETP not only encourages firms to invest more in R&D, but also promotes regional industrial upgrading from a traditional economy to a low-carbon economy, which further reduces emissions and energy consumption. Collectively, CETP can be regarded as an excellent policy instrument promoting IFCER and green economic development.

In view of the applied methodology and results in this paper, it contributes to the literature in the following ways. First, while abundant literature (e.g., Streimikiene and Roos 2009; Gulbrandsen and Stenqvist 2013; Borghesi et al. 2015; Dong et al. 2019; Zhou et al. 2019; Zhu et al. 2020; Zhang et al. 2020a, b; Zhou and Liu 2020) examines the impact of CETP on green economies, relatively little attention is paid to the impact on the associated carbon finance (e.g., Liu and Wei 2016; Yi et al. 2018). This paper studies the impact of CETP on IFCER and CEI by specifically considering the mediating effects of R&D and industrial upgrading, which not only clarifies the economic mechanisms linking CETP to IFCER as well as CEI, but also broadens our understanding about how CETP and IFCER are beneficial.

Second, this paper develops a composite index to quantify IFCER from different dimensions. The novelty of this index arises from the fact that it contains a rich set of measures describing carbon finance, including the depth and efficiency in the use of low-carbon funds, availability of financial services and cost of financial services. The index is expected to integrate the effectiveness of CETP from multiple perspectives.

Finally, while previous studies (e.g., Paoletta and Taschini 2008; Caney 2010; Sovacool et al. 2011; Chevallier 2011; Bredin and Muckley 2011; Laing et al. 2014; Reboredo and Ugando 2015; Joltreau and Sommerfeld 2019; Efthymiou and Papa-theodorou 2019) mainly analyze policies associated with CER in developed markets, few studies analyze similar issues in emerging markets with less sophisticated financial systems. Hence, as a study of China, the largest emerging market, this paper's observations on the causality and mediating effects from CETP to IFCER and CEI provide policy makers in other emerging markets with insights into possible economic mechanisms behind the effects as well as the benefits of CETP.

The rest of this paper is organized as follows. Section 2 provides the institutional background and literature review. Section 3 introduces the methodology and the data of this paper. Particularly, we develop a composite index of IFCER to describe the development of carbon finance in 30 regions of China. Section 4 empirically analyzes the impacts of CETP on IFCER and CEI, primarily using the DID method. This section also examines the robustness of the results by adopting alternative specifications and proxies. Numerous conditional tests and the analysis of economic mechanisms behind the effects of CETP are conducted as well. Section 5 concludes this paper and discusses possible policy implications.

2 Institutional background and literature review

2.1 Institutional background of CETP in China

To reduce carbon emissions, China's National Development and Reform Commission issued "Notice on the Piloting of Carbon Emissions Trading" in October 2011, which approved seven pilot regions for CETP, including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Fujian. CETP was first implemented in Guangdong on a trial basis in the first half of 2013, and then in other pilot regions between the second half of 2013 and the first half of 2014. CETP mainly covers (1) the establishment and compliance of carbon markets, (2) the inclusion of industries and the allocation of emissions allowances, (3) monitoring, reporting, and verifying the data of carbon emissions, and (4) CET. After more than a year of implementation, CET in the pilot regions gradually improved and steadily operated.

2.2 Literature review

Existing theoretical and empirical studies on CER, CER policies, and carbon finance can be divided into two categories. The first category pays attention to the effectiveness of CER policies and possible economic mechanisms behind its impact. Regarding the effectiveness of CER policies, no consensus has been reached. For example, the extant literature mostly confirms the effectiveness of CER policies (e.g., Wang and Wei 2014; Cheng et al. 2016; Fang et al. 2018; Zhang et al. 2019), while many papers (e.g., Streimikiene and Roos 2009; Gulbrandsen and Stenqvist 2013) do not.

As for the economic mechanisms behind the impact of CER policies on CER, prior studies have explored the roles of technological innovations, industrial upgrading, population density, economic growth, and foreign investment (e.g., Ma and Stern 2008; Su and Ang 2015; Wang and Wang 2017). Among them, technological innovations and industrial upgrading are considered the two most important channels (Cao and Karplus 2014; Yu et al. 2015). On the one hand, technological innovations can reduce energy consumption and the growth of carbon emissions (Zhang et al. 2017a; b). On the other hand, industrial upgrading results in the transformation of high-carbon manufacturing industries, and in turn reduces their carbon emissions (Zhou and Liu 2020). While the existing literature

mostly examines the channels through which CER policies impact carbon emissions, this paper pays a great deal of attention to the economic mechanisms behind the effects of CETP on IFCER.

The second category of research is on development of carbon markets, often in three aspects. First, academics make efforts to forecast prices of carbon financial derivatives (e.g., Paoletta and Taschini 2008; Chevallier 2011; Bredin and Muckley 2011; Zhao et al. 2018) and to distinguish deterministic factors of the prices (Bredin and Muckley 2011; Yu and Malloy 2014). Second, there exists numerous studies exploring the evolution of global carbon markets as well as their shortcomings, difficulties, and solutions (e.g., Braun 2009; Caney 2010; Sovacool et al. 2011; Hall et al. 2018; Zhou and Li 2019). The third aspect is regarding risk measures associated with carbon trading, including the price risk of derivatives, policy risk, market risk, and technology risk (e.g., Blyth and Buun 2011; Reboredo and Ugando 2015; Wu and Kung 2020).

Given the existing literature, limited studies examine the impact of CET on carbon finance. Moreover, to my knowledge, there is, so far, no satisfactory measure of carbon finance covering all possible dimensions. Motivated by the insufficiency, this paper will first develop a composite measure comprehensively capturing IFCER in China. Then, applying the measure, we analyze the impacts of CETP on IFCER and CEI.

3 Hypotheses, data, and methodology

3.1 Hypothesis development

One primary effect of CETP of interest in this paper is on IFCER. Given that the ultimate goal of CETP is CER, which is usually the main purpose of the relevant literature, for comparison, we also employ CEI as an alternative primary variable to measure the direct effects of CETP. In the following, we develop the first hypothesis to test the effects or effectiveness of CETP as follows:

Hypothesis 1 CETP increases IFCER and reduces CEI.

As observed in Fig. 1 and Table 2, possibly because of the spillover effect of CETP, IFCER is higher in some non-pilot regions, such as Hebei, Shandong, Jiangsu, Zhejiang, Jiangxi, Henan, Shaanxi, Shanxi, Anhui, Hunan, Guizhou, and Liaoning. Note that these regions are geographically close to the pilot regions, which arouses our interest in whether IFCER and CEI in the neighborhoods of the pilot regions could be influenced by CETP. If yes, there could exist a spillover effect that explains why those non-pilot regions have higher IFCER.

Hypothesis 2 The effects of CETP in the pilot regions can spill over to the non-pilot regions geographically nearby.

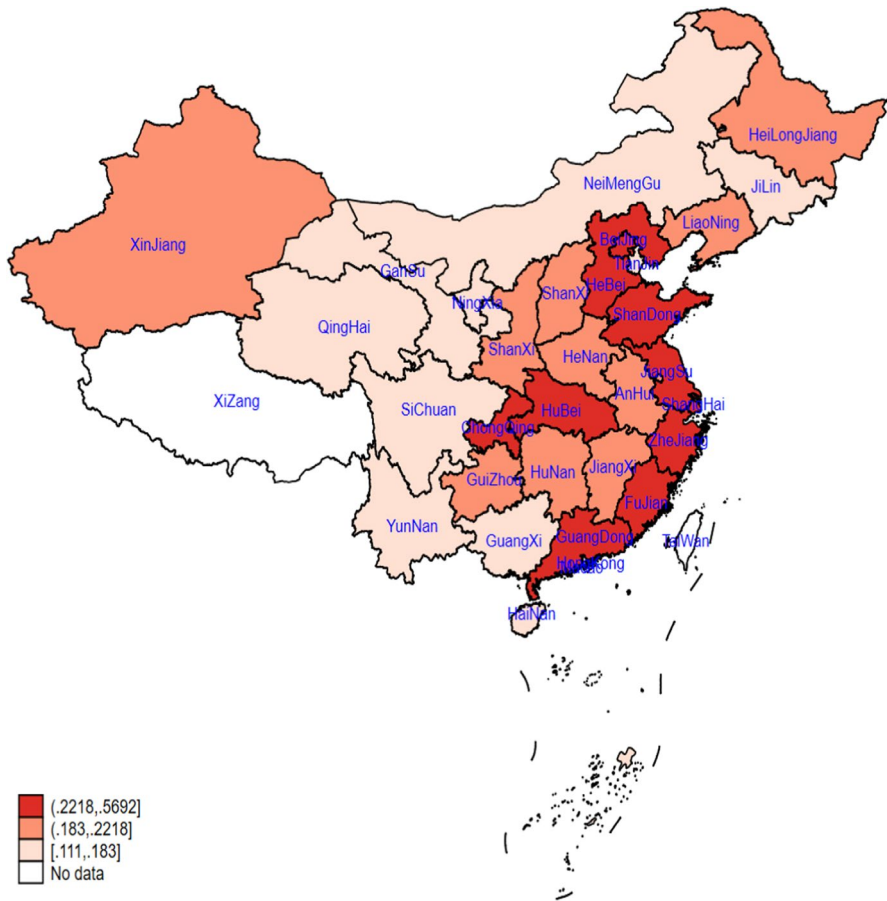


Fig. 1 Average IFCER by province, 2004–2019

The next issue of interest is the persistence of the effects of CETP. Since CETP requires lots of funding and investments, if the government was not serious, the effect could be temporary. Moreover, given the time-to-build property of (physical) investments, the effects of CETP on IFCER and CEI should be persistent. If the effects increasingly strengthen, the evidence supports that the initial success of CETP could generate more opportunities for IFCER in the subsequent years.

