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Have China's pilot emissions trading schemes promoted carbon emission reductions?– the evidence from industrial sub-sectors at the provincial level

Haijun Zhang [a, b], Maosheng Duan [a, b, *], Zhe Deng [a, b]

[a] Institute of Energy, Environment and Economy, Tsinghua University. Beijing, 100084, China
[b] China Carbon Market Research Center, Tsinghua University. Beijing 100084, China

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ABSTRACT

Scholars and policy makers put great emphasis on analyzing the mitigation effect of an emissions trading scheme (ETS), while empirical researches on the mitigation effects of China's pilot ETSs are both thin and with significant limitations. This paper tries to analyze this issue from the perspective of industrial sub-sectors at the provincial level. We first calculate the carbon emissions of 37 individual industrial sub-sectors in each of China's 26 provinces from 2005 to 2015, covering both direct and indirect emissions. Cautiously identifying the industrial sub-sectors covered by China's pilot ETSs, we explore the causal impact of China's pilot ETSs on reducing carbon emissions at the initial stage (2013–2015) and analyze the paths of achieved emission reductions, applying a difference-in-difference (DID) model and a combination of DID estimator and propensity score matching technique. Our results yield robust evidence that China's pilot ETSs have significantly promoted carbon emission reductions of the covered industrial sub-sectors, and this impact has presented an overall enhanced trend according to year-by-year analysis. The results also show that the pilot ETSs have failed to enable covered industrial sub-sectors to effectively cut carbon intensity and the impact on carbon intensity is not obvious in any of the first three years, and the carbon emission reductions have mainly been achieved through the decreased outputs of industrial sub-sectors. China's policy makers should tighten the free allowance allocation approaches in order to facilitate low-carbon technology innovations and reduce carbon intensity of industrial sectors.

1. Introduction

Global climate change, which is caused by excessive anthropogenic greenhouse gas (GHG) emissions, has become a major environmental threat facing humanity. Aiming at curbing GHG emissions and facilitating a transition to low-carbon economy, emissions trading scheme (ETS) has found increasingly wider attention and application globally (ICAP, 2018; Wang et al., 2018a,b). By setting an emissions cap, an ETS encourages cleaner production of enterprises and facilitates emission reductions in a cost-effective way (Wang and Wang, 2015; Singh and Weninger, 2017). A thorough understanding of the emission reduction effect of an ETS serves as the premise for improving the system design.

China has become the world's largest GHG emitter and one of the priority spots for global emission mitigation (Wu, 2010; Liu et al., 2016a; Mi et al., 2017). In 2011, China announced to start its pilot ETSs in two provinces, i.e. Hubei and Guangdong, and five municipalities, i.e. Beijing, Shanghai, Tianjin, Chongqing and Shenzhen. Whether the pilot systems have promoted carbon emission reductions has been of great interest to policy makers and scholars. By definition, a cap-and-trade system will produce emission reductions as long as the cap is set tight enough and regulated emitters are not in gross violation of the scheme (Martin et al., 2016). But even in the case of decreasing emissions cap, the observed decline in emissions cannot be automatically attributed to the ETS, because there could be many other policies or context factors that can promote emission reductions, e.g. mandatory energy efficiency improvement policy. This is especially true for China

* Corresponding author. Institute of Energy, Environment and Economy, Tsinghua University. Beijing, 100084, China.
E-mail address: duanmsh@mail.tsinghua.edu.cn (M. Duan).

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where many policies that may have carbon mitigation impacts are implemented in parallel (Nam et al., 2014; Duan et al., 2017; Yi et al., 2019). Furthermore, the emission caps adopted by the pilot systems are de facto flexible ones rather than absolute ones as in the European Union (EU) ETS, i.e. the caps are mainly determined by allocation approaches which for many covered sectors are not historical production-based but real-production-based (Zhang, 2015; Lo, 2016; Qi and Cheng, 2018). In this context, a thorough understanding of the contribution of China's pilot ETSs on emission reductions is not only urgently needed from a theoretical point of view but also crucial for informed decision-making by the ETS authorities.

An increasing number of literatures have been paying attention to the contributions of China's pilot ETSs to mitigating carbon emissions. A majority of them conduct ex ante quantitative analysis mainly adopting computable general equilibrium (CGE) models (Hübler et al., 2014; Tang et al., 2016; Fan et al., 2016; Mu et al., 2018; Li et al., 2018; Lin and Jia, 2018), or conduct theoretical analysis on the mitigation potential of the mechanism design (Jiang et al., 2014b; Qi et al., 2014; Wu et al., 2014). Some ex post studies have conducted comparative analysis of the changes in carbon emissions and/or carbon intensity in pilot areas/covered industries between different years to discuss the emission reduction effects of China's pilot ETSs (Guan et al., 2016; China Beijing Environment Exchange, 2017; Guangdong Research Center on Climate Change, 2016; Shenzhen Carbon Emissions Exchange, 2015). For example, Guan et al. (2016) explore the impact of emission trading on carbon emissions and carbon intensity by discussing the trends of them in pilot regions from 1997 to 2012. The annual "Carbon Market Operation Report" of Beijing (China Beijing Environment Exchange, 2017) claims that over the past years from 2013 to 2015, the total carbon emissions of key emitters in Beijing decreased by about 4.5%, 5.96% and 6.17%, and the carbon emissions per 10,000 yuan of GDP decreased by 6.69%, 7.17% and 9.3% compared to the year before, respectively. However, these analyses do not rule out the influence of other policies and context factors, and do not support an attribution analysis.

There are some studies evaluating the causal impact of ETS on reducing carbon emissions using panel data, but most of them focus on the EU ETS (Abrell et al., 2011; Jaraitė and Di Maria, 2014; Petrick and Wagner, 2014; Wagner et al., 2014; Bel and Joseph, 2015; Klemetsen and Einar, 2016). These studies mainly use enterprise-level data to quantitatively analyze the impact of EU ETS on carbon emissions or carbon intensity, taking into account other factors such as firm characteristics, economic conditions, etc., and the methods adopted include difference-in-difference (DID) models, a combination of DID estimators and propensity score matching technique (PSM-DID) and dynamic panel data models, etc.. However, only a very limited number of such studies focus on the causal analysis of the mitigation impact of China's pilot ETSs, probably owing to the recency of the policy and a lack of suitable emissions data. Given that this is the specific focus of this paper, only studies dealing with this issue are discussed in detail below.

