Does China's carbon emissions trading policy improve the technology innovation of relevant enterprises?

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Abstract
China's carbon emissions trading (CET) policy aims to force relevant enterprises to implement low-carbon technology innovation and address environmental challenges through marketization means. However, how China's CET policy may affect enterprise technology innovation and whether this effect may differ in industries remain to be further investigated. Therefore, based on the panel data of listed enterprises covered by the CET policy in China during 2009–2017, this paper employs the difference-in-difference (DID) and DID-based propensity score matching models to evaluate the effect of CET on technology innovation. The empirical results indicate that the effect of China's CET on the technology innovation of related enterprises is generally not significant during the sample period, but this effect presents evident industrial heterogeneity. Specifically, among the eight CET-covered industries, the CET policy helps to improve technology innovation for power and aviation enterprises but not in the other six industries (i.e., steel, chemical, building material, petrochemical, nonferrous metals, and paper), which implies that China's CET policy still has great potential for promoting the technology innovation of related enterprises. In addition, the central findings remain robust when the system generalized method of moment and DID-based coarsened exact matching models are applied to consider the influence of omitted variables, unobservable confounders, and different matching methods.

KEYWORDS
carbon emissions trading, CET-covered enterprises, DID models, environmental management, technology innovation

1 | INTRODUCTION

Within 40 years of reforming and opening, China has made great achievements in economic growth. During 1978–2018, its gross domestic product jumped from the world's ninth to the second.1 Meanwhile, China's total CO2 emissions first exceeded the United States in 2006 and became the world's largest CO2 emitter (Mi et al., 2017; Zhang, Peng, & Su, 2017). In 2017, the CO2 emissions in China reached 9.23 billion tons, accounting for 27.6% of the world (BP, 2018).

In face of severe domestic environmental problems and tremendous international community pressure (Song, Wang, & Sun, 2018), China is striving to comply with the Paris Agreement. Chinese government has made a series of ambitious commitments to reduce CO2 emissions in recent years. For example, in 2009, China officially proposed its carbon intensity (CO2 emissions per unit of gross domestic product) constraint target which stated that the carbon intensity of 2015 will be 17% lower than that of 20102 (Zhou & Jiang, 2019);

and China also promised to reduce carbon intensity by 40–45%, based on its 2005 level, by 2020. In 2015, China further proposed to lower carbon intensity by 60–65% by 2030, compared with the 2005 level (Mi et al., 2016). In addition, in 2014, China and United States issued the Joint Statement on Climate Change. In this statement, China committed to attain the CO₂ emissions peak by 2030 and strive to realize the peak early (Mi et al., 2017). In 2017, the report of the 19th National Congress of the Communist Party of China stated that China would promote a sound economic structure that facilitates green, low-carbon, and circular development. Meanwhile, China also committed to promote green development and solve prominent environmental problems, to develop a new mode of modernization with humans developing in harmony with nature. Through persistent efforts, China has realized remarkable achievement of reducing CO₂ emissions. By the end of 2017, China’s carbon intensity had decreased by 46% compared with 2005, and the 2020 carbon intensity reduction target had been achieved in advance.

CET is considered one of the important means to reduce CO₂ emissions and mitigate climate warming (Chameides & Oppenheimer, 2007; Fan, Li, & Wu, 2016; Zhang & Hao, 2017; Zhang, Wang, & Tan, 2015). Since the issue of Kyoto Protocol by the United Nations, the CET scheme has been launched in many countries (Bataille, Guivarch, Hallegatte, Rogelj, & Waisman, 2018). In order to meet the requirement about gradually establishing a domestic carbon emissions trading market in the 12th Five-Year Plan and promote the application of market mechanism to achieve the goal of controlling greenhouse gas emissions at a lower cost in 2020, China’s National Development and Reform Commission approved seven provinces and cities (i.e., Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Hubei, and Shenzhen) to carry out carbon trading pilot work in 2011. In this way, it also aims to accelerate the transformation of economic development mode and the upgrading of industrial structure. Meanwhile, the CET pilot covers eight energy-and-carbon-intensive industries (i.e., steel, power, aviation, chemical, building, petrochemical, nonferrous metals, and paper). According to the Carbon Trading Blue Book: China Carbon Trading Report (2017), the first compliance of the carbon trading market was in 2013, and carbon quotas were officially listed and traded in the pilot markets. Afterwards, starting with the power industry, China launched the national carbon trading market in the end of 2017. Thus, China is estimated to exceed the European Union Emissions Trading System (EU ETS) to become the world’s largest carbon trading market (Weng & Xu, 2018). As of 2018, China’s carbon trading pilot has been operating for 5 years and accumulated various experiences and lessons. Therefore, it is necessary to assess the actual effectiveness of carbon trading up to now.

Furthermore, in 2012, the 18th National Congress of the Communist Party of China proposed the innovation-driven development strategy. It called for the economic growth to shift from the traditional factor-driven and investment-driven modes to the innovation-driven mode. Meanwhile, as the primary driving force for economic development, enterprise technology innovation has attracted wide attention (Doran & Ryan, 2016; Larrey et al., 2019; Zhou, Zhang, Wen, Zeng, & Chen, 2018). Porter and Linde (1995) propose that reasonable environmental policies can generate the “innovation offsets” effect and stimulate enterprises to carry out more innovative activities, and the “innovation offsets” effect will make up or even exceed environmental regulation costs, to achieve the “win–win” condition of both enterprise productivity and competitiveness, which is called the Porter hypothesis (Ambec, Cohen, Elgie, & Lanoie, 2013). However, the key to achieving “win–win” lies in the scale of the “innovation offset” effect. More precisely, it largely depends on whether environmental policies can promote the technology innovations of enterprises.