Hypothesis 3 The effects of CETP are persistent.

After examining the effectiveness and persistence of CETP, we next concern the CETP effects across regions by conducting heterogeneity analyses. In Hypothesis 2, we have examined the effects of CETP in non-pilot regions nearly the pilot regions. To dig deeper, of interest are other conditional analyses on essential factors, such as residents' wealth and geographical locations. Concerning residents' wealth, carbon

emissions are intuitively related to income (GDP per capita). The well-known Environmental Kuznets curve illustrates that there is an inverted U-shaped relationship between them (Cole et al. 1997; Dasgupta et al. 2002; Stern 2004). Zhang et al. (2017a; b) observe that there is also an inverted U-shaped relationship between urbanization and carbon emissions.

Thus, the impact of CETP on IFCER in wealthy regions is expectedly different from that in less-wealthy regions. Due to the fact that wealthy regions usually have more developed local economies, better infrastructures, more available financial instruments, and more active CET, which generates more demand for CER and more opportunities for firms to access IFCER, once CETP is implemented. We expect that CETP has a greater impact on IFCER in wealthy regions than in less wealthy regions.

Hypothesis 4a The effects of CETP are stronger in wealthy regions.

As for geographical locations, following Huang et al. (2014) and Yang et al. (2020), we divide China into three economic zones—the eastern, central, and western regions with different industrial gradients and various development stages.⁶ Among the economic zones the natural resources, infrastructure, regional development policies vary. The gaps keep widening over time (Wang et al. 2018). For example, as Cheng et al. (2019) argue, the western regions contain mainly resource-intensive and labor-intensive industries. In the short term, they face huge environmental costs and industrial transformation pressure but will receive structural dividends in the long run. The eastern regions contain mainly capital-intensive and technology-intensive industries that are propelled by current incentive policies to optimize industrial structure and develop green economies.

On the one hand, the eastern (coastal) provinces are considered to have an advantage of easy access to marine transportation. Their economies are often more developed and more likely to have mature financial markets with adequate financial instruments and participants than the western and central (inland) provinces. It follows that given CETP as an official guideline toward CER, firms associated with low carbon economy are more willing to locate and operate in eastern regions. The flourishing business further deepens IFCER and accelerates the development of carbon finance. On the other hand, because the central and western regions in China are mostly dominated by heavy industry sectors relying on fossil fuels, their IFCER lags behind those in the eastern regions. Thereby, we expect that CETP has a stronger effect on IFCER in eastern regions than in western and central regions.

⁶ According to the “Report on the Seventh Five-Year-Plan” published in 1986, China was divided into three regions: the eastern, central and western regions. In 1997, the National People’s Congress decided to establish Chongqing as a municipality directly under the central government and to include it in the western regions. As a consequence, the eastern regions include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; the central regions include Shanxi, Nei Mongol, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi; the western regions include Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

Hypothesis 4b The effects of CETP are stronger in eastern regions.

The final hypothesis explores possible economic mechanisms behind the effects of CETP. For example, it is possible that there could be indirect effects between CETP and IFCER, first from CETP to a mediating variable, and second from the mediating variable to IFCER.

Following MacKinnon et al. (2000) and Zhou and Liu (2020), this paper proposes two mediating variables—R&D (lnR&D) and the proportion of tertiary industries (lnIndu3)—to investigate the economic mechanisms linking CETP to IFCER. The hypothesis is constructed as follows:

Hypothesis 5 There exist mediating effects linking CETP to IFCER and CEI.

3.2 Description of the employed variables and data

3.2.1 Developing a composite index of IFCER

Following De Souza Cunha et al. (2021), Mohsin et al. (2020), Chen et al. (2020), we construct a composite IFCER index on an annual basis to measure carbon finance. As shown in Table 1, the IFCER index, similar to the one proposed by Liu et al. (2018), is based on four dimensions, including market depth, efficiency of the use of CER funds, availability of financial services, and cost of financial services.⁷ First, measured by the total issuances of stocks, funds, and bonds (direct financing) associated with low carbon economy to the total number of emissions control firms in a given region (Chen et al. 2020), the market depth reflects the involvement of the region in IFCER. The more actively a region involves, the deeper the carbon markets in the region (Linnenluecke et al. 2016; Koch and Mama 2019; Mohsin et al. 2020). The annual data are obtained from the WIND database, the Oriental Wealth Network, and the Green Financial Bond Database of the China Financial Information Network.

The second dimension—efficiency of the use of CER funds—is measured by the ratio of CER in a region to the sum of issued stocks, bonds and funds associated with low carbon economy. CER is derived following the IPCC (Intergovernmental Panel on Climate Change) accounting methodology.⁸ The efficiency of the use of CER funds captures the strength of CER after a region receives CER funds. The larger the ratio, the higher the efficiency of the use of CER funds (Liao and Shi 2018). The data on an annual basis are available from China Energy Statistical Yearbook and China Environmental Statistical Yearbook.

As for the third dimension of IFCER, following Mohsin et al. (2020), the availability of financial services is computed as the ratio of the total number of financial institutions to the total number of emissions control firms in a region or

⁷ “Appendix 1” presents a theoretical analysis to explore possible dimensions of IFCER.

⁸ According to the IPCC accounting method, total carbon emissions = Σ energy consumption CO₂ emissions intensity. Please see Ji et al. (2021) for the calculation details.

Table 1 The IFCER index

Dimension	Calculation	Predicted impact	Data on an annual basis
Market depth	Total issuance of stocks associated with low carbon economy/total number of emissions control firms	Positive (+)	Total issuance of stocks comes from The WIND database. Total number of emissions control firms is available from the China Environment Yearbook
	Total issuance of bonds associated with low carbon economy/Total number of emissions control firms	Positive (+)	The Eastmoney securities https://www.eastmoney.com/
	Total issue of funds associated with low carbon economy/Total number of emissions control firms	Positive (+)	The Green Financial Bond Database of the China Financial Information Network http://greenfinance.xinhua08.com/
Efficiency of the use of CER funds	Annual reduction rate of carbon emissions/Scale of financial instruments associated with low carbon economy	Positive (+)	China Energy Statistical Yearbook and China Environmental Statistical Yearbook
Availability of financial services	Total number of financial institutions/Total number of emissions control firms	Positive (+)	China Regional Financial Operation Report by the People's Bank of China
Cost of financial services	RMB-weighted lending rates	Negative (–)	China Regional Financial Operation Report by the People's Bank of China

This table reports four dimensions in which the IFCER index is measured and the associated calculation and the predicted sign of the effect. The four dimensions include market depth, efficiency of the use of CER funds, availability of financial services, and cost of financial services

the availability of indirect financing. The higher the ratio in a region, the more the IFCER services are available to firms. The associated data are collected from the China Regional Financial Operation Report released by the People’s Bank of China.

The fourth dimension is the cost of financial services measured by the weighted-average RMB lending rates in a region at the end of the year. The higher the interest rate in a region, the higher cost the financial services in the region (Boissinot et al. 2016; Mohsin et al. 2019). The data come from the China Regional Financial Operation Report.

Since CETP took effect in most pilot regions between the second half of 2013 and the first half of 2014, year 2014 is regarded as the breakpoint of the implementation of CETP. That is, years 2004–2013 are classified as the years before the implementation of CETP, while 2014–2019 are the years after the implementation of CETP. First, each of the six indicators under the four dimensions is standardized as follows:

$$\begin{aligned}
 X_{jit}^+ &= \frac{x_{jit} - m_{jt}}{M_{jt} - m_{jt}}, j = 1, 2, \dots, 5, \\
 X_{jit}^- &= \frac{M_{jt} - x_{jit}}{M_{jt} - m_{jt}}, j = 6,
 \end{aligned}
 \tag{1}$$

where i, j , and t are the index regions, indicators, and years, respectively, $j = 1, 2, \dots, 6$, $i = 1, 2, \dots, 30$, $t = 2004, \dots, 2013$. x_{jit} denotes the value of indicator j in region i over year t , X_{jit}^+ (X_{jit}^-) denotes indicator j with a positive (negative) effect, M_{jt} and m_{jt} denote the maximum and minimum of indicator j across regions over year t . Then, we assign X_{jit}^+ (X_{jit}^-) to X_{jit} , for $j = 1, 2, \dots$, and 5 ($j = 6$).

Second, the coefficient of variation is used to calculate the weights of the indicators in Table 1. Specifically, the six indicators are weighted in the following scheme:

$$\omega_{jt} = V_{jt} / \sum_j V_{jt}, \quad V_{jt} = \sigma_{jt} / \bar{X}_{jt},
 \tag{2}$$

where ω_{jt} is the weight of indicator j in year t , \bar{X}_{jt} and σ_{jt} are, respectively, the mean and the standard deviation of indicator j over regions ($X_{jit}, i = 1, 2, \dots, 30$), and V_{jt} represents the coefficient of variation of the indicator.

Thirdly, the composite index of the six indicators measuring IFCER in region i is calculated as:

$$\text{IFCER}_{it} = 1 - \sqrt{\frac{\sum_j (1 - X_{jit})^2 \omega_{jt}^2}{\sum_j \omega_{jt}^2}}.
 \tag{3}$$

The index lies between 0 and 1. A higher IFCER_{it} implies a more active carbon finance.