Shen et al. (2017) use the enterprise-level panel data of listed firms and adopt a DID model to analyze the impact of China's pilot ETSs on the carbon emissions of regulated firms. However, the study uses the firm's charges for disposing pollutants as a proxy to measure their carbon emissions, which may result in estimation bias. Due to the non-availability of carbon emissions data at the enterprise-level in China's pilots, some studies turn to provincial-level panel data to conduct the research (Zhang et al., 2017; Huang et al., 2018; Dong et al., 2019). These studies take the pilot provinces as the treatment group and calculate the carbon emissions of each province based on fossil fuel consumptions, then use panel data of China's provinces and apply DID or PSM-DID estimations, they find that China's pilot ETSs have reduced carbon emissions in the pilot provinces. For example, Zhang et al. (2017) use panel data of China's 30 provinces during 2000–2013 to analyze the effect of China's initial pilots on carbon emission reductions in 2012–2013 by applying PSM-DID method. However, since the pilots cover a limited number of sectors in the pilot regions, e.g. Guangdong pilot covers four industrial sectors during 2013–2015 etc., the use of provincial data as a whole may lead to the issue of overestimation of coverage. China's carbon emissions mainly come from industrial production (Yang et al., 2017; Zhao et al., 2017b), and industrial sectors are the main control targets of the pilots, hence some studies use panel data of provincial industries to conduct the research. Fan et al. (2017) calculate the fossil-fuel-based carbon emissions of China's 30 provincial industries during 2010–2014 and apply PSM-DID to estimate the policy effect. Further, Zhang et al. (2019) also use panel data of provincial industries from 2006 to 2015 and assess the impact of pilot ETSs on carbon emissions and carbon intensity based on DID estimations. They find that the pilot ETSs decreased both carbon emissions and carbon intensity of the industries in pilot provinces. However, these studies still regard the provincial industry as a whole, and do not identify the actual covered industrial sectors for each pilot. Moreover, covering both direct and indirect carbon emissions[1] is an important feature that distinguishes China's pilots from other schemes, it is therefore essential to include indirect emissions when considering total emissions, while the aforementioned studies do not.

Different from previous studies, this paper contributes to the existing literatures from three aspects. Firstly, our analysis is done from the perspective of the industrial sub-sectors at the provincial level. Specifically, we split the industrial sector of each province into 37 sub-sectors according to *the Industrial Classification for National Economic Activities*, and figure out the specific covered industrial sub-sectors of the pilot ETSs, which are regarded as the treatment group. Such research design not only maps the actual coverage of the pilots, but also greatly expands the sample size of the analytical data set. Secondly, we calculate the carbon emissions of 37 industrial sub-sectors in each of China's 26 provinces over 2005–2015. Unlike previous studies which have considered only direct carbon emissions, this paper also includes indirect emissions and thus has corrected the miscalculation of total carbon emissions of relevant sub-sectors. And with additional sectoral economic indicators such as the gross output value, employment, etc., we construct a comprehensive data set containing multiple information of every single industrial sub-sector. Thirdly, we apply both DID and the cutting-edge PSM-DID (based on various matching algorithms) methods to estimate the results, which may yield more robust estimations in the case of large sample data set. Under such research settings, we analyze the mitigation effect of China's pilot ETSs on carbon emissions and carbon intensity, and identify the paths of achieved emission reductions by covered industrial sub-sectors, namely, by reducing production and/or by cutting carbon intensity.

The rest of this paper is structured as follows. Section 2 describes the research design and the methodology applied. Section 3 introduces the calculation of the carbon emissions and carbon intensity used in this paper, and describes the control variables. Section 4 shows the empirical results, discussions and robustness check of underlying assumptions. Section 5 concludes the article and provides policy implications.

[1] Indirect carbon emissions refer to carbon emissions caused by the use of purchased electricity and heat.

2. Research design and methodology

2.1. Research design

China's seven pilots are geographically located in different parts of the country and have different scheme designs due to their respective economic aggregates and carbon emissions (Qi et al., 2014; Zhang et al., 2014). But they share some same design principles, one of which is "seizing large enterprises and releasing small and medium ones". Therefore, mainly large-scale emission sources with robust data basis and large mitigation potentials are covered, which are generally from a limited number of key emitting sub-sectors (Jiang et al., 2014a; Liu et al., 2015a; Wang et al., 2018b). From the perspective of industrial sub-sectors, China's pilot ETSs can be regarded as a "quasi experiment". In this sense, we take industrial sub-sectors covered by pilots as the treatment group, uncovered industrial sub-sectors in pilot regions and non-pilot regions as the control group, and define year 2013–2015 as the treatment period,[2] then we can analyze the causal impact of China's pilot ETSs by comparing the changes in carbon emissions of the treatment and control groups before and after the policy intervention.

2.2. Methodology

2.2.1. Difference-in-difference model

We first apply the DID models, an effective tool to correct the heterogeneity bias caused by some unobservable factors, to quantitatively assess the resulting impact by comparing the changes between the treatment and control groups before and after the intervention of certain policies. For each dependent variable, we estimate 4 regressions by gradually adding individual fixed effects, province-year fixed effects and time varying control variables. The complete DID model is as follows,

$$logY_{it} = \beta_0 + \beta_1 G_i + \delta ETS_{it} + x_{it}\beta + u_i + d_{pt} + \varepsilon_{it} \quad (1)$$

Where, Y_{it} is the dependent variable for a given industrial sub-sector i in year t. We specify our model in logarithmic form to focus on the relative change. G_i is the group dummy, if $i \in$ treatment group, $G_i = 1$; otherwise, $G_i = 0$. ETS_{it} is the treatment dummy, if $i \in$ treatment group, and $t \in$ treatment period (2013–2015), then $ETS_{it} = 1$; otherwise $ETS_{it} = 0$. Plus, u_i represents the individual fixed effect of each sub-sector, d_{pt} represents the province-year fixed effect such as macroeconomic conditions, $x_{it.}$ is the observed time-varying covariates which can provide more explanatory information, ε_{it} is the idiosyncratic error term. The estimate $\hat{\delta}$, coefficient of ETS_{it}, is the DID estimator we are interested in, which is the Average Treatment effect on the Treated (ATT), indicating the degree that the covered industrial sub-sectors are motivated by the pilots to reduce carbon emissions or carbon intensity relative to uncovered ones.

2.2.2. Propensity score matching and difference-in-difference

When conducting causal analysis with the DID method, note that there are significant differences in the characteristics of the treatment and control groups. Non-overlapping bias and the density weighting bias could result if such differences are correlated to the dynamics of the dependent variables (Heckman et al., 1998; Abadie, 2005). Therefore, we combine propensity score matching technique and DID estimators to overcome this problem, which can yield more robust results. The generalized DID matching estimator used in this study follows Heckman et al. (1997, 1998) as below,

$$\widehat{ATT} = \frac{1}{N_1} \sum_{i,\ i \in I_1 \cap S_p} \left[(y_{1t'i} - y_{0ti}) - \sum_{j,\ j \in I_2 \cap S_p} w(i,j) \left(y_{0t'j} - y_{0tj} \right) \right] \quad (2)$$

Where, the post-treatment period is t', the pre-treatment period is t; I_1 is the set of the treatment group, I_2 is the set of the control group, S_p is the set on the common support; N_1 is the number of treatment group individuals contained in set $I_1 \cap S_p$, $w(i,j)$ is the weight corresponding to the pair *(i, j)*. In this paper, various matching algorithms are adopted to determine the weight, including one-to-four nearest neighbor matching, radius matching and kernel matching, aiming at providing robust results regardless of matching algorithms.