At present, there are three main views on the effect of environmental policy on enterprise technology innovation. First, the traditional view holds that environmental policies obstruct technology innovation of enterprises (Carriónflores, Innes, & Sam, 2013). The introduction of an environmental policy may increase the cost of enterprises and weaken the technology innovation ability of regulated enterprises. Second, many studies argue that environmental policies promote the technology innovation of enterprises (Chang & Sam, 2015; He & Shen, 2017; Rubashkina, Galeotti, & Verdolini, 2015), because a well-designed environmental policy can promote enterprises to carry out more innovative activities to make up for the cost of environmental regulation. For example, Chang and Sam (2015) adopt an instrumental variable Poisson framework to estimate the effects of Voluntary P2 Activities on the patenting of environmental technologies, and their results indicate that the adoption of Voluntary P2 Activities leads to a statistically and economically significant increase in the number of environmental patents in the manufacturing sector. He and Shen (2017) leverage the context of ISO 14001 certification among Chinese listed firms to investigate the effect of environmental management system certification on enterprise technology innovation, and their results show that ISO 14001 environmental certification facilitates enterprise technology innovation. Finally, some literature insists that the relationship between environmental policies and enterprise technology innovation is uncertain (Albrizio, Kozluk, & Zipperer, 2017; Brunnermeier & Cohen, 2003; Ramanathan, Ramanathan, & Bentley, 2018; Wagner, 2008). For instance, Brunnermeier and Cohen (2003) employ a panel data model to study the determinants of environmental innovation in U.S. manufacturing industries and find that pollution control costs are positively correlated with environmental patent counts; however, government monitoring has no significant impact on patent applications.

Therefore, it is necessary to assess the actual effectiveness of carbon trading up to now.
As China's economy enters a "new normal" state, the economic growth rate has gradually slowed down. Meanwhile, China is also facing the constraints of resources and environment (Song et al., 2018). In this situation, the CET scheme not only controls total carbon emissions but also forces relevant enterprises to eliminate backward production capacity and achieve transformation and upgrading. This process may affect enterprise technology innovation ability (Hu, Wang, & Li, 2017; Liao, 2018b), which further affects their sustainable development. More importantly, enterprises are the backbone of national economy, and the innovative ability of enterprises plays a decisive role in national economic transformation and green, low-carbon, and circular development (Gault, 2018; Mousavi, Bossink, & Vliet, 2018). Therefore, it is crucial for China to assess the effect of CET on enterprise technology innovation. Meanwhile, this assessment is meaningful to the transformation of drivers behind China's economic growth and the sound development of carbon trading market. Moreover, as the world's largest developing country and carbon-emitting country, China plays a vital role in global carbon emissions abatement (Shao, 2019; Xun, 2013). The results in this paper will help policy makers perfect the CET system and may also promote the CET-covered enterprises to carry out low-carbon technology innovation to better achieve the reduction of carbon emissions in China.

The contribution of this paper mainly consists of three aspects. First, current research on CET mainly focuses on the macro level (i.e., national level, regional level, etc.), but enterprises are the main participants of the CET; therefore, from the micro enterprise level, this paper applies the traditional difference-in-difference (DID) model and the difference-in-difference-based propensity score matching (PSM-DID) model to inspect the effect of CET on enterprise technology innovation in a reliable manner. Second, previous studies on CET mainly concentrate on a particular industry (i.e., power industry, steel industry, etc.), but the characteristics of enterprises are quite different in various industries; thus, from the perspective of various industries, this paper explores the industrial heterogeneity of CET on enterprise technology innovation, so as to provide a better understanding of the regulatory effect of CET on enterprise technology innovation.

Finally, in order to test the reliability of research results, this paper uses a variety of econometric models for robustness checks. Specifically, we apply a system generalized method of moment (SGMM) method to consider the influence of time-variant unobservable confounders. In addition, based on the common matching method, this paper further proposes a DID-based coarsened exact matching (CEM-DID) to estimate the policy effect of CET on enterprise technology innovation.

The remainder of this paper is organized as follows. Section 2 provides a literature review, Section 3 introduces data description, Section 4 presents research methods, Section 5 puts forward empirical results and analyses, and Section 6 concludes the paper with some key policy implications.

## 2 | RELEVANT LITERATURE REVIEW

### 2.1 | Carbon emissions trading

To promote the application of market mechanism and achieve the goals of controlling greenhouse gas emissions at a lower cost, China initiated the CET pilot scheme in seven provinces and cities in 2011. By doing this, China also wants to achieve the purpose of forcing enterprises to carry out low-carbon technology innovation and accelerate the transformation of economic development mode and the upgrading of industrial structure. Subsequently, research on China's CET has been expanding. At present, global studies on CET have been increasing over time, which can be roughly divided into two categories, that is, the operating mechanisms of CET and the effect of CET on CO₂ emissions.

On the one hand, regarding the operating mechanism of the CET, the existing research mainly focuses on the setting of carbon price, the allocation of carbon quota, the scope of coverage, etc. For example, Zhang and Wei (2010) summarize the operating mechanism and economic effect of the EU ETS based on empirical studies on the EU ETS. Li and Lu (2015) argue that the unified carbon price policy is conducive to economic growth, environmental quality improvement, and energy demand reduction. However, the carbon price level needs to be flexibly set by the government according to demand. Zhu, Zhang, Li, Wang, and Guo (2017) find that the free allocation of carbon quota can cause a competitiveness distortion among domestic normal and outdated capacities. Due to governmental intention to promote outdated capacity withdrawal and production-level upgrading, an output-based allocation approach is strongly suggested for China's iron and steel sector. Liu, Sun, Chen, and Zhao (2016) calculate the abatement cost of China's electric power generation sector under different auctioning rates and find that when the auctioning rate increases, the carbon abatement cost increases accordingly. In addition, when the allowance auction rate is 5%, the total additional cost of the electric power generation sector will increase by 0.244 Yuan/kW h. Lin and Jia (2017) argue that CO₂ prices will increase from 0.12% to 1.64% in different coverage scenarios. Meanwhile, if the rational choice of the carbon rights suppliers and demanders in ETS market is made by the government, the carbon price will be guaranteed within a reasonable range. Moreover, they also believe that when more industries are covered, the CET market will be more stable.

On the other hand, there are two mainstream views for the effect of CET on CO₂ emissions. One view is that CET can promote carbon emissions abatement. For example, Tang, Wu, Yu, and Bao (2015) find that China's unified carbon trading market mechanism can effectively reduce national carbon emissions by 15–20%. Jong, Covenenber, and Woedman (2014) state that the EU ETS has an inhibitory effect on environmental pollution. Zhang, Peng, Ma, and Shen (2017) argue that China's CET has a debilitating effect on carbon emissions in the
pilot areas. Additionally, another view insists that CET cannot promote carbon emissions reduction. For instance, Chappin and Dijkema (2009) employ an agent-based model to investigate the effect of CET on the decisions of power companies in an oligopolistic market and find that the economic effect of CET is not sufficient to outweigh the economic incentives to choose for coal. Thus, the carbon abatement effect of the EU ETS is not significant. Kettner, Koppl, Schleicher, and Thenius (2008) find that the EU ETS has no significant effect on carbon abatement of 24 member countries, which is mainly caused by the serious excess of carbon credit allocation in the EU and the failure of price adjustment mechanism.