Table 2 The index of IFCER in the pilot and non-pilot regions before and after CETP

Region	Before CETP			After CETP		
	Mean	Maximum	Minimum	Mean	Maximum	Minimum
<i>Pilot</i>						
Beijing	0.415	0.564	0.241	0.553	0.621	0.481
Tianjin	0.124	0.163	0.041	0.160	0.304	0.085
Shanghai	0.403	0.541	0.227	0.535	0.618	0.460
Fujian	0.319	0.376	0.193	0.408	0.523	0.346
Hubei	0.169	0.240	0.071	0.194	0.314	0.118
Guangdong	0.443	0.517	0.288	0.569	0.683	0.443
Chongqing	0.149	0.196	0.060	0.176	0.313	0.080
Mean	0.289	0.371	0.160	0.371	0.482	0.287
<i>Non-pilot</i>						
Hebei	0.243	0.397	0.150	0.244	0.392	0.129
Shanxi	0.186	0.259	0.073	0.209	0.364	0.130
Nei Mongol	0.167	0.254	0.066	0.173	0.312	0.101
Liaoning	0.165	0.227	0.074	0.209	0.343	0.130
Jilin	0.146	0.206	0.056	0.169	0.313	0.103
Heilongjiang	0.149	0.216	0.065	0.199	0.337	0.124
Jiangsu	0.223	0.257	0.135	0.307	0.403	0.218
Zhejiang	0.204	0.257	0.133	0.295	0.404	0.189
Anhui	0.158	0.260	0.075	0.198	0.332	0.109
Jiangxi	0.141	0.182	0.074	0.194	0.337	0.094
Shandong	0.236	0.288	0.151	0.313	0.405	0.215
Henan	0.188	0.274	0.100	0.208	0.332	0.094
Hunan	0.163	0.228	0.088	0.218	0.334	0.124
Guangxi	0.137	0.175	0.049	0.183	0.314	0.115
Hainan	0.073	0.117	0.015	0.111	0.268	0.026
Sichuan	0.198	0.251	0.115	0.244	0.351	0.148
Guizhou	0.201	0.279	0.083	0.189	0.341	0.117
Yunnan	0.134	0.200	0.058	0.164	0.303	0.092
Shaanxi	0.144	0.208	0.057	0.183	0.307	0.111
Gansu	0.142	0.196	0.053	0.158	0.316	0.075
Qinghai	0.108	0.162	0.032	0.144	0.295	0.032
Ningxia	0.125	0.208	0.042	0.141	0.333	0.020
Xinjiang	0.148	0.211	0.054	0.197	0.351	0.099
Mean	0.164	0.231	0.078	0.202	0.339	0.113

The reported statistics include means, maximums, minimums of the employed 30 pilot and non-pilot regions before and after (the implementation of) CETP

3.2.2 IFCER across regions

According to the results of the IFCER index reported in Table 2, first, the maximum value of IFCER is 0.683 in Guangdong, the minimum value is 0.015 in Hainan, and the average value of IFCER from 2004 to 2019 is 0.211. Second, IFCER is increasing over time, implying that IFCER in China is gradually improving. Thirdly, IFCER of the seven pilot regions is generally higher than that of the non-pilot regions, especially after the implementation of CETP, supporting that the CETP effect are prominent.

Based on the means of IFCER in regions reported in Fig. 1 and Table 2, China can be divided roughly into three echelons of low-carbon development. The first echelon is represented by seven pilot regions as well as coastal regions such as Jiangsu and Zhejiang. The average IFCER in Guangdong after the implementation of CETP reaches 0.569, ranks first in China, possibly because Guangdong is overall a relatively developed region and has very active carbon markets. Beijing, Shanghai, Fujian, Zhejiang and Jiangsu closely follow Guangdong in terms of IFCER.

Beijing, the capital city of China, is known as the political and cultural center, while Shanghai and Fujian are major coastal economic regions. There exist abundant projects and funding associated with low carbon economy, which facilitates and accelerates the development of carbon finance. Regions such as Zhejiang and Jiangsu have well-developed financial markets and can attract plentiful capital inflows. IFCERs of inland regions such as Chongqing and Hubei are lower than those of the coastal pilot regions, probably due to their geographical locations. In fact, CET in those inland regions is still at an early stage, although their IFCER have been improving.

The second echelon includes provinces Shaanxi, Liaoning, Jiangxi, Hunan, and so on whose IFCER values range between 0.15 and 0.3. These non-pilot regions are located near some pilot regions and are possibly affected by the spillover effect from the pilot regions. It follows that the spillover raises CET and IFCER in these non-pilot regions. The third echelon is represented by Qinghai, Gansu, Ningxia, and so on whose average IFCER values are low and below 0.15. Their low IFCER probably results from their low levels of economic prosperity, geographical locations, or others, which we shall pay attention to later.

3.2.3 Other variables and data sources

There are additional data sources of control variables that may affect IFCER and CEI in the corresponding regressions. They include GDP per capita (PGDP), the proportion of secondary industries (Indu2), the proportion of tertiary industries (Indu3), foreign direct investment (FDI), energy consumption intensity (ECI), and environmental support (ES). Except ECI and ES collected from the China Energy Statistical Yearbook and the China Environment Yearbook, other variables are available from the China Statistical Yearbook. All variables are obtained on an annual basis.

3.3 The baseline model

The sample used in this paper consists of 22 provinces and 4 direct-controlled municipalities, and 4 autonomous regions in China from 2004 to 2019,⁹ all of which are partitioned into seven pilot and 23 non-pilot regions. The pilot regions are applied as the treatment group where CETP takes effect, while other non-pilot regions are the control group where CETP is not implemented. One primary variable of interest in this paper is IFCER. Since the ultimate goal of CETP is to achieve CER, for comparison, we also employ CEI as an alternative primary variable to measure the direct effect of CETP.

To verify the impacts of CETP on IFCER and CEI, we apply a DID model to our analysis. This paper forms a quasi-natural experiment for comparative analysis by dividing provinces, direct-controlled municipalities, and autonomous regions in China into the pilot regions and the non-pilot regions, based on the implementation of CETP. The CETP effects on IFCER and CEI as are tested as follows:

$$\ln \text{IFCER}_{it} = \beta_0 + \beta_1 \text{Treatment}_i \times \text{Time}_t + \sum \alpha_i \text{Control}_{it} + \gamma_i + \delta_t + \varepsilon_{it}, \quad (4)$$

$$\ln \text{CEI}_{it} = b_0 + b_1 \text{Treatment}_i \times \text{Time}_t + \sum a_i \text{Control}_{it} + r_i + p_t + \epsilon_{it}, \quad (5)$$

where i and t are the index regions and years, respectively. $\ln \text{IFCER}_{it}$ and $\ln \text{CEI}_{it}$, respectively, denote the logarithms of IFCER and CEI. Treatment_i is a dummy variable taking a value of one if CETP takes effect in region i or the region is a pilot region, and zero otherwise. Time_t is a dummy variable taking a value of one when CETP takes effect in year t , and zero otherwise. Hence, $(\text{Treatment}_i \times \text{Time}_t)$ is considered a region-time interaction dummy variable associated with the implementation of CETP. If CETP significantly improves IFCER in the pilot regions, then the coefficient should be significantly positive.

Control_{it} denotes the set of control variables that may affect IFCER, including PGDP, Indu2, FDI, ECI, and ES. γ_i and r_t represent the region fixed effects, while δ_t and p_t denote the time fixed effects. Please see “Appendix 3” of this paper for the derivations of all variables.

4 Empirical results

4.1 Descriptive statistics and parallel trend tests

4.1.1 Descriptive statistics

Table 3 reports the descriptive statistics of the main variables in this paper. For example, the mean of IFCER is 0.211 and the mean of (TreatmentTime) is 0.102,

⁹ Hong Kong, Macau, Taiwan, and Tibet are excluded.

Table 3 Descriptive statistics

Variables	Mean	Standard deviation	Minimum	Maximum
IFCER	0.211	0.122	0.015	0.683
CO2	1.388	0.786	− 0.803	2.166
lnECI	1.119	0.693	0.210	4.467
lnES	4.934	1.040	1.668	7.256
lnFDI	7.993	1.472	3.802	11.736
lnIndu2	0.431	0.082	0.160	0.620
lnIndu3	0.396	0.195	0.158	0.534
<i>PGDP</i>	10.341	0.688	8.349	12.011
lnR&D	4.845	1.485	0.467	7.760
Treatment × time	0.102	0.303	0	1

This tables reports the descriptive statistics of the main variables of regressions in this paper. The reported statistics include means, standard deviations, maximums, and minimums. For definitions and calculations of these variables, please see “Appendix 3” of this paper

implying 10.2% of region-year observations in which CETP takes effect. Among the control variables, the mean value of *PGDP* is 10.341 with a standard deviation of 0.688. The mean of *Indu2* is 0.431, while that of *Indu3* is 0.396, indicating that secondary industries are proportionally larger than tertiary industries in most regions of China.