The matching process is performed at period t, that is, the baseline year before the ETS started. Under such matching process, it is natural to estimate the results when the treatment and control groups have same time span, therefore, we use PSM-DID to conduct the year-by-year analysis (DID estimations are also provided for references). China announced to set up pilot ETSs in October 2011, and they were launched and began official transactions successively since 2013. Since choosing 2012 as the pre-treatment baseline year may give rise to an announcement effect[3] (Wagner et al., 2014), 2011 is made the baseline year in this study.

When conducting the matching, we first refer to Fowlie et al. (2012) and Wagner et al. (2014), and choose the pre-treatment dependent variables as well as the sector attributes for matching, hereafter referred as baseline specifications. What's more, we match on pre-treatment gross outputs and its square term, pre-treatment gross outputs per capita and its square term, ratio of fixed assets, profitability and sector attributes as alternative specifications, where logit regressions are used to calculate the propensity score. For the propensity score matching model and the test of covariate balancing, please refer to Appendix B. Since the alternative specification has better covariate balancing, it is our preferred specification.

3. Data

According to our research design, we first split the industry of each province into industrial sub-sectors over 2005–2015 according to *the Industrial Classification for National Economic Activities*, and figure out the specific covered industrial sub-sectors of the pilot ETSs from 2013 to 2015 through a thorough literature review and expert interviews (as listed in Appendix A). The industrial classification for national economic activities underwent an adjustment in 2011 (from GB/T4754-2002 to GB/T4754-2011). In order to maintain consistency among industry classification for the entire period, we merge several sub-sectors and thus each province presents 40 industrial sub-sectors.[4] In addition, we drop 3

[2] The compliance of Chongqing pilot for 2013 and 2014 are conducted together, hence the scheme is viewed to start in 2013. Although Hubei pilot started in 2014, all preparations had been initiated with the launch of other pilots in 2013, and the impact of Hubei pilot are considered to start in 2013 either in this study.

[3] Enterprises may take emissions reduction measures before the schemes are officially started.

[4] Namely, we merge "Manufacture of Rubber" and "Manufacture of Plastic" into "Manufacture of Rubber and Plastic", "Manufacture of Automobile" and "Manufacture of Railroads, Ships, Aerospace and Other Transport Equipment" into "Manufacture of Automobile, Railroads, Ships, Aerospace and Other Transport Equipment".

industrial sub-sectors where most of the observations were zero.[5]

3.1. Carbon emissions

Carbon emissions consist of direct and indirect emissions. We calculate the direct carbon emissions of every industrial sub-sector in each province from 2005 to 2015, following the methods provided by the Inter-governmental Panel on Climate Change (IPCC) and *the Guidelines for the Preparation of Provincial GHG Emission Inventories* issued by the National Development and Reform Commission (NDRC) of China,

$$DCE_i^{nt} = \sum_j ENC_{ij}^{nt} * NCV_j * O_j * \frac{44}{12} \tag{3}$$

Where n denotes provinces, t denotes years, i represents industrial sub-sectors and j represents fuels. DCE_i^{nt} is the direct carbon emissions, ENC_{ij}^{nt} refers to the corresponding energy consumptions of the jth fuels,[6] NCV_j represents the net caloric value, O_j denote oxygenation efficiency, 44/12 is molecular weight ratio of CO_2 to C. NCV_j and O_j are figures provided by NDRC, whose values fit China's reality more, and some of the missing values refer to literatures such as Shan et al.(2018). The annual data of ENC_{ij}^{nt} is obtained from provincial statistical yearbooks. For sub-sectors that do not provide detailed fuel categories, this paper refers to the method of Shan et al. (2018) by dividing the gross industrial carbon emissions, obtained from provincial energy balanced sheets, according to their sectoral energy consumptions. In this paper, the process emissions of certain sub-sectors are not considered.

Second, indirect carbon emissions are covered in all pilots, which is a major feature that distinguishes China's pilots from other schemes and serves as a compromise in the current situation where China's electricity prices are regulated,

$$ICE_i^{nt} = ELC_i^{nt} * ELF^{nt} \tag{4}$$

Where, ICE_i^{nt} is the indirect carbon emissions of industrial sub-sector i in province n in year t; ELC_i^{nt} refers to the corresponding electricity consumptions obtained from provincial yearbooks; ELF^{nt} refers to the electricity emission factors obtained from the annual *China Regional Grid Baseline Emission Factor* issued by NDRC.

Third, add up direct and indirect carbon emissions and we obtain the total carbon emissions,

$$CE_i^{nt} = DCE_i^{nt} + ICE_i^{nt} \tag{5}$$

Attention should be given to the fact that electricity consumptions of the power sector is basically self-produced. Its indirect emissions have actually been included in direct emissions. Therefore, the indirect emissions for power sector are excluded.

In practice, detailed sector energy consumptions are not provided in the yearbooks of Shanghai, Zhejiang, Jiangsu, Sichuan, and Tibet, hence Shanghai pilot is not included in this study. In addition, the Shenzhen pilot is not at the provincial level, but is within Guangdong Province, thus it is excluded in this analysis either. Finally, we obtain 7657 non-zero province-industry-year observations upon data availability.

[5] Namely, we drop "Mining Assistant Activities", "Mining of Other Ores" and "Metal Products, Machinery and Equipment Repair".

[6] Energy consumptions include 16 kinds of fuels, including raw coal, clean coal, other coal washing, coke, other coking products, crude oil, gasoline, kerosene, diesel oil, fuel oil, other petroleum products, liquid petroleum gas, refinery dry gas, natural gas, liquid natural gas and coke oven gas and other gas.

3.2. Carbon intensity

Carbon intensity is captured by carbon emissions per unit output of a specific industrial sub-sector, ie,

$$CI_i^{nt} = CE_i^{nt} / GO_i^{nt} \tag{6}$$

Where, CI_i^{nt} refers to the carbon intensity of industrial sub-sector i in province n in year t; GO_i^{nt} refers to the gross outputs collected from provincial statistical yearbooks, which are converted into the 2004 constant price by using index of the Producer Price Index of industrial producers provided by the *China's Price Statistics Yearbook*.