2.2 Enterprise innovation

At present, studies on the effect of environmental policy on enterprise innovation basically focus on two aspects, that is, the driving factors of enterprise innovation and the performance of enterprise innovation.

On the one hand, regarding the driving factors of enterprise innovation, existing literature briefly pools driving factors of enterprise innovation into three parts: the push of technology, the pull of demand, and the promotion of supervision. For instance, Rio, Penasco, and Romerojordan (2015) insist that regulation is a positive and significant driver of eco-innovation. Tsai and Liao (2017) find that market demand can pressure the enterprises to conduct eco-innovation. Costantini, Crespi, Martini, and Pennacchio (2015) explore the effect of demand-pull and technology-push in shaping technological patterns in the bio-fuel sector, and their results show that both demand-pull and technology-push are the factors that spur the innovative activities of enterprises. Zhao, Zhao, Zeng, and Zhang (2015) present a structural equation model to explore the effect of Chinese environmental policy on Chinese firm behavior and competitiveness. Specifically, as for Chinese electric power and iron and steel firms, the results show that both the administrative-based and market-based environmental policies can promote technology innovation and competitiveness of enterprises. Johnstone et al. (2017) find that the stringency of environmental regulations is a significant determinant in improving operational efficiency, spurring energy efficiency, and promoting low-carbon technology innovation. But these effects turn negative once the level of stringency leaps over a certain threshold. In addition, some scholars state that environmental policies cannot promote enterprise innovation. For instance, Albrizio et al. (2017) investigate the impact of environmental policies stringency on industry-level and firm-level productivity growth, and their results indicate that environmental policies cannot promote innovation for the average firm; no evidence of the Porter hypothesis is found.

On the other hand, in regard to the performance of enterprise innovation, existing research mainly focuses on the productivity, economic benefits and competitiveness. For example, Tang, Walsh, Ler ner, Fitza, and Li (2018) state that green product innovation and green process innovation both can improve firm performance. Rubashkina et al. (2015) investigate the effect of technology innovation on enterprise productivity, and their results show that technology innovation cannot further improve enterprise productivity. Ramanathan et al. (2018) employ a data envelopment analysis approach to evaluate the effect of environmental regulations’ flexibility on the relationship between innovation and financial performance in enterprises, and their results indicate that when firms feel that the environmental regulations are flexible, their innovation capabilities significantly influence their financial performance; however, when they feel that they face more inflexible regulations, their innovation capabilities are not effective in improving the financial performance. Liao (2018a) surveys 366 enterprises in the manufacturing and service industries and finds that environmental innovation has a positive effect on the financial performance of enterprises.

In summary, previous relevant literature has already evaluated the CET policy and focused on the effect of environmental policies on technology innovation, but there are still some apparent shortcomings. First, energy-and-carbon-intensive enterprises are the dominant players of CET, but existing CET research mainly focuses on the regional level or a few industries, while scarce studies investigate the effect of CET on technology innovation of enterprises from a micro level (i.e., firm level). Thus, it is difficult to directly and reliably evaluate the regulatory effect of CET. Second, although existing studies have discussed the effect of environmental policies on enterprise innovation, few studies explore the effect of China’s CET on the technology innovation of CET-covered enterprises. In particular, many studies ignore the heterogeneity among industries that regulated enterprises belong to. Therefore, it is difficult to systematically evaluate the effect of China’s ongoing CET on technology innovation of CET-covered enterprises. Given these shortcomings, this paper first evaluates the effect of China’s CET on the technology innovation of CET-covered enterprises from the micro level and then explores the heterogeneity among industries that China’s CET-covered enterprises belong to and corresponding causes of the industrial heterogeneity.

3 | DATA DESCRIPTIONS

3.1 Data sources

As the CET policy only covers eight energy-and-carbon-intensive industries (i.e., steel, power, aviation, chemical, building material, petrochemical, nonferrous metals, and paper), this paper selects 456 energy-and-carbon-intensive enterprises listed on Shanghai and Shenzhen Stock Exchange as research objects, and the sample period ranges from 2009 to 2017. The industry classifications are defined by China Securities Regulatory Commission and shown in Table 1. Because China’s current CET policy only covers the enterprises of eight energy- and carbon-intensive industries in the pilots, this paper treats these enterprises as the treatment group and the enterprises of these eight industries out of the pilots as the control group. The main financial statements and capital market information data used in this paper are obtained from the WIND and CSMAR databases, and the patent data of listed enterprises come from the Intellectual Property Office of the People’s Republic of China.
3.2 Variable descriptive statistics

According to Amore and Bennedsen (2016), this paper uses the total counts of invention patents granted in each year to measure the technology innovation of enterprises. China’s Patent Granted System has three categories: invention patents, utility patents, and design patents. Among them, invention patents have the highest novelty and technological inventiveness. To be granted, the application for an invention patent must meet the requirement of "novelty, inventiveness, and practical applicability." Thus, this paper focuses on the counts of invention patents granted.

The explanatory variables are Pilot and T, all of which are dummy variables. indicates that the enterprise is located in the CET pilot, and zero otherwise. T = 1 indicates that the CET policy has been implemented, and zero otherwise. Based on previous relevant research (Barasa, Knoben, Vermeulen, Kimuyu, & Kinyanjui, 2017; Bronzini & Piselli, 2016; Guo, Guo, & Jiang, 2016; Howell, 2016; Rong, Wu, & Boeing, 2017), this paper selects the age of listing, per capita fixed assets, and enterprise ownership as control variables. Table 2 shows the definitions and data sources of all variables. Table 3 reports the summary of their descriptive statistics. As seen from Table 3, the patent counts vary widely, with an average of 10.39 and a maximum of 983.00. Moreover, those enterprises have high capital intensity, and the per capita fixed assets of employees are 1.26 million yuan (RMB). In addition, the average age of listing is 10 years. For financial variables, the returns on assets are relatively low, with an average of 2.75%, whereas the leverage ratio is relatively high, at 52.43%, and Tobin’s Q is also high, with an average of 1.71. Besides, among the enterprises surveyed, there are more state-owned enterprises, reaching 58%.

4 METHODS

4.1 The DID model

The implementation of CET is mainly for energy-and-carbon-intensive enterprises in the pilot areas but not for the enterprises outside the pilot. Thus, the implementation of CET can be seen as a quasi-natural experimental process. We set Patent as a random variable of enterprise technology innovation. Specifically, Pilot = 1 and Pilot = 0.