4.1.2 Parallel trend test

Before proceeding to the estimation of our baseline regressions with DID, it is necessary to test whether the hypothesis of parallel trend is satisfied for the treatment (pilot) and control (non-pilot) groups. The parallel trend test is shown in Fig. 2 providing visual chronological changes in IFCER in the pilot and the non-pilot regions, particularly surrounding the implementation of CETP. Before that (2004–2013), IFCER in the treatment and control groups both exhibited a rising trend. Afterwards (2014–2019), the rising trend maintains and accelerates particularly after 2017. In addition, Fig. 2 shows that after the implementation of CETP, IFCER of the treatment group increases on average more than those of the control group, preliminarily supporting that CETP has a positive impact on IFCER. Both the treatment and control groups satisfy the parallel trend, an important assumption to apply the DID model.

4.2 Analyses of empirical results

4.2.1 Results of the baseline models

To test Hypothesis 1, Table 4 reports the effects of CETP on IFCER and CEI under the baseline models, Eqs. (4) and (5). As shown in the table, the dependent variable

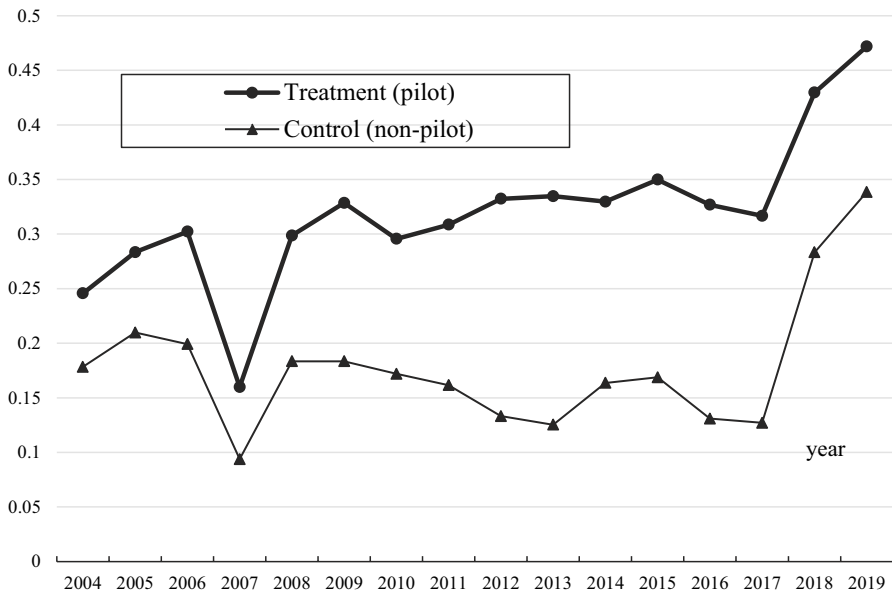


Fig. 2 Average growth rates of IFCER in the pilot and the non-pilot regions. This figure plots visual chronological changes in the two IFCER indices associated with the pilot and non-pilot regions

for the models under columns (1) and (2) is $\ln\text{IFCER}$, and the two regression models reflect the impact of (the implementation of) CETP on IFCER in regions without and with control variables. The results of the baseline models with $\ln\text{CEI}$ as the dependent variable are reported under columns (3) and (4) without and with control variables, respectively.

As a result, the coefficients of $\ln\text{IFCER}$ on (TreatmentTime) under columns (1) and (2) are significantly positive at least at the 10% level, indicating that CETP has a positive effect on improving IFCER in each region. Specifically, the coefficient of $\ln\text{IFCER}$ on (TreatmentTime) under columns (1) and (2) is, respectively, 8.8% (2.3%) at least at the 10% level of significance. In other words, the implementation of CETP raises $\ln\text{IFCER}$ by 8.8% (2.3%) without (with) the control variables. By contrast, the coefficients of $\ln\text{CEI}$ on (TreatmentTime) under columns (3) and (4) are significantly negative, respectively, -20.8% and -18.0%. It implies that the implementation of CETP reduces $\ln\text{CEI}$ by 20.8% (18.0%) without (with) the control variables. The evidence firmly supports Hypothesis 1 and the effective roles of CETP in increasing IFCER and reducing carbon emissions.

Among the control variables, first, FDI promotes IFCER. FDI can bring advanced management and green technologies to low-carbon firms, which enables them to effectively use IFCER and promotes IFCER. Second, Indu2 has a negative impact on IFCER. A larger share of secondary sector implies a lower capacity to accommodate industries and firms promoting CER, leading to a negative impact on IFCER. Third, ECI has a positive effect on IFCER. Given the China's ultimate goal of CER, a higher energy consumption of a region implies higher necessity of CER in the

Table 4 Regression results of the baseline model

Variable	lnIFCER		lnCEI	
	(1)	(2)	(3)	(4)
Constant	0.202*** (0.000)	− 0.618*** (0.000)	5.366*** (0.000)	0.204*** (0.006)
Treatment × time	0.088*** (0.000)	0.023* (0.086)	− 0.208*** (0.000)	− 0.180*** (0.000)
PGDP		0.006** (0.041)		0.517*** (0.000)
lnIndu2		− 0.158*** (0.000)		0.223*** (0.002)
lnFDI		0.055*** (0.000)		0.016*** (0.002)
lnECI		0.069*** (0.000)		0.039** (0.025)
lnES		0.024*** (0.008)		− 0.028* (0.075)
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R ²	0.36	0.46	0.45	0.81
N	480	480	480	480

This table reports the estimates under the baseline models with DID as follows:

$$\ln\text{IFCER}_{it} = \beta_0 + \beta_1 \text{Treatment}_i \times \text{Time}_t + \sum \alpha_i \text{Control}_{it} + \gamma_i + \delta_t + \varepsilon_{it},$$

$$\ln\text{CEI}_{it} = b_0 + b_1 \text{Treatment}_i \times \text{Time}_t + \sum \alpha_i \text{Control}_{it} + r_i + p_t + \epsilon_{it},$$

where *i* and *t* are the index regions and years, respectively. $\ln I_{it}$ and $\ln CEI_{it}$, respectively, denote the logarithms of IFCER and CEI. Treatment_i is a dummy variable taking a value of one if CETP takes effect in region *i* or the region is a pilot region, and zero otherwise. Time_t is a dummy variable taking a value of one when CETP takes effect in year *t*, and zero otherwise. $\text{Treatment}_i \times \text{Time}_t$ is a region-time interaction dummy variable of the implementation of CETP. Control_{it} denotes control variables that include GDP per capita (PGDP), the proportion of secondary industry value added (Indu2), foreign direct investment (FDI), energy consumption intensity (ECI), and environmental support (ES). For the detailed derivations of all variables, please see “Appendix 3” of this paper. γ_i and r_t represent the region fixed effects, while δ_t and p_t denote the time fixed effects. *P*-values are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

region, attracting more capital flows into IFCER. Fourth, the positive (negative) effect of ES on IFCER and CEI indicates that ES by regional government can be regarded as its attitude toward CER. Plausibly, more ES attracts IFCER and reduces carbon emissions.

4.2.2 The spillover effects of CETP nearby the pilot regions

Going a step further, this subsection examines Hypothesis 2 by conducting tests to distinguish the existence of the spillover effects of CETP in the non-pilot regions nearby the pilot regions. To do so, we assess the effects of CETP only in the non-pilot regions and slightly modify Eqs. (4) and (5) by replacing (TreatmentTime) with (NeighborTime). Neighbor_i is a dummy variable and takes a value of one, if region *i* is Hebei, Shandong, Jiangsu, Zhejiang, Jiangxi, Henan, Shaanxi, Shanxi, Anhui, Hunan, Guizhou, and Liaoning that are geographically close to the pilot regions, and zero otherwise. If the coefficients of $\ln\text{IFCER}$ and $\ln\text{CEI}$ on (NeighborTime) in the non-pilot regions are significantly different from zero, then the spillover effect exists. Moreover, we can distinguish the strength of the spillover effects by comparing the

Table 5 The effects of CETP in the pilot and the non-pilot regions

Variable	lnIFCER		lnCEI	
	Pilot (1)	Non-pilot (2)	Pilot (3)	Non-pilot (4)
Constant	- 0.690* (0.056)	- 0.534*** (0.001)	8.183*** (0.000)	0.981** (0.022)
Treatment × time	0.068*** (0.004)		- 0.111* (0.057)	
Neighbor × time		0.004* (0.074)		- 0.033** (0.029)
PGDP	0.132*** (0.000)	0.009 (0.505)	0.727*** (0.000)	0.334*** (0.000)
lnIndu2	- 0.242*** (0.000)	- 0.058* (0.083)	0.901*** (0.000)	0.069 (0.451)
lnFDI	0.123*** (0.000)	0.042*** (0.000)	0.132*** (0.001)	0.067*** (0.003)
lnECI	0.249*** (0.000)	0.061*** (0.000)	0.433*** (0.003)	0.068** (0.047)
lnES	0.066*** (0.008)	0.035*** (0.001)	0.129** (0.015)	- 0.038 (0.125)
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R ²	0.44	0.49	0.82	0.77
N	112	368	112	368

This table reports the estimates of the baseline models in the pilot and the non-pilot regions. Under columns (1) and (3), the applied regression models are Eqs. (4) and (5), respectively. Under columns (2) and (4), the applied regression models are almost identical to Eqs. (4) and (5), respectively, except that the independent variable (Treatment_{*i*} × Time_{*t*}) in Eqs. (4) and (5) is replaced with (Neighbor_{*i*} × Time_{*t*}). Treatment_{*i*} takes a value of one, if region *i* is one of the pilot regions, including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Fujian, and zero otherwise. Neighbor_{*i*} a dummy variable and takes a value of one, if region *i* is Hebei, Shandong, Jiangsu, Zhejiang, Jiangxi, Henan, Shaanxi, Shanxi, Anhui, Hunan, Guizhou, or Liaoning, and zero otherwise. For the detailed derivations of all variables, please see “Appendix 3” of this paper. *P*-values are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

coefficient magnitudes between (TreatmentTime) and (NeighborTime). Table 5 reports the results.