3.3. Control variables

According to relevant literatures and the needs of our analysis, the following control variables are chosen in this paper. First, we include economic indicators in our regressions, and the ideal indicator is the sectoral gross value added (GVA) or GVA per capita along with its square-term. However, to the best of our knowledge these indicators are not longitudinally available for China's provincial industrial sub-sectors. Instead, we choose the gross outputs and gross outputs per capita of a sub-sector to reflect its macroeconomic conditions, similar to some existing literatures (Shao et al., 2011; Yang and Li, 2015; Duan et al., 2016). Second, some studies suggest that whether a company is state-owned may have an impact on its innovation and management (Jefferson et al., 2006; Liu and Cheng, 2014; Zhou et al., 2017), which may affect the dependent variables in this study. Therefore, the ratio of state-owned assets in a sub-sector is controlled. In addition, some believe that whether a company's assets have sufficient liquidity is an important criterion for determining its effectiveness in R&D activities (Liu and Wang, 2017; Qiu and Wei, 2016). Thus, the ratio of fixed assets of a sub-sector is included as well. Finally, the profitability of a company is likely to be a factor influencing corporate technological innovation and mitigation strategies, so we also control the profitability of a sub-sector (Jaraitė and Di Maria, 2014).

All the data come from the statistical yearbooks for each province of China, *China Energy Statistical Yearbook* and *China Labour Statistical Yearbook*, and we obtain a panel data of industrial sub-sectors at the provincial level over 2005–2015 which is deflated to 2004 constant price. To guard against outliers, we cut off the observations beyond 2 times the interquartile range with respect to the first and third quartile by sector. Table 1 shows the summary statistics and detailed calculations of the key variables.

4. Results and discussions

4.1. The overall impacts of China's pilot ETSs

4.1.1. The overall impact on carbon emissions

This section presents the DID estimators based on multi-period panel data (2005–2015) focusing on the causal impact of China's pilot ETSs on carbon emissions. Table 2 shows the results of four regressions where the dependent variable is the amount of carbon emissions (in log). The first specification does not control any fixed effects, while the second includes individual fixed effects and the third includes both individual fixed effects and province-year specific time trends. The fourth specification further adds control variables to capture the influence of other factors on outcome variables. The first specification suggests that the pilots had a non-significant negative impact on carbon emissions of the covered sub-sectors. However, the results of the second and third specifications

Table 1
Descriptive statistics.

Variables	Treatment group		Control group		Calculation method
	Mean	N	Mean	N	
Carbon emissions (CE)/tons	8.87E+06 (1.51E+07)	650	5.60E+06 (1.45E+07)	7207	Section 3.1
Carbon Intensity (CI)/(t/¥10,000)	1.54 (1.90)	650	2.81 (8.72)	7207	Section 3.2
Gross outputs (GO)/¥10,000	6.21E+06 (9.21E+06)	650	2.99E+06 (6.25E+06)	7207	Gross outputs of a sector
Gross outputs per capita (GOP)/¥ per capita	1.02E+06 (9.88E+05)	650	6.40E+05 (7.28E+05)	7201	Gross outputs/employment
State-owned assets ratio (SAR)	0.53 (0.30)	623	0.42 (0.33)	4628	State-owned assets/total assets
Fixed assets ratio (FAR)	0.34 (0.17)	630	0.37 (0.15)	5335	Fixed assets/total assets
Profitability (PROF)	0.07 (0.08)	650	0.07 (0.09)	6889	Profits/operating income

Table 2
The overall impact of China's pilot ETSs on carbon emissions.

	(1)	(2)	(3)	(4)
ETS	−0.0293	−0.281***	−0.360***	−0.179***
	(0.195)	(0.0376)	(0.0538)	(0.0437)
G	1.087***	−0.961***	−0.353	−2.250***
	(0.102)	(0.0971)	(0.233)	(0.300)
lnGO				0.296
				(0.187)
$[\ln GO]^2$				0.00717
				(0.00655)
SAR				0.0644
				(0.0713)
FAR				0.0938
				(0.141)
PROF				−0.698***
				(0.180)
Individual fixed effects	No	Yes	Yes	Yes
Province-by-year fixed effects	No	No	Yes	Yes
Observations	7857	7857	7857	4578
Adjusted R^2	0.015	0.938	0.942	0.956

Note: Standard errors are clustered at the individual units and t statistics are shown in the respective parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3
The overall impact of China's pilot ETSs on carbon intensity.

	(1)	(2)	(3)	(4)
ETS	0.259**	0.174***	−0.0586	−0.0375
	(0.118)	(0.0363)	(0.0532)	(0.0427)
G	−0.235***	−3.907***	−3.931***	−2.751***
	(0.0634)	(0.146)	(0.232)	(0.201)
lnGOP				0.699***
				(0.203)
$[\ln GOP]^2$				−0.0485***
				(0.00777)
SAR				0.0994
				(0.0724)
FAR				0.0810
				(0.138)
PROF				−0.641***
				(0.173)
Individual fixed effects	No	Yes	Yes	Yes
Province-by-year fixed effects	No	No	Yes	Yes
Observations	7854	7854	7854	4577
Adjusted R^2	0.074	0.841	0.853	0.907

Note: Standard errors are clustered at the individual units and t statistics are shown in the respective parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

indicate that pilots had a statistically significant negative impact on the carbon emissions. As to the fourth specification, which is our preferred one, the parameter estimate suggests that China's pilot ETSs reduced the carbon emissions of the ETS-covered sub-sectors, which is statistically significant as well.

The coefficient of ETS in specification (4) is considerably smaller than that of specification (3), indicating that control variables may exert an impact on sectoral carbon emissions. Specification (4) shows that a sub-sector's carbon emissions increase as the gross outputs increase, but the emissions do not show a tendency to decrease as expected when the gross outputs reach a certain level. Moreover, the coefficient of profitability indicates that enhanced profitability of the sub-sectors motivates their technological innovation and thus facilitates the reduction of emissions. In addition, the estimates of state assets ratio and fixed assets ratio are not statistically significant from zero.

4.1.2. The overall impact on carbon intensity

In addition to facilitating carbon emission reductions, another role of the pilot ETSs is to promote technological innovations of enterprises and reduce their carbon intensity. Table 3 shows parameter estimates and robust standard errors for the regressions where the dependent variable is carbon intensity (in log). This section also contains four regressions, the controlled fixed effects and control variables of each regression are set in a manner similar to that in Section 4.1.1. The first two specifications suggest the pilots had a strong and positive impact on carbon intensity. But once controlling for individual fixed effects and province-year fixed effects, which are our preferred specifications, the third and fourth specifications consistently show that pilot ETSs did not have a statistical significant impact on the carbon intensity of covered industrial sub-sectors.