### TABLE 1 New industry classification

<table>
<thead>
<tr>
<th>Industry</th>
<th>CSRC industry classification standard three-level code</th>
<th>CSRC industry classification standard three-level industry name</th>
<th>CSRC industry classification standard first-level industry name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Petrochemical</td>
<td>C25</td>
<td>Petroleum processing, coking and nuclear fuel processing industry</td>
<td>Manufacturing</td>
</tr>
<tr>
<td>Chemical</td>
<td>C26</td>
<td>Chemical raw materials and chemical products manufacturing</td>
<td></td>
</tr>
<tr>
<td>Building</td>
<td>C30</td>
<td>Nonmetallic mineral products industry</td>
<td></td>
</tr>
<tr>
<td>Steel</td>
<td>C31</td>
<td>Ferrous metal smelting and rolling processing industry</td>
<td></td>
</tr>
<tr>
<td>Nonferrous</td>
<td>C32</td>
<td>Nonferrous metal smelting and rolling processing industry</td>
<td></td>
</tr>
<tr>
<td>Paper</td>
<td>C22</td>
<td>Paper and paper products</td>
<td></td>
</tr>
<tr>
<td>Power</td>
<td>D44, D45</td>
<td>Electricity, heat, gas production and supply</td>
<td></td>
</tr>
<tr>
<td>Aviation</td>
<td>G56</td>
<td>Air transport industry</td>
<td></td>
</tr>
</tbody>
</table>

Abbreviation: CSRC, China Securities Regulatory Commission.

### TABLE 2 Variables and data descriptions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Calculation method</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patent</td>
<td>Invention patent counts</td>
<td>Invention patent grant counts per year</td>
<td>Piece</td>
</tr>
<tr>
<td>Roa</td>
<td>Return on assets</td>
<td>The ratio of total operating income to total assets</td>
<td>%</td>
</tr>
<tr>
<td>Lev</td>
<td>Leverage</td>
<td>The ratio of total debts and total assets</td>
<td>%</td>
</tr>
<tr>
<td>Age</td>
<td>Age of listing</td>
<td>Years since an enterprise has been listed</td>
<td>Year</td>
</tr>
<tr>
<td>Tq</td>
<td>Tobin’s Q</td>
<td>The ratio of enterprise market value to asset replacement cost</td>
<td>%</td>
</tr>
<tr>
<td>Cpl</td>
<td>Per capita fixed assets</td>
<td>The ratio of fixed assets to total employees</td>
<td>Ten thousand Yuan/person</td>
</tr>
<tr>
<td>Poe</td>
<td>Enterprise ownership</td>
<td>It is equal to one if the enterprise is state-owned, and zero otherwise</td>
<td>-</td>
</tr>
</tbody>
</table>

Note. The data above are mainly from the databases of WIND, CSMAR, and the patent database of the Intellectual Property Office of the People’s Republic of China.
respectively denote the enterprises covered by the CET policy (the treatment group) and those that are not covered (the control group). Only the enterprises in the treatment group are affected by the CET. Therefore, the effect of CET on technology innovation of treatment group is \( E(\text{Patent}|\text{Pilot} = 1) \), whereas the effect of the control group is \( E(\text{Patent}|\text{Pilot} = 0) \). Thus, we can obtain the causal relationship of the CET on different energy-and-carbon-intensive enterprises. That is, the pure effect of CET on technology innovation of the treatment group is defined as

\[
Y = E(\text{Patent}|\text{Pilot} = 1) - E(\text{Patent}|\text{Pilot} = 0). \tag{1}
\]

Based on the quasi-natural experiment of establishing carbon trading pilots in two provinces and five cities in the end of 2011, this paper defines the period from 2000 to 2011 as that before CET, whereas the period from 2012 to 2017 as that after implementation of CET. Then, this paper evaluates the effect of CET on enterprise technology innovation by comparing the difference between the treatment group and the control group before and after the launch of CET based on the following DID model:

\[
\ln\text{Patent}_i = \alpha_0 + \alpha_1 \ln\text{Age}_i + \alpha_2 \ln\text{Cpl}_i + \alpha_3 \ln\text{Poe}_i + f_i + \epsilon_i. \tag{2}
\]

where \( \ln\text{Patent} \) represents the logarithm of invention patent granted counts. \( TP \) stands for the interaction term, that is, \( TP = T \times \text{Pilot}. \) \( T = 0 \) and \( T = 1 \) refer to preimplementation and postimplementation, respectively. In addition, \( \text{Pilot} = 1 \) refers to enterprises in the CET pilots, otherwise \( \text{Pilot} = 0. \) \( \ln\text{Age} \) denotes the logarithm of the years since the enterprise has been listed. \( \ln\text{Cpl} \) represents the logarithm of per capita fixed assets. \( \text{Poe} \) is the dummy variable of enterprise ownership, and \( \text{Poe} = 1 \) if the enterprise is a state-owned enterprise, otherwise \( \text{Poe} = 0. \) Coefficient \( \alpha_1 \) indicates the separated pure effect of CET on enterprise technology innovation.

### 4.2 The DID-based propensity score matching model

China’s CET is an environmental policy that was designed within a quasi-experimental framework. Therefore, the hidden treatment effect and reverse causal relationship may exist during the research (Zhang & Liu, 2018; Zhang, Peng, Ma, & Shen, 2017). Thus, this paper uses the propensity score matching (PSM) method to calculate the propensity scores for each enterprise. Then, in order to handle the hidden treatment effect and reverse causal relationship, we screen out enterprises with no systematic difference based on the propensity scores. Therefore, we can achieve the purpose of controlling self-selection bias (Lechner, 2002; Rosenbaum & Rubin, 1983). In this paper, self-selection bias refers to the nonrandom selection of carbon trading enterprises due to various observable individual characteristics. This means that the change in enterprise technology innovation may be attributed to not only CET but also to other significant individual characteristics, such as enterprise economic performance, and enterprise size. Therefore, the PSM is employed to ensure that the effect of CET on enterprise technology innovation is not disturbed by self-selection bias. On the basis of PSM, this paper selects nonpilot enterprises that are similar to those pilot enterprises in individual characteristics, rather than comparing all the original samples. We employ PSM to control the self-selection bias, but this procedure cannot well solve the group-specific difference (i.e., enterprise heterogeneity between pilot enterprises and nonpilot enterprises) and the time-specific difference. To accurately and quantitatively evaluate the effect of CET on enterprise technology innovation, we use a DID model to estimate the effect after the process of PSM, and specific procedures are as follows.