As a result, the coefficient of lnIFCER on (TreatmentTime) for the pilot regions under column (1) and that on (NeighborTime) for the non-pilot regions under column (2) is, respectively, 0.064 and 0.004 and significant at the 1% level. Moreover, the coefficient on (TreatmentTime) is larger than that on (NeighborTime) in magnitude. Similarly, under columns (3) and (4), the coefficients of lnCEI on (TreatmentTime) and (NeighborTime) are, respectively, -0.111 and -0.033 and significant at least at the 10% level, and the coefficient magnitude on (TreatmentTime) is larger than that on (NeighborTime). This indicates that CETP improves IFCER and reduces CEI mainly in the pilot regions. Interestingly, the existence of the spillover effect affects (in the same directions but to a lesser extent) IFCER and CEI in the regions nearby the pilot regions, which confirms Hypothesis 2.

4.2.3 Persistence of the CETP effects

In this subsection, we shift our attention to Hypothesis 3 and examine the persistence of the CETP effects on IFCER and CEI. To accommodate the impacts of CETP over up to the sixth year after the implementation of CETP, we slightly revise Eqs. (4) and (5) as follows:

Table 6 Estimation results of dynamic impact effect

Variable	lnIFCER		lnCEI	
	(1)	(2)	(3)	(4)
Constant	0.204*** (0.000)	- 0.604*** (0.000)	5.371*** (0.000)	0.140* (0.094)
Treatment × time ¹	0.046* (0.088)	0.020** (0.025)	- 0.179 (0.122)	- 0.122** (0.025)
Treatment × time ²	0.067** (0.014)	0.015* (0.055)	- 0.173 (0.134)	- 0.146*** (0.008)
Treatment × time ³	0.043** (0.019)	0.024** (0.035)	- 0.149 (0.198)	- 0.205*** (0.000)
Treatment × time ⁴	0.033** (0.019)	0.048* (0.060)	- 0.165 (0.153)	- 0.238*** (0.000)
Treatment × time ⁵	0.146*** (0.000)	0.056** (0.031)	- 0.238** (0.039)	- 0.210*** (0.000)
Treatment × time ⁶	0.189*** (0.000)	0.091*** (0.000)	- 0.262** (0.023)	- 0.216*** (0.000)
PGDP		0.061* (0.064)		0.512*** (0.000)
lnIndu2		- 0.157*** (0.000)		0.210** (0.004)
lnFDI		0.055*** (0.000)		0.024* (0.084)
lnECI		0.067*** (0.000)		0.043** (0.027)
lnES		0.024*** (0.009)		- 0.019* (0.052)
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R ²	0.36	0.47	0.03	0.81
N	480	480	480	480

This table reports the estimates under the baseline models with DID as follows:

$$\ln IFCE_{it} = \beta_0 + \beta_1 \text{Treatment}_i \times \text{Time}_t^k + \sum \alpha_i \text{Control}_{it} + \gamma_i + \delta_t + \varepsilon_{it},$$

$$\ln CEI_{it} = b_0 + b_1 \text{Treatment}_i \times \text{Time}_t^k + \sum a_i \text{Control}_{it} + r_i + p_t + \varepsilon_{it}$$

where *i* and *t* are index regions and years, respectively. *lnI_{it}* and *lnCEI_{it}* respectively denote the logarithms of IFCER and CEI. *Treatment_i* is a dummy variable taking a value of one if CETP takes effect in region *i* or the region is a pilot region, and zero otherwise. *Treatment_i × Time_t^k* is the region-time interaction dummy variable associated with CETP indicating year *k* after the implementation of CETP. Year 2013 is recognized as the implementation time of CETP in the pilot regions. Thus, *k* = 1, 2, 3, 4, 5, and 6 for years 2014, 2015, 2016, 2017, 2018, and 2019, respectively. *Control_{it}* denotes control variables that include GDP per capita (PGDP), the proportion of secondary industry value added (Indu2), foreign direct investment (FDI), energy consumption intensity (ECI), and environmental support (ES). For the detailed derivations of all variables, please see “Appendix 3” of this paper. *γ_i* and *r_t* represent the region fixed effects, while *δ_t* and *p_t* denote the time fixed effects. *P*-values are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

$$\ln IFCE_{it} = \beta_0 + \sum_{k=1}^6 \beta_k \text{Treatment}_i \times \text{Time}_t^k + \sum \alpha_i \text{Control}_{it} + \gamma_i + \delta_t + \varepsilon_{it}, \quad (6)$$

$$\ln CEI_{it} = \beta_0 + \sum_{k=1}^6 \beta_k \text{Treatment}_i \times \text{Time}_t^k + \sum \alpha_i \text{Control}_{it} + \gamma_i + \delta_t + \varepsilon_{it}, \quad (7)$$

where *Treatment_i × Time_t^k* is the region-time interaction dummy variable of CETP in year *k* after the implementation of CETP. Since year 2013 is recognized as the implementation time of CETP in the pilot regions, *k* = *n* if *T* = 2013 + *n*, *n* = 1, 2, 3,

4, 5, and 6. Using the DID model, this paper estimates Eqs. (6) and (7) and shows the results in Table 6.

The dependent variable under columns (1) and (2) is $\ln\text{IFCER}$, while that under columns (3) and (4) is $\ln\text{CEI}$. The models under columns (1) and (3) do not include control variables, while the models under columns (2) and (4) do. As a result, the coefficients of $\ln\text{IFCER}$ on $(\text{Treatment} \times \text{time})$ from one to six years after the implementation of CETP are all significantly positive, regardless of the inclusion of control variables, implying that CETP has a persistent positive impact on IFCER for up to six years after the implementation of CETP. Moreover, the coefficients on $\ln\text{IFCER}$ $(\text{Treatment} \times \text{time}^k, k = 1, \dots, 6)$ under column (2) are increasing with k . They are, respectively, 0.020, 0.015, 0.024, 0.048, 0.056, and 0.091, for $k = 1, \dots, 6$, supporting that the effect of CETP on IFCER strengthens over time.

The absence of control variables under column (3) makes the regression results confusing. The coefficients on $(\text{Treatment} \times \text{time}^k, k = 1, \dots, 6)$ are mostly insignificant. However, once including the control variables under column (4), the coefficients all turn to be significantly negative for one to six years after the implementation of CETP. For example, CEI is reduced by 12.2% in the first year after the implementation of CETP at the 5% level of significance, by 14.6% in the second year at the 1% level of significance, and by 21.6% in the sixth year at the 1% level of significance. The evidence on $\ln\text{IFCER}$ and $\ln\text{CEI}$ verifies the persistence of the CETP effects and confirms Hypothesis 3.

4.3 Robustness tests

Up to now, we have applied baseline regressions to verify Hypotheses 1, 2, and 3. Before proceeding any further, this subsection ensures the reliability of our previous results by conducting five robustness tests.

4.3.1 An alternative measure of ES

The first robustness test is to apply an alternative measure of ES as a control variable in the baseline models—Eqs. (4) and (5)—originally using the investment in environmental pollution control to measure the regional ES, similar in essence to mostly prior studies. This issue is important because, through moderate interventions, e.g., public spending on human resources, R&D, or others, governments can prompt a sustainable green economy and lower risks, leading to reductions in obstacles and higher returns on firms' investments (Taghizadeh-Hesary et al. 2021; Zhang et al. 2021). Now, following Ji et al. (2021), we attempt to make a revision and employ the amount of industrial pollution treatment completed to measure ES. Then, we re-estimate the baseline models and report the results in Table 7.

The results show that the coefficient of $\ln\text{IFCER}$ is significantly positive, while that of $\ln\text{CEI}$ is significantly negative. Although there are differences in the estimated values of the CETP effects, they are consistent with the results of the baseline model, supporting the robustness of the positive effect of CETP on IFCER and the negative effect on CEI.

Table 7 Robustness test with an alternative proxy for environment supports

Variable	lnIFCER (1)	lnCEI (2)
Treatment × time	0.029* (0.032)	– 0.166*** (0.000)
Controls	Yes	Yes
Time fixed effect	Yes	Yes
Region fixed effect	Yes	Yes
R^2	0.42	0.44
N	480	480

This table reports the estimates under the baseline models identical to those in Table 4, except applying an alternative proxy, the amount of industrial pollution treatment completed, for environment supports (ES), one of the control variables in the baseline models. Please see the legend for Table 4 for their specifications. For brevity, only the statistics associated with (Treatment × time) reported. For the detailed derivations of all variables, please see “Appendix 3” of this paper. P -values are given in parentheses. * and *** indicate significance at the 10% and 1% levels, respectively

4.3.2 An alternative sample period

Since 2018, the National Development and Reform Commission of the People’s Republic of China has successively issued a series of policies (e.g., Development and Reform Environmental Resources [2019] No. 689, Development and Reform Price Regulation [2018] No. 943, etc.). Similar to CETP, those policies are mainly to promote green development. They mostly make efforts to reform regional environmental resources and encourage regions to build a market-oriented green system. To ensure that the observed impacts are not driven by other green development policies, this paper changes the sample period to years 2004–2017 to measure the effects of CETP on IFCER and CEI. Table 8 shows the results. Basically, CETP still has a significantly positive (negative) impact on IFCER (CEI). In fact, we also employ other possible sample periods, and the conclusions are qualitatively the same, which supports the robustness of the effects of CETP.