Regarding the control variables, different from the results on carbon emissions, the gross outputs per capita and its square term show that as the gross outputs per capita rise, carbon intensity increases; but when the former reaches a certain level, the latter decreases. While the profitability of a sector has a significant negative impact on its carbon intensity. Still, the ratio of fixed assets and the ratio of state-owned assets are both statistically insignificant.

4.2. The impact of China's pilot ETSs on a yearly basis

4.2.1. The impact on carbon emissions on a yearly basis

As mentioned in Section 2.2.2, in order to reduce the systematic differences in the characteristics between the treatment and control groups and avoid the endogeneity problems caused by missing variables, we apply PSM-DID estimation with multiple matching algorithms to provide more robust estimations, meanwhile DID estimates are first provided for reference.

The DID estimates are shown in Table 4, where specifications (1)–(2), (3)–(4), (5)–(6) show the estimated effects of 2013, 2014 and 2015, respectively. For specifications (1) (3) (5) with individual fixed effects and province-year fixed effects, the results show that the policy impact increased from 2013 to 2015. As to our preferred specifications (2) (4) (6) where time-varying control variables are further controlled, the estimates show that in 2013 the pilots promoted emission reductions, and in 2014, the result shows similar case, but it becomes no longer statistically significant. Nonetheless, the results of 2013 and 2014 are not much different in magnitude, and both of them are significantly lower than that of 2015, indicating the impact on carbon emissions grew with its implementation.

A further examination based on PSM-DID is presented in Table 5, where Columns (1) to (3) show the PSM-DID estimators whose matching algorithms are nearest neighbor matching (1:4), radius matching and kernel matching, respectively. In the baseline specifications which match on pre-treatment carbon emissions and sectors, the results show that compared to uncovered ones, ETS-covered industrial sub-sectors significantly promoted their emission reductions in each of the years from 2013 to 2015, and with the deepening of policy implementation, the policy impact presented an increasing trend, though the results based on nearest neighbor matching are not statistically significant in 2013 and 2014. As to our preferred alternative specifications with better covariate balancing, the estimated results are somewhat different. In 2013 and 2014, the estimates obtained from multiple matching algorithms are smaller than those in the baseline specifications, and more importantly, they are no longer statistically significant, which may suggest that the pilots do not cause the covered sub-sectors to mitigate emissions in the two years. This is in line with the general understanding of China's pilot ETSs. ETS is a new policy attempt in China which requires considerable preparation and demonstration, but the pilots have been launched quite in a rush in order to meet the deployment of the competent authorities. Not surprisingly, most of them lack solid legal foundation and the enterprises are not familiar enough with the concepts and operation of the system (Xiong et al., 2017; Zhao et al., 2017a). When it comes to the carbon market, the low transparency in the price formation and low liquidity in transaction cast doubts on the efficiency and effectiveness of the schemes (Munnings et al., 2016; Xian et al., 2019). Therefore, it is understandable if pilot ETSs did not achieve the desired effects at the initial stage. Even so, the estimates for 2015 are still very robust in the alternative specifications – the magnitude exceeds those of the previous two years and the results are statistically significant, which also shows that the emission reduction effects of the pilot ETSs would become increasingly obvious with the improvement of policy implementation.

4.2.2. *The impact on carbon intensity on a yearly basis*

In this section, examination will be extended to each individual year to determine the impact of pilot ETSs on carbon intensity. In line with the research design in Section 4.2.1, both DID and PSM-DID estimates are provided.

The DID estimate are shown in Table 6. Similarly, specifications (1)–(2), (3)–(4), (5)–(6) give the estimates of the impact of pilots on carbon intensity in 2013, 2014 and 2015, respectively. In specifications (1) (3) (5), the results indicate that the pilots might improve the carbon intensity of covered sub-sectors. But apparently, as to our preferred specifications (2) (4) (6), which control for multiple fixed effects and time-varying control variables, the DID estimators show consistently that the pilot ETSs did not exert a significant impact on carbon intensity of the covered industrial sub-sectors in any of the given years.

When it comes to the PSM-DID estimators, the results are completely similar to those of DID estimations, all of which are of small magnitude and low significance, both in the baseline specifications and the alternative specifications (see Table 7). In summary, all estimates consistently show that in any year of the ETS implementation, carbon intensity of the covered industrial sub-sectors was not influenced by the pilot ETSs.

4.3. *Discussions*

To summarize, in line with previous analyses of the emission reduction effects of China's pilot ETSs, this study also shows that the pilots reduced the carbon emissions of the covered industrial sub-sectors. Meanwhile, based on year-by-year examination we further find that the impact of China's pilot ETSs on carbon emissions might be unstable in the first two years, but it presented an improved trend as the policy was further implemented. However, different from the findings of Zhang et al. (2019) that the pilot ETSs led to a decreased industrial carbon intensity of the pilot provinces, our estimates show that the pilot ETSs exerted merely no impact on the carbon intensity of the covered industrial sub-sectors, and this is the case in every year during the initial period of the pilots. The difference between our studies may be that we study the issue from the perspective of industrial sub-sectors at the provincial level while they from the perspective of provincial industries, therefore our analysis further controls the characteristics of the sub-sectors. Also, we identify the actual industrial sub-sector coverage of the pilot ETSs while they do not, and the uncovered sub-sectors may

Table 4
The impact of China's pilot ETSs on carbon emissions on a yearly basis (DID).

	2013		2014		2015	
	(1)	(2)	(3)	(4)	(5)	(6)
ETS	−0.266***	−0.150**	−0.323***	−0.118	−0.441***	−0.190**
	(0.0729)	(0.0626)	(0.0927)	(0.0851)	(0.103)	(0.0924)
Controls	No	Yes	No	Yes	No	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1440	915	1436	937	1442	949
Adjusted R^2	0.960	0.970	0.951	0.959	0.944	0.960

Note: Applying two-way fixed effects models. Standard errors are clustered at the individual units and t statistics are shown in the respective parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5
The impact of China's pilot ETSs on carbon emissions on a yearly basis (PSM-DID).

	(1)	(2)	(3)	(4)	(5)
	Estimation algorithm			Observations	
	NN(1:4)	Radius	Kernel	Treatment group	Control group
2013	−0.080	−0.115*	−0.124**	56	588
(baseline specification)	(0.075)	(0.063)	(0.059)		
2013	−0.085	−0.075	−0.075	56	491
(alternative specification)	(0.073)	(0.072)	(0.064)		
2014	−0.082	−0.149*	−0.170**	56	583
(baseline specification)	(0.101)	(0.078)	(0.074)		
2014	−0.136	−0.050	−0.127	56	486
(alternative specification)	(0.095)	(0.082)	(0.082)		
2015	−0.218**	−0.211**	−0.245***	56	585
(baseline specification)	(0.088)	(0.082)	(0.078)		
2015	−0.223**	−0.182**	−0.247***	56	489
(alternative specification)	(0.099)	(0.085)	(0.087)		

Note: Standard errors are clustered at the individual level and t statistics are shown in the respective parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6
The impact of China's pilot ETSs on carbon intensity on a yearly basis (DID).