#### 4.2.1 Estimate the propensity scores of enterprises covered by CET

Due to the individual characteristics of enterprises influencing whether enterprises are covered by the CET policy or not, the process of PSM is actually used to calculate a “propensity score” for each enterprise by observable individual characteristics. Namely, the propensity score implies the probability of an enterprise covered by the CET policy. This paper calculates the propensity score through the Logit regression, as shown in Equation (3).

\[
P(X_i) = \Pr(\text{Pilot}_i = 1|X_i) = \frac{\exp(X_i \beta)}{1 + \exp(X_i \beta)}. \tag{3}
\]

where \( X_i \) represents the observable individual characteristics of an enterprise, which may influence whether an enterprise will be covered

---

**TABLE 3** Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
<th>Min</th>
<th>Q25</th>
<th>Median</th>
<th>Q75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patent</td>
<td>10.39</td>
<td>48.60</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>5.00</td>
<td>983.00</td>
</tr>
<tr>
<td>Roa</td>
<td>2.75</td>
<td>7.31</td>
<td>-91.83</td>
<td>0.64</td>
<td>2.73</td>
<td>5.76</td>
<td>74.11</td>
</tr>
<tr>
<td>Lev</td>
<td>52.43</td>
<td>81.76</td>
<td>0.71</td>
<td>33.53</td>
<td>51.49</td>
<td>67.76</td>
<td>4615.94</td>
</tr>
<tr>
<td>Age</td>
<td>10.90</td>
<td>6.04</td>
<td>1.00</td>
<td>6.00</td>
<td>11.00</td>
<td>16.00</td>
<td>25.00</td>
</tr>
<tr>
<td>Tq</td>
<td>1.71</td>
<td>1.94</td>
<td>0.06</td>
<td>0.66</td>
<td>1.25</td>
<td>2.09</td>
<td>54.28</td>
</tr>
<tr>
<td>Cpl</td>
<td>126.39</td>
<td>340.62</td>
<td>0.01</td>
<td>31.10</td>
<td>58.40</td>
<td>110.03</td>
<td>9.30</td>
</tr>
<tr>
<td>Poe</td>
<td>0.58</td>
<td>0.49</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note. The sample size is 3414; Q25 and Q75 denote the 25% and 75% quantiles, respectively.
by the CET. The propensity score \( P(X) \) implies the conditional probability that enterprises will be covered by CET with the characteristics of \( X \). The individual characteristics selected in this paper include Age, Cpl, and Poe. Pilot is a dummy variable; Pilot = 1 implies that enterprise \( i \) is covered by the CET, and otherwise Pilot = 0. \( \beta \) is the regression coefficient.

### 4.2.2 Select the nonpilot enterprises to match the pilot enterprises

To control the self-selection bias, this paper employs the nearest-neighbor matching to select nonpilot enterprises that are similar to pilot enterprises in observable individual characteristics. According to nearest-neighbor matching, each pilot enterprise is matched to the \( N \) nearest neighbors from nonpilot enterprises (see Equation 4). Based on Abadie and Imbens (2011) and the sample size in this paper, here we choose .

\[
D(m,n) = \min|P_m - P_n|.
\]

where \( P_m \) and \( P_n \) imply the propensity score of pilot enterprise \( m \) and nonpilot enterprise \( n \), respectively, and \( D(m,n) \) represents the minimum distance of propensity scores. After eliminating the self-selection bias by PSM, we employ the DID model to estimate the pure effect of CET on enterprise technology innovation, and model specification is similar to Equation (2).

### 5 RESULTS AND ANALYSES

#### 5.1 The effect of CET on enterprise technology innovation in eight industries

According to Equation (2), the effect of CET on enterprise technology innovation in the eight major industries can be estimated, and the results are shown in Table 4. Model 1 is a benchmark model that does not contain any control variables, whereas Models 2, 3, and 4 add the control variables in turn. As seen from Table 4, in the process of adding control variables from Model 1 to Model 4, the significance and coefficient direction of key explanatory variable TP do not change. This implies that the results estimated by the DID are relatively robust. Based on Table 4, we can obtain several important findings, as follows:

First, after implementing CET, the technology innovation of CET-covered enterprises improves in general, but the degree of improvement is not significant. From Model 1 to Model 4 in Table 4, we can see that the coefficient of key explanatory variable TP is positive, but the regression coefficient is not significant. This result suggests that although CET promotes more CET-covered enterprises to carry out innovative activities, the effect is still weak, which implies that up to now, there is still a long way to go to achieve the original intention of initiating the CET policy. We infer that in the process of implementing CET, each CET pilot takes mandatory measures to supervise the enterprises that satisfy the inclusion criteria,13 and every year, the enterprises obtain a certain amount of carbon emissions allowance through the benchmarking, grandfathering, or auctioning methods. (Zhang et al., 2015). Facing the mandatory administrative policy, enterprises will face many restrictions on carbon emissions (Cao, Ho, Jorgenson, & Nielsen, 2019). Meanwhile, enterprises have less time and flexibility in choosing the appropriate technology or making research and development (R&D) adjustments (Albrizio et al., 2017). To fulfill the target of reducing carbon emissions in a short time, the CET-covered enterprises may adjust input and output levels and energy structure to reduce fossil energy consumption (Mi, Meng, Green, Coffman, & Guan, 2018). In addition, after implementing the CET, these CET-covered enterprises may directly reduce carbon emissions by purchasing advanced production equipment or introducing low-carbon production technologies to improve energy efficiency and increase production efficiency (Kromer, Bandivadekar, & Evans, 2010). All of these approaches may adjust the energy consumption structure and improve the equipment level for enterprises, but in the end, these methods do not significantly improve the technology innovation in enterprises. In addition, the implementation of environmental policies has limited impact in the short term, although the impact of these policies will increase gradually over time (Ramanathan et al., 2018). In China, the CET policy was only initiated for approximately 6 years, but technology innovation often needs a long-term process (Wicki & Hansen, 2019). Because the process of technology innovation is full of uncertainties, enterprise R&D does not always lead to successful technology innovation outcomes. Thus, the effect of CET on technology innovation of CET-covered enterprises appears weak now but may turn more significant over time.