4.3.3 A random sampling method

To make sure that the CETP effects may be confounded by outliers or other unobservable effects, in this subsection and the following subsection, procedures of random sampling methods are used to re-select subsamples of regions to form a new treatment group and control group. First, we repeat the random resampling of pilot and non-pilot regions for regressions for 500 times. Each time, we randomly re-select 4 out of the 7 original pilot regions and 12 out of the 23 original non-pilot regions. Then, the re-selected 16 pilot and non-pilot

Table 8 Robustness test with a smaller sample interval

Variable	lnIFCER		lnCEI	
	(1)	(2)	(3)	(4)
Treatment × time	0.052*** (0.000)	0.052*** (0.000)	− 0.194*** (0.000)	− 0.157*** (0.000)
Controls	No	Yes	No	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R^2	0.35	0.42	0.38	0.84
N	420	420	420	420

This table reports the estimates under the baseline models identical to those in Table 4, except shrinking the sample period to 2004–2017. For brevity, only the statistics associated with (Treatment × time) reported. For the detailed derivations of all variables, please see “Appendix 3” of this paper. P -values are given in parentheses. *** indicates significance at the 1% level

Table 9 Robustness test with random sampling methods

Variable	lnIFCER		lnCEI	
	(1)	(2)	(3)	(4)
Treatment × time	0.108* (0.059)	0.016*** (0.000)	− 0.260*** (0.006)	− 0.067*** (0.000)
Controls	No	Yes	No	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R^2	0.53	0.48	0.57	0.65
N	256	256	256	256

This table reports the estimates under the baseline models identical to those in Table 4, applying the random sampling method. The random resampling of pilot and non-pilot regions for regressions are repeated 500 times. Each time, 4 out of the 7 original pilot regions and 12 out of the 23 original non-pilot regions are re-selected as the new treatment group and control group of the baseline regressions. This procedure generates 500 parameter estimates. The standard deviations of this sample of 500 parameter estimates are used to generate the standard errors of the parameter estimates. The reported statics are based on the 500 parameter estimates. For brevity, only the statistics associated with (Treatment × time) reported. For the detailed derivations of all variables, please see “Appendix 3” of this paper. P -values are given in parentheses. * and *** indicate significance at the 10% and 1% levels, respectively

regions are employed as the sample of the regressions under the baseline models, Eqs. (4) and (5). This procedure generates 500 parameter estimates. The standard deviations of this sample of 500 parameter estimates are used to generate the standard errors of the parameter estimates. Table 9 reports the means of t -statistics of the selected coefficients, using the corresponding 500 parameter estimates.

If CETP still has significantly positive effects on CEI and IFCER, our previous results are considered robust. As expected, the evidence shows that CETP is significantly positive (negatively) associated with $\ln\text{IFCER}$ ($\ln\text{CEI}$) at least at the 10% level, regardless of the inclusion of the control variables. The observed consistency with Table 4 confirms the robustness of our results.

4.3.4 Placebo tests

In this subsection, this paper conducts the placebo tests by randomly designating the pilot and not-pilot regions. Different from the formations of the treatment and control groups in the previous subsection, pilot regions in this subsection are not necessarily included in the treatment group. Instead, the treatment group consists of seven regions that are completely randomly selected from the 30 regions, and other 23 regions constitute the control group. The random sampling is repeated 500 times, each of which is separately followed by regressions of Eqs. (4) and (5) with the randomly selected treatment and control groups. Figure 3 plots the probability density functions of the estimated coefficients of $\ln\text{IFCER}$ and $\ln\text{CEI}$ on (TreatmentTime) in the left and right halves, respectively. The evidence shows both sets of estimated coefficients concentrate around zero. It follows that the random sampling will not generate meaningful results and the CETP effects estimated previously are unlikely to be driven by other unobservable factors.

4.3.5 The PSM-DID method

CETP was first implemented in Guangdong on a trial basis in the first half of 2013 and then implemented in other pilot regions between the second half of 2013 and the first half of 2014. Based on these disparities, we employ DID to estimate the effects associated with the implementation of CETP. However, although known to lessen most of the problems associated with endogeneity, DID does not prevent possible sample selection biases. For example, the selection of pilot regions may not be completely random. Given the large disparities in environmental support and economic development across regions, the PSM method, proposed by Rosenbaum and Rubin (1983), is powerful to predict the similarity of probabilities to balance the distribution of the observed covariates between the treatment and control groups. To reduce possible endogeneity due to the non-random sample selection or match the pilot and non-pilot regions with similar probability of implementing CETP, we apply the PSM-DID method proposed by Heckman et al. (1997) as a robustness test.

A balance test applying all control variables is applied to check whether there is a significant difference in the selected variables between the pilot and the matched non-pilot regions with and without PSM. If there is no significant difference, then PSM is appropriate. As reported in Table 10, the standard deviations of all variables reduce after applying PSM, and the covariates between the pilot and non-pilot regions are insignificantly different, meeting the parallel hypothesis required by DID. Thus, with PSM, the distributions of the selected variables between the pilot and the matched non-pilot regions are relatively balanced.

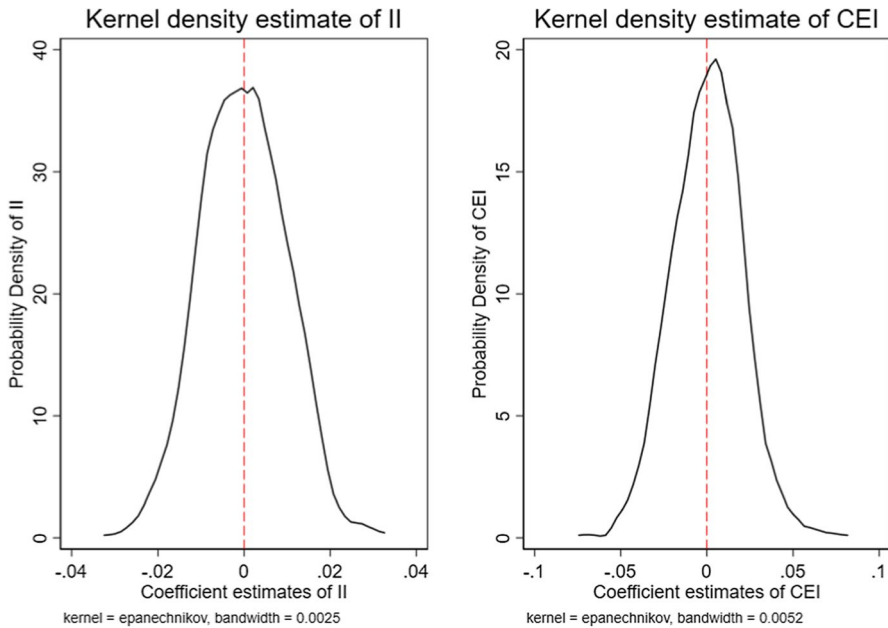


Fig. 3 The probability density functions of the estimated coefficients. This figure plots the probability density functions of the estimated coefficients of $\ln\text{IFCER}$ and $\ln\text{CEI}$ on (TreatmentTime) in the left and right halves, respectively. First, the treatment group consists of seven regions randomly selected from the 30 regions, and other 23 regions constitute the control group. Second, the random sampling is repeated 500 times, each of which is followed separately by regressions as follows. $\ln\text{IFCER}_{it} = \beta_0 + \beta_1 \text{Treatment}_i \times \text{Time}_t + \sum \alpha_i \text{Control}_{it} + \gamma_i + \delta_t + \varepsilon_{it}$, where i and t index regions and years, respectively. $\ln\text{IFCER}_{it}$ and $\ln\text{CEI}_{it}$, respectively, denote the logarithms of IFCER and CEI. Treatment_i is a dummy variable taking a value of one if CETP takes effect in region i or the region is a pilot region, and zero otherwise. Time_t is a dummy variable taking a value of one when CETP takes effect in year t , and zero otherwise. $\text{Treatment}_i \times \text{Time}_t$ is a region-time interaction dummy variable of the implementation of CETP. Control_{it} denotes control variables that include GDP per capita (PGDP), the proportion of secondary industry value added (Indu2), foreign direct investment (FDI), energy consumption intensity (ECI), and environmental support (ES). For the detailed derivations of all variables, please see “Appendix 3” of this paper. γ_i and r_t represent the region fixed effects, while δ_t and p_t denote the time fixed effects

First, a PSM approach is used to match the pilot and non-pilot regions, so that there is no significant difference between the pilot and the matched non-pilot regions. Second, a DID model is used to estimate the impacts of CETP on IFCER and CEI. The estimation results using PSM-DID are documented in Table 11. As a result, the CETP effects are rather clear, employing PSM-DID. The coefficients, signs, and significance levels of the CETP effects in the regressions with $\ln\text{IFCER}$ and $\ln\text{CEI}$ as the dependent variables are generally consistent with the previous results, as documented in Table 4, supporting their robustness.