	2013		2014		2015	
	(1)	(2)	(3)	(4)	(5)	(6)
ETS	−0.134*	−0.0687	−0.133	−0.0460	−0.185*	−0.140
	(0.0684)	(0.0621)	(0.0827)	(0.0805)	(0.0961)	(0.0919)
Controls	No	Yes	No	Yes	No	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1440	915	1436	937	1442	948
Adjusted R^2	0.906	0.930	0.864	0.913	0.862	0.922

Note: Applying two-way fixed effects models. Standard errors are clustered at the individual units and t statistics are shown in the respective parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 7
The impact of China's pilot ETSs on carbon intensity on a yearly basis (PSM-DID).

	(1)	(2)	(3)	(4)	(5)
	Estimation algorithm			Observations	
	NN(1:4)	Radius	Kernel	Treatment group	Control group
2013	−0.027	0.010	−0.029	56	588
(baseline specification)	(0.084)	(0.086)	(0.080)		
2013	0.039	0.100	0.056	56	491
(alternative specification)	(0.098)	(0.093)	(0.085)		
2014	−0.027	0.010	−0.029	56	583
(baseline specification)	(0.084)	(0.086)	(0.080)		
2014	0.039	0.100	0.056	56	486
(alternative specification)	(0.098)	(0.093)	(0.085)		
2015	−0.024	0.023	−0.051	56	585
(baseline specification)	(0.092)	(0.090)	(0.084)		
2015	−0.021	0.075	0.023	51	489
(alternative specification)	(0.101)	(0.091)	(0.084)		

Note: Standard errors are clustered at the individual units and t statistics are shown in the respective parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

exert an impact on the analysis results considering that the overall tendency of carbon intensity in China's all industries is declining (Liu et al., 2015b; Yang et al., 2017).

In combination of the results from Section 4.1 and 4.2, it can be concluded that the emission reductions achieved by covered industrial sub-sectors are not achieved through the reduction of carbon intensity, but very likely through production capacity reduction. This is not what we wish for, since we would prefer the pilots to boost the low-carbon development of industries through reducing carbon intensity. Therefore, policy makers should continue to tighten the free allowance allocation methods and reduce the supply of allowances to stabilize the market carbon price and function the price discovery ability of the carbon markets (Zhang et al., 2015; Liu and Wang, 2017; Wang et al., 2018a), thus

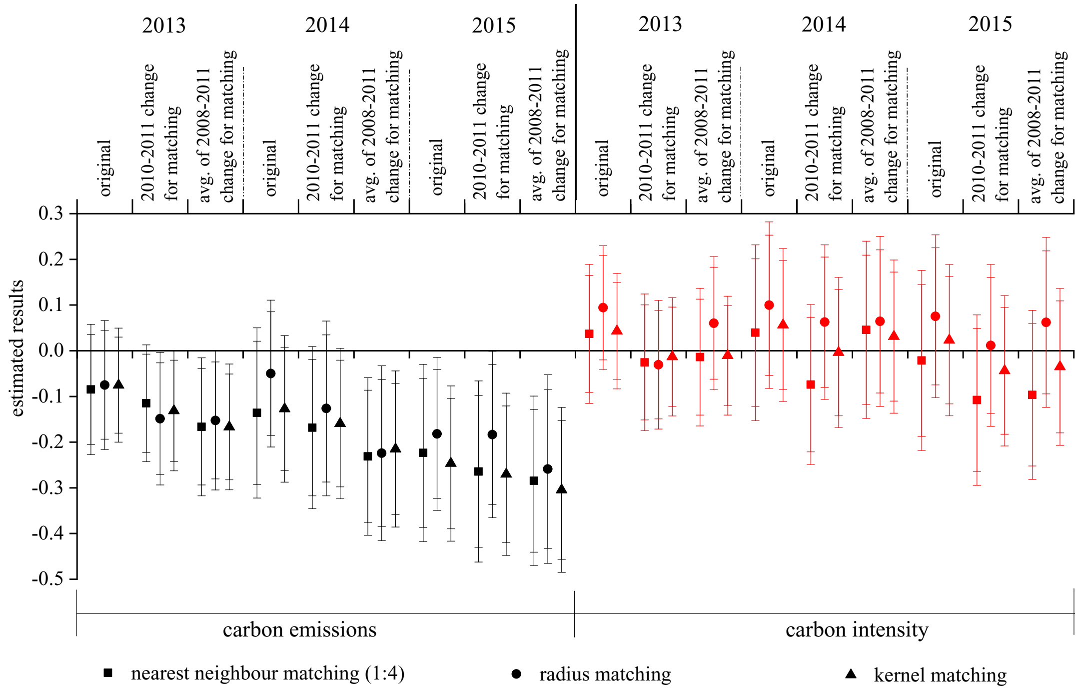

Fig. 1. Comparison of estimates when matching on levels and pre-treatment trends. Note: Error bars represent the 90% and 95% confidence interval, respectively.

facilitating low-carbon technology innovations and achieving double declines in both carbon emissions and carbon intensity.

4.4. Robustness check

Consistent estimations of the ATT above are predicted on a number of underlying assumptions. As to the DID estimation, the key assumption is the parallel trend assumption (Chan et al., 2013), which suggests that given there is no ETS, there should be no systematic difference in the trends of the dependent variables between the treatment and control groups over time. The second one is that the start of China's pilot ETSs is mean independent of the error term. Violation of this assumption is unlikely to happen since ETS is a measure to assist the achievement of China's announced GHG mitigation targets and to shift China's economic development mode.

As to the PSM-DID estimation, the first assumption is unconfoundedness, which is similar to the parallel trend assumption (Fowlie et al., 2012). The second one is the common support assumption, which is directly testable since the covariates for matching overlap in the two groups. The third one is the "Stable Unit Treatment Value Assumption (SUTVA)", which suggests that there is no spillover effect, that is, the participation of an individual in the program does not affect the others. In this section, we apply various strategies to test these assumptions.