Finally, from the perspective of control variables, the control variables of Age and Poe have significant impact on enterprise technology innovation. As shown in the results of Models 1 and 4 in Table 4 before and after adding the control variables, the coefficients of the key explanatory variable TP are 0.0238 and 0.0116, respectively, which means that after adding the control variables, the CET improves.

### Table 4 The effect of carbon emissions trading on enterprise innovation in the eight major industries

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>0.0238</td>
<td>0.0213</td>
<td>0.0183</td>
<td>0.0116</td>
</tr>
<tr>
<td>Lnage</td>
<td>-0.0975***</td>
<td>-0.1457***</td>
<td>-0.1418***</td>
<td></td>
</tr>
<tr>
<td>Poe</td>
<td>0.1543***</td>
<td>0.1611***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lncpl</td>
<td></td>
<td>-0.0145</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.6350***</td>
<td>0.8313***</td>
<td>0.8216***</td>
<td>0.8644***</td>
</tr>
<tr>
<td>Sector fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.0260</td>
<td>0.0294</td>
<td>0.0318</td>
<td>0.0317</td>
</tr>
<tr>
<td>Observation</td>
<td>3,413</td>
<td>3,413</td>
<td>3,413</td>
<td>3,413</td>
</tr>
</tbody>
</table>

*significance at 10% level.
**significance at 5% level.
***significance at 1% level.

13http://zfxxgk.ndrc.gov.cn/web/iteminfo.jsp?id=2385
TABLE 5  The effect of carbon emissions trading on enterprise innovation in various industries

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>-0.2109</td>
<td>-0.2173</td>
<td>0.3501**</td>
<td>0.3723**</td>
<td>0.4830***</td>
<td>0.4410**</td>
<td>-0.0948</td>
<td>0.0552</td>
<td>0.1307</td>
<td>0.1557</td>
<td>-0.5735</td>
<td>1.625**</td>
<td>-0.1911</td>
<td>-0.1549</td>
<td>-0.1014</td>
<td>0.1463</td>
</tr>
<tr>
<td>Lnage</td>
<td>0.7804***</td>
<td>1.1116***</td>
<td>-0.3462***</td>
<td>-0.3197***</td>
<td>-0.5202**</td>
<td>-0.5131</td>
<td>-0.2399***</td>
<td>-0.2585***</td>
<td>0.2489***</td>
<td>0.2595***</td>
<td>-0.5516***</td>
<td>2.0924</td>
<td>-0.4658***</td>
<td>-0.5160***</td>
<td>0.0872</td>
<td>0.1651**</td>
</tr>
<tr>
<td>Lncpl</td>
<td>0.8907***</td>
<td>0.9025***</td>
<td>0.1106***</td>
<td>0.1339***</td>
<td>0.0718</td>
<td>0.0916</td>
<td>-0.0679</td>
<td>-0.1443***</td>
<td>-0.0184</td>
<td>-0.0293</td>
<td>0.3107***</td>
<td>0.1347</td>
<td>0.4233***</td>
<td>0.4840***</td>
<td>-0.0676</td>
<td>-0.0733</td>
</tr>
<tr>
<td>Poe</td>
<td>0.4197</td>
<td>0.4667</td>
<td>-0.2462**</td>
<td>-0.3879**</td>
<td>1.6220**</td>
<td>1.5451</td>
<td>0.2438***</td>
<td>0.2771***</td>
<td>-0.3394***</td>
<td>-0.3329***</td>
<td>1.6774***</td>
<td>1.7871***</td>
<td>1.0274***</td>
<td>1.1333***</td>
<td>0.0053</td>
<td>0.0903</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.4755***</td>
<td>-5.3175***</td>
<td>0.5315**</td>
<td>0.4922**</td>
<td>-0.6995*</td>
<td>0.7368**</td>
<td>1.2706***</td>
<td>1.6334***</td>
<td>-0.0639</td>
<td>-0.0237</td>
<td>-0.9396*</td>
<td>-5.7894</td>
<td>-0.0921</td>
<td>-0.3065</td>
<td>0.5294</td>
<td>0.5347</td>
</tr>
</tbody>
</table>

*significance at 10% level.
**significance at 5% level.
***significance at 1% level.
the technology innovation of listed enterprises by 0.0116%. Therefore, if those variables that affect enterprise technology innovation are not controlled, the effect of CET on enterprise technology innovation may be overestimated. In Model 4, Age has significant negative effect on the technology innovation of CET-covered enterprises, which is similar to the findings of Johnstone et al. (2017) and Atanassov (2013). For instance, Atanassov (2013) states that firm age is negatively related to innovation and younger firms tend to innovate more. Moreover, Poe has significant positive effect on the technology innovation of CET-covered enterprises, which may be because state-owned enterprises adopt different governance methods from other ownership enterprises (Rong et al., 2017), and it is easier for them to use administrative means to coordinate and allocate resources for improving their technology innovation level (Sun, Tong, & Tong, 2002).

5.2 The effect of CET on enterprise technology innovation in various industries

According to Equation (2), the effect of CET on enterprise technology innovation of various industries can be estimated, and the results are shown in Table 5. We can find that there is significant industrial heterogeneity in the effect of CET on enterprise technology innovation. Specifically, in the power and aviation industries, the key explanatory variables are significantly positive at the 5% level, but the coefficients are not significant in the steel, chemical, building materials, petrochemical, nonferrous metal, and paper industries. Some detailed findings are summarized as follows.

For one thing, CET significantly improves the technology innovation for the enterprises in the power industry. As shown in Table 5, in the power industry, regardless of the DID model or PSM-DID model employed, the key explanatory variable TP is significantly positive at the 5% level. This indicates that the result has certain robustness that the CET contributes to improving the technology innovation levels of enterprises in power industry. As we know, power industry is an industry with the largest carbon emissions in China (Wen, Di, Yu, & Zhang, 2017). According to China Electric Power Yearbook 2018, in 2017, the installed generating capacity reached 1,770 GW, of which 60% was thermal power. Their total carbon emissions exceed 3 billion tons, approximately one-third of China’s total carbon emissions in 2017. In addition, the total carbon emissions by power industry in China will continue to increase, due to the rapid urbanization and industrialization (Li, Huang, & Li, 2014). Whether in China’s CET pilot or in the national carbon market, power industry is always the first industry to be covered. Notably, for the first stage of China’s national carbon market, only the power industry is covered, involving 1,700 power enterprises. Meanwhile, Chinese government has also introduced a series of reform measures for this industry in recent years. As a result, power enterprises face grim situation of carbon emissions reduction, large-scale energy-saving renovations and environmental protection transformations, thus leading to special operational business pressure. To address the pressure, power enterprises tend to reduce abatement costs through carbon emission trading and technology upgrades. Therefore, the intrinsic motivation of technology innovation in power enterprises is stimulated, and they actively respond to carbon trading market and devote to their technology innovation, so as to rapidly transform and upgrade towards modern energy systems (Zhang, Wang, & Liu, 2016).