Table 10 Balance test for each variable with and without PSM

Variable	Mean of the treatment group	Mean of the control group	Standard deviation	<i>t</i> value
<i>PGDP</i>				
Without PSM	10.841	10.189	102.8	9.57***
With PSM	10.786	10.848	9.8	0.78
<i>lnIndu2</i>				
Without PSM	− 0.922	− 0.845	10.5	0.57
With PSM	− 0.910	− 0.833	− 4.3	− 0.32
<i>lnFDI</i>				
Without PSM	9.156	7.638	− 18.7	− 0.96
With PSM	9.018	9.091	− 0.4	− 0.02
<i>lnECI</i>				
Without PSM	0.687	1.251	− 25.8	− 1.03
With PSM	0.710	0.724	− 2.5	− 0.27
<i>lnES</i>				
Without PSM	4.598	4.307	59.0	0.65
With PSM	4.541	4.524	3.4	0.27

This table reports the results of a balance test applied to check whether there is a significant difference in the observable variables without and with PSM between the pilot (treatment) regions and non-pilot (control) regions. *** indicates significance at the 1% level. For the detailed derivations of all variables, please see “Appendix 3” of this paper

Table 11 The PSM-DID model

Variable	lnIFCER		lnCEI	
	(1)	(2)	(3)	(4)
Treatment × time	0.135*** (0.000)	0.019** (0.017)	− 0.215* (0.072)	− 0.164*** (0.000)
Controls	No	Yes	No	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R^2	0.12	0.33	0.76	0.80
<i>N</i>	429	429	429	429

This table reports the estimates under the baseline models identical to those in Table 4, except using PSM-DID. A PSM approach is then used to match the pilot and non-pilot regions so that there is no significant difference between the pilot and non-pilot regions before the implementation of CETP as far as possible. For the detailed derivations of all variables, please see “Appendix 3” of this paper. *P*-values are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Table 12 Conditional analyses

Variable	Level of income		Location		
	Wealthy (1)	Less wealthy (2)	Eastern (3)	Central (4)	Western (5)
Treatment × time	0.035** (0.030)	0.002* (0.070)	0.036** (0.042)	− 0.030 (0.240)	− 0.039 (0.249)
Controls	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes
R^2	0.60	0.19	0.43	0.22	0.22
N	176	304	176	160	144

This table conducts conditional analyses on GDP per capita and on geographical locations by applying the estimates under the baseline model with DID as follows:

$$\ln\text{IFCER}_{it} = \beta_0 + \beta_1 \text{Treatment}_i \times \text{Time}_t + \sum \alpha_i \text{Control}_{it} + \gamma_i + \delta_t + \varepsilon_{it},$$

where i and t index regions and years, respectively. $\ln\text{IFCER}_{it}$ denotes the logarithms of IFCER. Treatment_i is a dummy variable taking a value of one if CETP takes effect in region i or the region is a pilot region, and zero otherwise. Time_t is a dummy variable taking a value of one when CETP takes effect in year t , and zero otherwise. $\text{Treatment}_i \times \text{Time}_t$ is a region-time interaction dummy variable of the implementation of CETP. Control_{it} denotes control variables that include GDP per capita (PGDP), the proportion of secondary industry value added (Indu2), foreign direct investment (FDI), energy consumption intensity (ECI), and environmental support (ES). For the detailed derivations of all control variables, please see “Appendix 3” of this paper. γ_i denotes the region fixed effect, while δ_t is the time fixed effect. This table divides the sample into wealthy regions and less wealthy regions, based on GDP per capita, under columns (1) and (2), respectively. Based on geographical locations, columns (1), (2), and (3), respectively, divide the regions into eastern, central and western regions. P -values are given in parentheses. * and ** indicate significance at the 10% and 5% levels, respectively

4.4 Heterogeneity analyses

In this subsection, we turn our attention to Hypotheses 4a and 4b by testing whether and how the effects of CETP on IFCER vary across regions, based on GDP per capita and geographical locations.¹⁰ An exploration of this heterogeneity issue can provide insight into how the effects of CETP work and help design subsequent policies more precise and effective for sustainable development.

4.4.1 GDP per capita

To verify Hypothesis 4a, a conditional test on GDP per capita is conducted to examine whether the impact of CETP on IFCER in wealthy regions is different from that in less-wealthy regions. First, based on the average of GDP per capita across regions

¹⁰ For simplicity, from now on, we only discuss the effect of CETP on IFCER. The untabulated results on CEI (available upon request) are consistent with our previous conclusions.

from 2004 to 2019, 11 regions above the average are categorized as the wealthy regions, while the other 19 regions below the average are categorized as the less-wealthy regions. Second, using these two subsamples, we run the baseline regression, Eq. (4), and report the results under columns (1) and (2) of Table 12. As a result, the coefficients of IFCER on (TreatmentTime) in wealthy and less wealthy regions are both significantly positive, but the regression coefficient of IFCER in less wealthy regions is smaller than that in wealthy regions. It implies that the effects of CETP are stronger in wealthy regions and lends support to Hypothesis 4a.

4.4.2 Geographical locations

Now, we attempt to test Hypothesis 4b by analyzing a conditional test on geographical locations to examine whether the impact of CETP on IFCER varies across geographical locations. First, all regions are divided into three groups, eastern, central and western regions, based on the geographical locations. Second, employing these three subsamples, we estimate the baseline regression, Eq. (4), and report the results of location heterogeneity under columns (3), (4), and (5) of Table 12, respectively. Evidence shows that the coefficient on (Treatment×time) in eastern regions is significantly positive, while those in central and western regions are insignificantly negative. The results clearly confirm our belief and Hypothesis 4b that the impact of the implementation of CETP on IFCER in eastern regions is stronger than those in central and western regions.

4.5 Economic mechanisms behind the effects of CETP

The previous empirical analyses in this paper have confirmed that CETP can improve IFCER. In this subsection, we are interested in how CETP increases IFCER or the validity of Hypothesis 5 that there exist possible economic mechanisms behind the effects of CETP on IFCER. We propose R&D and Indu3 as two possible mediating variables. Then, we propose models, similar to Wen et al. (2018), to test whether CETP raises IFCER through the two mediating variables as follows:

$$\ln\text{IFCER}_{it} = \alpha_0 + \alpha_1 \text{Treatment}_i \times \text{time}_t + \sum \beta_i \text{Control}_{it} + u_i + v_t + \varepsilon_{it}, \quad (8)$$

$$\text{Mech}_{it} = \alpha_0 + \alpha_2 \text{Treatment}_i \times \text{time}_t + \sum \beta_i \text{Control}_{it} + u_i + v_t + \varepsilon_{it}, \quad (9)$$

$$\ln\text{IFCER}_{it} = \alpha_0 + \alpha_3 \text{Treatment}_i \times \text{time}_t + \alpha_4 \text{Mech}_{it} + \sum \beta_i \text{Control}_{it} + u_i + v_t + \varepsilon_{it}, \quad (10)$$

Table 13 The mediating effects

Mediating variable	R&D		Indu3	
	InFCER	InR&D	InFCER	InIndu3
Explanatory variable	(1)	(2)	(4)	(5)
Treatment × time	0.023* (0.086)	0.155** (0.011)	0.023* (0.086)	0.034*** (0.006)
InR&D			0.027*** (0.041)	
InIndu3			0.024*** (0.005)	
Controls	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes
R ²	0.46	0.49	0.46	0.35
N	480	480	480	480

This table reports the estimates under the followings models with DID:

$$\text{InFCER}_{it} = \alpha_0 + \alpha_1 \text{Treatment}_t \times \text{time}_t + \sum \beta_i \text{Control}_{it} + u_i + v_t + \epsilon_{it}$$

$$\text{Mech}_{it} = \alpha_0 + \alpha_2 \text{Treatment}_t \times \text{time}_t + \sum \beta_i \text{Control}_{it} + u_i + v_t + \epsilon_{it}$$

$\text{InFCER}_{it} = \alpha_0 + \alpha_3 \text{Treatment}_t \times \text{time}_t + \alpha_4 \text{Mech}_{it} + \sum \beta_i \text{Control}_{it} + u_i + v_t + \epsilon_{it}$
 where i and t index regions and years, respectively. InFCER_{it} denotes the logarithm of IFCER. Mech_{it} is the mechanism variable, either $\ln\text{R\&D}$ or $\ln\text{Indu3}$. Treatment_t is a dummy variable taking a value of one if CETP takes effect in region i or the region is a pilot region, and zero otherwise. Time_t is a dummy variable taking a value of one when CETP takes effect in year t , and zero otherwise. $\text{Treatment}_t \times \text{Time}_t$ is a region-time interaction dummy variable of the implementation of CETP. Control_{it} denotes control variables that include GDP per capita (PGDP), the proportion of secondary industry value added (Indu2), foreign direct investment (FDI), energy consumption intensity (ECI), and environmental support (ES). For the detailed derivations of all variables, please see "Appendix 3" of this paper. u_i denotes the region fixed effect, while v_t is the time fixed effect. P -values are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

where $Mech_{it}$ is the selected mediating variable, $\ln R\&D$ or $\ln Indu3$. First, in Eq. (8), we mainly check whether the coefficient of $\ln IFCER$ on $(Treatment \times time)$ ($\hat{\alpha}_1$) is significantly positive. If yes, CETP significantly improves IFCER. Second, Eq. (9) is designed to examine whether CETP stimulates the mediating variable or the coefficient of $Mech$ on $(Treatment \times time)$ ($\hat{\alpha}_2$) is significantly different from zero. Third, Eq. (10) is to test the existence of the mediating effect, indicated by $\hat{\alpha}_4$, with controls for the implementation of CETP. If $\hat{\alpha}_2$ and $\hat{\alpha}_4$ are both significantly different from zero, there exists a mediating (indirect) effect, first from CETP to $Mech$, and then from $Mech$ to IFCER. The effect can be quantified as $(\hat{\alpha}_2 \times \hat{\alpha}_4)$. Similarly, if $\hat{\alpha}_3$ is significantly different from zero, there is a direct effect of CETP on IFCER. Table 13 reports the results.