4.4.1. Parallel trend assumptions/unconfoundedness

Since this assumption assumes the treatment and control groups share parallel trends if there were no ETS, it is more credible if their trends are already parallel at the pre-treatment period. Fig. C1 in Appendix C plots the trends for the outcome variables, showing that the two groups were indeed sharing similar trends prior to treatment. Here, we will examine the assumption from another perspective by referring to Petrick and Wagner (2014), i.e., using the changes instead of levels of the pre-treatment dependent variables for matching. If the two groups share similar trends before ETS started, the results obtained by matching on the changes should be comparable to the original results matching on the levels. Fig. 1 shows the comparison of estimates when matching on pre-treatment levels and trends of the dependent variables based on alternative specifications.[7]

The left part of Fig. 1 shows the matched DID estimators whose matching covariates are the levels of carbon emissions in 2011, the change in carbon emissions from 2010 to 2011, and the average of 3 changes in carbon emissions from 2008 to 2011 (the other matching covariates remain the same). The matching algorithms do not have much influence on the results. In 2013 and 2014, the results matching on average of 3 changes are much different from that of the original ones, which turn from insignificant to significantly negative. Even so, their magnitude and confidence intervals are still comparable to original results. In 2015, the results based on other matching strategies and original results are consistently statistically negative. The results also show the tendency that with the implementation of the pilot ETSs, the impact on carbon emissions gradually increases.

Similarly, the right part of Fig. 1 shows the PSM-DID estimators based on the levels of 2011 carbon intensity, the change in carbon intensity from 2010 to 2011, and the average of 3 changes in carbon intensity from 2008 to 2011. The results based on the other two matching strategies and the original results are comparable, both the magnitude and the significance level. Therefore, it can be concluded that the treatment and control groups have similar trends before the pilots started, which lend support to the parallel trend assumption/unconfoundness in this paper.

[7] Baseline specification comparisons are not shown but are available on request.

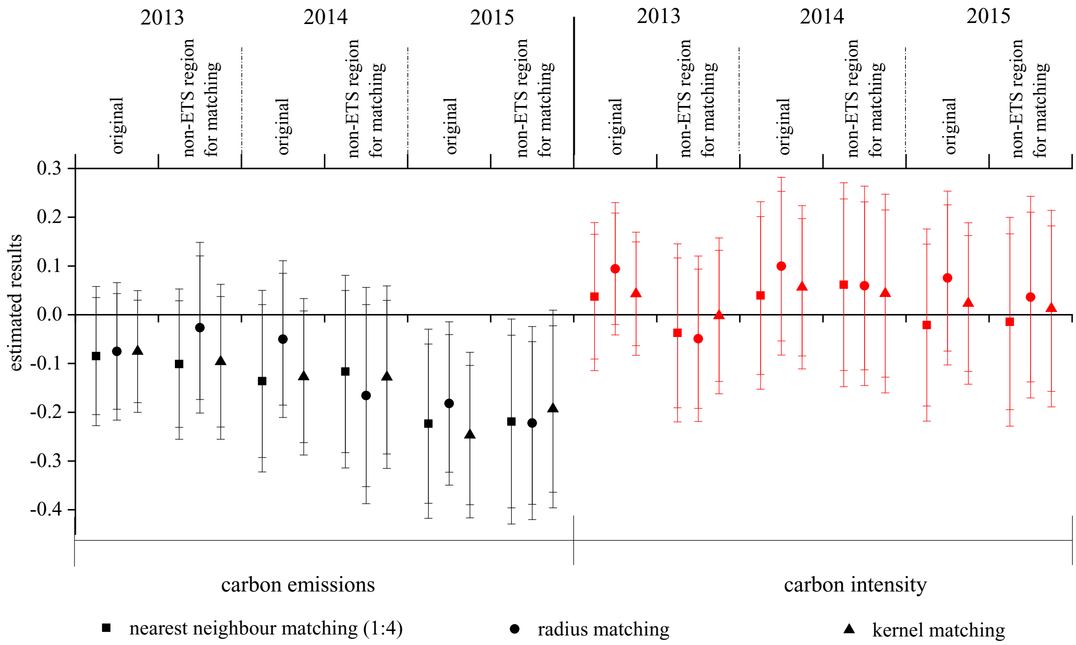

Fig. 2. Comparison of estimates using original control group and reestablished control group. Note: Error bars represent the 90% and 95% confidence interval, respectively.

4.4.2. Stable Unit Treatment Value Assumption (SUTVA)

In order to test the SUTVA, we refer to the ideas provided by Fowlie et al. (2012) and Petrick and Wagner (2014). Taking the estimated impact on emissions as an example, if there is a spillover effect, the emissions from the ETS-covered sub-sectors may be transferred to the uncovered sub-sectors. Hence, if the control group contains only the sub-sectors in the non-pilot areas, the new estimates should be smaller than the original results. The analysis of the impact on carbon intensity was performed in a similar manner, and both results are shown in Fig. 2.

For both carbon emissions and carbon intensity, the original results and the estimates with the new control group are considerably similar in both magnitude and significance level in any given year. Therefore, it can be concluded that the control group established in this study does not give rise to obvious spillover effect, which indirectly verifies the SUTVA assumption of the matched DID models.

5. Conclusions

In this paper, the carbon emissions and carbon intensity of 37 industrial sub-sectors in each of China's 26 provinces from 2005 to 2015 are calculated, then the causal impacts of China's pilot ETSs on carbon emissions and carbon intensity are analyzed using both DID models and PSM-DID models. Robust estimated results are obtained through the cross validation using multiple analytical methods, which provide answers to two key issues:

First, the estimates show that China's pilot ETSs are effective in reducing carbon emissions – the pilot ETSs have enabled covered industrial sub-sectors to significantly reduce carbon emissions compared to uncovered ones after the pilots started. Meanwhile, the impact may not be obvious at the beginning, likely due to the fact that China's pilots had flaws in its design and the companies have not familiarized themselves with the schemes. Anyhow, as the policy was further implemented, the impact on carbon emissions have gradually become more prominent. In 2015, the pilot ETSs have significantly facilitated the decline of carbon emissions.

Second, the pilot ETSs have not promoted the decline of carbon intensity of covered industrial sub-sectors, and this is the case in any given year during the initial period of the pilots. This means the carbon emission reductions achieved by covered industrial sub-sectors can mainly be attributed to production capacity cuts. Given that China is exploring to control not only its carbon emissions, but also its carbon intensity, China's policy makers should continue to improve the ETS mechanism design, tighten free allowance allocation approaches and boost low-carbon innovations, thus achieving double declines in both of them.

It is noteworthy that this paper only contains an attribution analysis of the impacts of China's pilot ETSs on carbon emissions and carbon intensity, without studying the abatement contributions made by different pilot ETSs due to their different designs, which could be an interesting topic for future studies. Through identifying the impacts of each pilot system and comparing their respective designs, such as cap setting, allowance allocation methods and enforcement of compliance, etc., one may figure out which designs are more suitable for China's specific national conditions.

Declarations of interest

None. The authors alone are responsible for the findings, interpretations and conclusions expressed in this paper.