For another, CET significantly improves the technology innovation of aviation enterprises. As shown in Table 5, in the aviation industry, the key explanatory variable TP is significantly positive. After controlling the self-selection bias through PSM-DID, the effect coefficient of CET decreases, but it is still significantly positive at the 5% level. This result suggests that after initiating CET, China’s aviation enterprises have carried out tremendous technology innovative activities. According to the Carbon Trading Blue Book: China Carbon Trading Report (2017), although the proportion of CO2 emissions in the aviation industry is not high in China, its growth rate ranks the first in the eight major industries covered by the CET. In addition, compared with traditional energy-intensive manufacturing, the aviation industry has had relatively higher energy efficiency. Unless subversive technological breakthroughs occur (i.e., new aviation biofuels), it will be very hard to further reduce carbon emissions through traditional carbon emissions abatement means (i.e., improving aircraft engine efficiency and optimizing airport operation; Zhou, Wang, Yu, Chen, & Zhu, 2016). Meanwhile, in the carbon trading market, the aviation industry often plays the role of a net demander (Nava, Meleo, Cassetta, & Morelli, 2018), so if carbon prices increase, the abatement costs of aviation enterprises will increase, which may bring great challenges to the overall operation of the aviation industry. Finally, in October 2016, International Civil Aviation Organization issued two important documents, which established the implementation framework of the International Aviation Carbon Offsetting and Emission Reduction Scheme and formed the first global industry abatement market mechanism. Thus, more attention has been paid to environmental protection of the aviation industry across the world. To address these pressures, China’s aviation enterprises have actively participated in carbon trading market to curb abatement costs and strive for multi-channel innovation. As a result, the CET policy has significantly driven the technology innovative activities and levels of China’s aviation enterprises, so as to achieve clean technology breakthroughs and relatively lower operating costs in the aviation industry.

9


The announcement of “Several Opinions on Further Deepening the Reform of the Power System” launched a new round of power system reform.

http://www.caac.gov.cn/XWZX/MHYW/201610/t20161007_40012.html


TABLE 6 Estimated results after adding other control variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total</th>
<th>Steel</th>
<th>Power</th>
<th>Aviation</th>
<th>Chemical</th>
<th>Building</th>
<th>Petrochemical</th>
<th>Nonferrous</th>
<th>Paper</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>0.0091</td>
<td>−0.4160</td>
<td>0.3277**</td>
<td>0.3905**</td>
<td>−0.0760</td>
<td>0.1194</td>
<td>−0.5308</td>
<td>−0.3288</td>
<td>−0.2039</td>
</tr>
<tr>
<td>Roa</td>
<td>0.0088***</td>
<td>−0.0425**</td>
<td>−0.0026</td>
<td>0.0497**</td>
<td>0.0186***</td>
<td>0.0165**</td>
<td>−0.0010</td>
<td>0.0073</td>
<td>0.0297***</td>
</tr>
<tr>
<td>Lev</td>
<td>0.0004***</td>
<td>−0.0334***</td>
<td>0.0034**</td>
<td>0.0043</td>
<td>−0.0004</td>
<td>0.0003*</td>
<td>−0.0142**</td>
<td>0.0055*</td>
<td>−0.0051</td>
</tr>
<tr>
<td>Lnclp</td>
<td>−0.1362***</td>
<td>0.9531***</td>
<td>−0.3419***</td>
<td>−0.3736</td>
<td>−0.1990***</td>
<td>0.2567***</td>
<td>−0.4551***</td>
<td>−0.5164***</td>
<td>0.1779**</td>
</tr>
<tr>
<td>Tq</td>
<td>−0.0419***</td>
<td>0.0486</td>
<td>0.0679</td>
<td>−0.1873</td>
<td>−0.0364*</td>
<td>−0.0231</td>
<td>−0.1696***</td>
<td>−0.1208***</td>
<td>−0.0418</td>
</tr>
<tr>
<td>Lnage</td>
<td>−0.0379***</td>
<td>0.9267***</td>
<td>0.1181***</td>
<td>0.1174</td>
<td>−0.1062**</td>
<td>−0.0409</td>
<td>0.2060**</td>
<td>0.3220***</td>
<td>−0.0641</td>
</tr>
<tr>
<td>Poe</td>
<td>0.1386***</td>
<td>0.2941</td>
<td>−0.2425**</td>
<td>1.3092</td>
<td>0.2410***</td>
<td>−0.3566***</td>
<td>1.8202***</td>
<td>0.9798***</td>
<td>0.0670</td>
</tr>
<tr>
<td>Constant</td>
<td>0.9843***</td>
<td>−2.6439**</td>
<td>0.1926</td>
<td>−1.4791***</td>
<td>1.3959***</td>
<td>−0.0335</td>
<td>0.3111</td>
<td>0.2825</td>
<td>0.5756</td>
</tr>
<tr>
<td>Sector fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.360</td>
<td>0.3151</td>
<td>0.1646</td>
<td>0.2822</td>
<td>0.1015</td>
<td>0.1342</td>
<td>0.5628</td>
<td>0.2013</td>
<td>0.1019</td>
</tr>
<tr>
<td>Observation</td>
<td>3,413</td>
<td>253</td>
<td>559</td>
<td>93</td>
<td>1,239</td>
<td>512</td>
<td>106</td>
<td>447</td>
<td>203</td>
</tr>
</tbody>
</table>

*significance at 10% level.
**significance at 5% level.
***significance at 1% level.