Concerning the mediating effect of R&D, Columns (1), (2), and (3) show the estimated results of Eqs. (8), (9), and (10), respectively. First, under column (1), the regression coefficient on $(Treatment \times time)$ ($\hat{\alpha}_1$) is 0.023 and significant at the 10% level, indicating that CETP increases IFCER. Second, $\hat{\alpha}_2$ under column (2) (0.155) is significant at the 5% level, indicating that CETP increases R&D. Third, the coefficients on $(Treatment \times time)$ ($\hat{\alpha}_3 = 0.027$) and on $(\ln R\&D)$ ($\hat{\alpha}_4 = 0.024$) under column (3) are both significant at the 1% level positive. This follows that the mediating effect of R&D exists and the indirect effect $(\hat{\alpha}_2 \times \hat{\alpha}_4)$ shares the same sign (direction) with the direct effect $(\hat{\alpha}_3)$, suggesting that CETP can further improve IFCER through R&D. The observed scenario is that first CETP attracts firms to invest in R&D; second, R&D can encourage technological innovations and improve energy efficiency, which generates more investment opportunities and further stimulates IFCER.

As for the mediating effect of tertiary industries, the results are shown under columns (4), (5), and (6). The coefficients under column (4) are identical to those under column (1), while the coefficient of $\ln Indu3$ on $(Treatment \times time)$ ($\hat{\alpha}_2$) under column (5) is significantly positive at the 1% level, indicating that the implementation of CETP results in industrial upgrading from secondary industries to tertiary industries, mainly covering service and financial firms. Under column (6), the coefficients on $(Treatment \times time)$ ($\hat{\alpha}_3$) and $\ln Indu3$ ($\hat{\alpha}_4$) are also significantly positive both at the 5% level, supporting the existence of the mediation effect. Given the positive sign of both the direct and indirect effects, it is possible CETP can first trigger industrial upgrading, and then the expanding tertiary industries induce demands for further CER and IFCER. According to the evidence associated with R&D and tertiary industries, Hypothesis 5 is confirmed.

5 Conclusion and policy implications

Developing a composite index to quantify IFCER, this paper employs data from 2004 to 2019 and the DID method to examine the impacts of CETP on IFCER and CEI. The evidence shows that, first, CETP increases IFCER and reduces CEI. Second, the effects of CETP in the pilot regions can spill over to the non-pilot regions nearby.

Third, the effects of CETP are persistent for up to six years. Fourth, the effects of CETP are robust to a variety of tests applying alternative proxies for major variables, changing the sample interval, using the alternative PSM-DID method, applying randomly selected samples and placebo tests. Fifth, additional conditional tests show that the effects of CETP are stronger in wealthy regions and in eastern regions.

Finally, the economic mechanisms behind the effects of CETP are observed. R&D and the proportion of tertiary industries play vital roles in linking CETP to IFCER and CEI. For example, CETP encourages firms to invest in R&D that in turn promote more technological innovations and improve energy efficiency, which generates more investment opportunities and further stimulates IFCER.

Based on the observed empirical findings, this paper has four policy implications as follows. First, in light of the existence of the spillover effect, as long as policy makers make efforts to develop the likes of CETP to reduce carbon emissions, the benefits should be more than expected. Second, the authority should be aware of possible mechanisms behind the effect of CETP on IFCER to accelerate the development and benefit from it. For example, the government may motivate firms to carry out R&D in low-carbon technologies by appropriately issuing additional free carbon emissions allowances to those firms with green outputs. Third, thanks to our conditional analyzes in Sect. 5.4, it is necessary to fully recognize relevant characteristics among regions and utilize their strength and roles in CER and CET to build effective carbon trading markets. Finally, many countries may recently experience difficulties in their economies (probably due to the COVID-19 pandemic), but it is worth keeping carrying out CER policies, similar to CETP, to not only clean air, but also encourage industrial upgrading and possibly accelerate green recovery, given the observed benefits in China.

Appendix 1: A summary of all abbreviations

Table 14 documents all abbreviations employed in this paper.

Appendix 2: Possible dimensions of IFCER

Following Chen et al. (2020), this section presents a theoretical analysis of possible influencing factors of IFCER. Suppose there are a representative firm and a financial institution in the economy. Assume that carbon emissions are generated by the firm and have a negative externality effect on the whole economic system, which will reduce the returns of the firm.

Before the implementation of CETP, no one provides financing to the firm for CER projects. The revenue function of the firm is:

$$\pi = Pq - qT, \quad (11)$$

Table 14 Abbreviations

Abbreviation	Standing for
CEI	Carbon emissions intensity
CER	Carbon emissions reduction
CET	Carbon emissions trading
CETP	Carbon emissions reduction policy
CO2	Carbon dioxide
DID	Difference in difference
ECI	Energy consumption intensity
ES	Environmental support
FDI	Foreign direct investment
IFCER	Investment and financing facilitating CER
Indu2	Secondary industries
Indu3	Tertiary industries
PGDP	GDP per capita
PSM-DID	Propensity-score-matching and difference-in-difference
R&D	Research and development

where π represents the revenue of the firm, q denotes the quantity of output of the firm and P is the output price. If there is no CET, since the government requires that CEI of the firm cannot exceed the specified quota, otherwise it will pay a penalty of qT , where T is the cost parameter associated with the penalty before the implementation of CETP.

After the implementation of CETP, IFCER is available for the firm. The return of the firm is as follows:

$$\pi = Pq - (1 - v_c^\mu)qt - v_c(1 + r_c), \quad (12)$$

where v_c denotes the total amount of financing with which the firm carries out technological innovation in order to achieve CER. μ is the elasticity of technological innovation,¹¹ $0 < \mu < 1$, v_c^μ is the degree of CER by the firm through technological innovation. t denotes the cost parameter of CET after the implementation of CETP, ($t < T$). $(1 - v_c^\mu)qt$ is considered the transaction cost of CET, including transaction fees and others. r_c is the interest rate at which financial institutions finance CER projects.

To determine the optimal financing size (v_c^*) for the firm, we take the first derivative of π with respect to (v_c) in Eq. (12) and let it equal zero as follows:

$$\frac{\partial \pi}{\partial v_c} = 0 \Rightarrow v_c^* = \left(\frac{\mu qt}{1 + r_c} \right)^{1/(1-\mu)}. \quad (13)$$

¹¹ The elasticity of technological innovation illustrates the degree of response of CER to changes in financing for technological innovations.

Then, substituting v_c^* in Eqs. (12) yields the following:

$$\pi^* = (P - t)q + \frac{(\mu qt)^{1/(1-\mu)}(1/\mu + 1)}{(1 + r_c)^{\mu/(1-\mu)}}. \quad (14)$$

Equation (14) describes the returns of the firm at the optimal financing size. To emphasize the difference between after and before the implementation of CETP, we take the difference between Eqs. (14) and (11) and derive the following:

$$\Delta\pi = \pi^* - \pi = (T - t)q + \frac{(\mu qt)^{1/(1-\mu)}(1/\mu + 1)}{(1 + r_c)^{\mu/(1-\mu)}}. \quad (15)$$

It can be seen that $\Delta\pi \geq 0$, which indicates that the revenue of the firm should increase after the implementation of CETP. There are two reasons. First, the transaction cost of the market decreases after the implementation of CETP, as indicated by the cost saving $(T - t)q$, given a fixed q . The cost saving reflects the benefit of the implementation CETP on CET.

The second term of the right-hand side in Eq. (15) can be regarded as the effect of financing CER projects on the revenue of the firm. Assuming a fixed q , the second term of the right-hand side $\left[\frac{(\mu qt)^{1/(1-\mu)}(1/\mu + 1)}{(1 + r_c)^{\mu/(1-\mu)}} \right]$ shows that given the existence of v_c^* or the sufficiency of funds, the benefit of the implementation of the firm depends on the technological innovation elasticity μ and the interest rate r_c . In the following, we attempt to explain why we propose the four dimensions in Sect. 3.2.1 to describe IFCER.

Explicitly, CER projects reducing CEI can be either financed through indirect financing (the first dimension of IFCER) or direct financing (the third dimension of IFCER), reflected by v_c . The larger the amount of financing for CER, the higher the level of carbon finance. With regard to the second dimension, the higher the elasticity of technological innovation (μ), the more efficient the use of funds, the more carbon dioxide emissions are reduced. Finally, as for the fourth dimension, the higher the cost of financial services, the lower income of the firm, the lower the level of carbon finance. Collectively, IFCER can be evaluated by the amount of direct and indirect financing for CER, the efficiency of the use of funds, and the cost of financial services.

Appendix 3: A summary of all variable definitions

Table 15 records all definitions and derivations of variables employed in this paper.

Table 15 The definitions and derivations of all variables

Variable	Derivation
IFCER	Calculated by coefficient of variation method
CEI	Calculated as the total carbon emissions divided by GDP
ECI	Calculated as the energy consumption divided by GDP
ES	Calculated as the investment in environmental pollution control deflated by GDP
FDI	Calculated as foreign direct investment deflated by GDP
Indu2	Calculated as the added value of secondary industries deflated by GDP
Indu3	Calculated by the added value of tertiary industries deflated by GDP
PGDP	Calculated as GDP per capita
R&D	Calculated as the R&D expenditures deflated by GDP
Treatment × time	Calculated as a region time interactive dummy variable

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