5.3 Robustness tests

5.3.1 Impact of other control variables

Some important omitted variables may affect the technology innovation of CET-covered enterprises. For instance, the enterprises with higher market value may be more willing to increase their R&D investment, and when ignoring enterprise market value, the estimated results may be biased. Thus, this paper employs Tobin’s Q to control enterprise market value (Aghion, Reenen, & Zingales, 2013; Nishitani & Kokubu, 2012). In addition, the financial structure may also have a certain impact on enterprise technology innovation. If an enterprise has high leverage, it may face a large financial constraint. Therefore, they will not increase R&D investment. In this paper, we use leverage to control the financial structure of the enterprise (Atanassov, 2013; Bronzini & Piselli, 2016). Finally, to some extent, the profitability of enterprises may affect the innovation investment; thus, this paper uses the return on assets to control the profitability of enterprises (Acharya & Xu, 2017; Amore, Schneider, & Zaldokas, 2013; Choi, Lee, & Williams, 2011). The estimated results are shown in Table 6. We can find that after adding the control variables, the overall effect of CET on CET-covered enterprises is still not significant, and the coefficient is still positive. This result is basically consistent with those in Table 4.

Moreover, the key explanatory variable is significantly positive at the 5% level in the power and aviation industries, which is consistent with the results in Table 5. For the other six major industries, the coefficients and significance of the key explanatory variables are basically similar to those in Table 5. Therefore, all of these confirm that the CET significantly improves the technology innovation of power and aviation industries, but there is no significant effect on the overall technology innovation. Thus, the empirical results of this paper have evident reliability.

5.3.2 Impact of confounders

It is possible that some unobservable confounders may affect the technology innovation of CET-covered enterprises. To gain the pure effect of CET on the innovation of CET-covered enterprises and rule out the influence of other time-invariant unobservable confounders, the SGMM approach is employed. Referring to Arellano and Bond (1995) and Blundell and Bond (1998), this paper constructs a dynamic panel data model through adding the lag term of invention patents counts on the right side of Equation (2). Meanwhile, in order to test the validity of the lag term and avoid over-identification problems, this paper conducts the Arellano-Bond (AB) test and Hansen test. The results are shown in Table 7, and we can find that, first, the second-order autocorrelation for the residual of all models cannot reject the null hypothesis, which indicates that there is no second-order serial correlation. In addition, the P value of the Hansen statistic is insignificant at the 10% level, and the null hypothesis cannot be rejected. Thus, the choice of SGMM is appropriate.

In addition, as for the eight major industries covered by CET, the coefficient and significance of TP are consistent with the regression results in Table 4. From various industries, CET significantly improves the technology innovation of enterprises in the power and aviation industries, whereas the other six industries do not, which is basically the same as the results above. Put another way, the empirical results of this paper have evident robustness.

5.3.3 Impact of matching method

This paper employs PSM to handle the hidden treatment effect and reverse causal relationship, thereby achieving the purpose of...
controlling self-selection bias. However, different matching methods may lead to different estimation results. To further verify the robustness of research results, this paper uses a coarsened exact matching (CEM) method to control self-selection bias. In fact, CEM is a nonparametric method that can evaluate the policy effect by controlling the self-selection bias in observation data. The purpose of CEM is to balance the distribution of covariates between the treatment group and control group as much as possible, to enhance the comparability between them (Iacus, King, & Porro, 2012). Compared with the PSM, CEM has two main advantages (Iacus, King, & Porro, 2019). First, CEM matches pilot enterprises with nonpilot ones directly according to the empirical distribution of the original data. Second, CEM can retain the original samples to the maximum extent so as to reflect the real situation when evaluating the policy effect. Finally, CEM can reduce the dependence on models. For example, PSM needs to use the logistic model to estimate the propensity scores of enterprises covered by CET and then match them, whereas CEM matches relevant enterprises directly according to the theoretical distribution of each variable. Therefore, in this paper, we implement the CEM on the data first, and then use DID to estimate the impact that CET has on enterprise technology innovation. As shown in Table 8, the CEM-DID estimation results are basically consistent with that by PSM-DID. For the power and aviation industries, the key explanatory variables TP is significantly positive at the 5% and 10% levels, respectively, which indicates that CET significantly promotes the technology innovation of enterprises in the power and aviation industries. However, it is still not significant for the other six industries. Meanwhile, the effect of China's CET on the technology innovation of all the eight major industries is generally not significant. The results of Tables 8 and 4 are basically unchanged, which largely support the robustness of the estimation results in this paper.

6 | CONCLUSIONS AND POLICY IMPLICATIONS

Based on the panel data of China's energy-and-carbon-intensive listed enterprises in 2009–2017, this paper employs the DID and PSM-DID
models to evaluate the effect of China’s CET on the technology innovation of enterprises covered by CET. Meanwhile, we also explore the industrial heterogeneity of the effect of CET on enterprise technology innovation. In summary, the main conclusions are as follows.

On the one hand, although China’s CET has positive effect on the technology innovation of energy-and-carbon-intensive enterprises covered by the CET policy, the degree of improvement is still relatively weak. Specifically, CET increases the technology innovation of China’s CET-covered enterprises by approximately 0.0116% during the sample period.

On the other hand, the effect of CET on the technology innovation of CET-covered enterprises presents obvious industrial heterogeneity. Specifically, the implementation of China’s CET helps to improve the technology innovation of enterprises in the power and aviation industries by 0.35% and 0.48% during the sample period, respectively. However, the CET has no significant effect on the technology innovation of enterprises in the steel, chemical, building material, petrochemical, nonferrous metal, and paper industries.

Based on the conclusions above, we also draw some policy implications for improving China’s carbon trading market and its guiding role in enterprise technology innovation. First, Chinese government can guide CET-covered enterprises to implement innovative activities through subsidies and special funds. Technology innovation is a complex and long-term process, with abundant uncertainties, and government guidance will stimulate related enterprises to produce the “innovation compensation” effect (Dou & Han, 2019) and reduce uncertainties in the technology innovation process. Meanwhile, it will also force related enterprises to reduce carbon emissions through technology innovation. Moreover, because China’s CET pilot policy promotes aviation enterprises to carry out more innovative activities, Chinese government may consider incorporating the aviation industry into the national carbon trading market as soon as possible. In this way, it can further motivate the innovation potential of aviation enterprises and fully embrace the superiority of CET. Finally, China’s CET-covered enterprises need to actively participate in carbon trading market. According to the characteristics of the enterprises, they need to proactively adjust their R&D status and promote enterprise transformation innovatively to strengthen their competitiveness in the industry.

As for the research in the future, there is still much related work to continue. First, with the gradual improvement of enterprise data, studies can be conducted to assess the effect of CET on green technology innovation of enterprises. Second, it will be interesting to explore the effect of CET on enterprise abatement costs. Finally, it is also worth to deeply detect the effect of CET on the competitiveness of related enterprises.

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CONFLICT OF INTEREST

The authors have no potential sources of conflict of interest.

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