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Appendix A. Industrial sub-sectors covered by the pilot ETSs

Table A.1
Industrial sub-sectors covered by China's pilot ETSs from 2013 to 2015

Pilot	Threshold for industry (tons CO_2/year)	Covered industrial sub-sectors
Beijing	>10,000 (2013–2014) >5000 (2015)	All industry sectors (Beijing Government, 2016)
Tianjin	>20,000	"Production and Supply of Electric Power and Heat Power", "Manufacture and Processing of Ferrous Metals", Manufacture of Chemical Raw Material and Chemical Products", "Extraction of Petroleum and Natural Gas", "Processing of Petroleum, Coking, Processing of Nuclear Fuel" (Liu et al., 2016b)
Chongqing	>20,000 (or 10,000 tce)	"Production and Supply of Electric Power and Heat Power", "Manufacture of Non-metallic Mineral Products", "Manufacture and Processing of Ferrous Metals", "Manufacture of Chemical Raw Material and Chemical Products", "Manufacture & Processing of Non-ferrous Metals" (China Climate Change Info-Net, 2012)
Guangdong	>20,000 (or 10,000 tce)	"Production and Supply of Electric Power and Heat Power", "Manufacture of Non-metallic Mineral Products", "Manufacture and Processing of Ferrous Metals", "Processing of Petroleum, Coking, Processing of Nuclear Fuel"
Hubei	>60,000 tce (Approx:120,000)	"Production and Supply of Electric Power and Heat Power", "Manufacture of Non-metallic Mineral Products", "Manufacture and Processing of Ferrous Metals", "Extraction of Petroleum and Natural Gas", "Manufacture of Chemical Raw Material and Chemical Products", "Manufacture & Processing of Non-ferrous Metals", "Manufacture of Paper and Paper Products", "Processing of Petroleum, Coking, Processing of Nuclear", "Manufacture of Automobile, Railroads, Ships, Aerospace and Other Transport Equipment", "Manufacture of General Purpose Machinery", "Manufacture of Special Purpose Machinery", "Manufacture of Foods", "Manufacture of Tobacco" (Liu et al., 2017)

Appendix B. Test of covariate balancing of PSM-DID

Table B.1
The estimated results of logit models

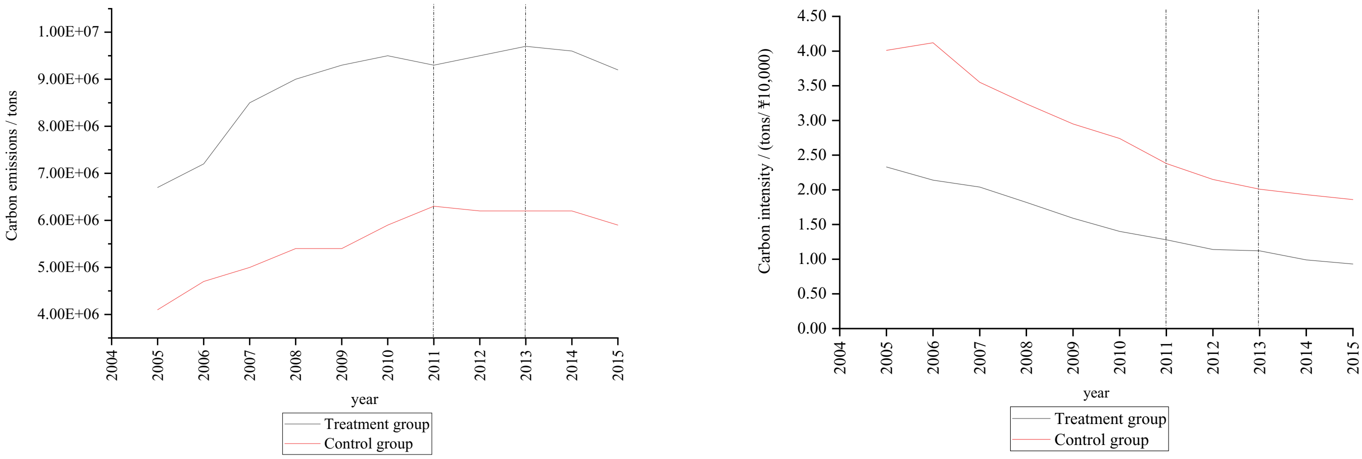
	(1)
lnCE	0.726**
	(0.367)
CI	−0.606***
	(0.218)
lnGO	3.170*
	(1.923)
[lnGO]^2	−0.120*
	(0.0675)
lnGOP	4.142
	(5.399)
[lnGOP]^2	−0.139
	(0.195)
FAR	−9.243***
	(1.939)
PROF	−9.206**
	(4.555)
Constant	−53.38
	(39.11)
Sector fixed effects	Yes
Observations	537
Pseudo R^2	0.229

Note:The dependent variable is treatment status, which equals one if a sector belong to treatment group, and zero otherwise. Standard errors are clustered at the individual units and t statistics are shown in the respective parentheses. All covariates in 2011. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Appendix C. Trends for outcome variables

Table B.2
Test of covariate balancing

Matching method	Variable	Sample	Mean treated	Mean control	%bias	%reduction of bias	*t*-test	p > t
Nearest neighbor	lnCE	U	14.50	13.32	51.90		3.40	0.00
		M	14.45	14.49	−1.70	96.70	−0.09	0.93
	CI	U	1.31	1.69	−15.20		−0.88	0.38
		M	1.31	1.51	−8.00	47.50	−0.63	0.53
	lnCI	U	−0.39	−0.54	10.70		0.72	0.47
		M	−0.41	−0.38	−1.70	84.00	−0.09	0.93
	lnGO	U	14.89	13.86	59.90		3.89	0.00
		M	14.86	14.87	−0.90	98.50	−0.05	0.96
	$[\ln GO]^2$	U	223.93	195.68	59.40		3.97	0.00
		M	222.88	223.42	−1.10	98.10	−0.06	0.95
	lnGOP	U	13.67	13.33	44.40		3.00	0.00
		M	13.64	13.68	−4.70	89.30	−0.27	0.79
	$[\ln GOP]^2$	U	187.29	178.21	43.50		2.98	0.00
		M	186.65	187.65	−4.80	89.00	−0.27	0.79
	SAR	U	0.56	0.44	36.30		2.34	0.02
		M	0.55	0.46	28.40	21.70	1.36	0.18
	FAR	U	0.32	0.36	−22.50		−1.72	0.09
		M	0.33	0.33	−1.70	92.20	−0.09	0.93
	PROF	U	0.07	0.08	−23.30		−1.55	0.12
		M	0.07	0.07	−3.40	85.40	−0.20	0.85
Radius	lnCE	U	14.50	13.32	51.90		3.40	0.00
		M	14.28	14.44	−7.10	86.40	−0.39	0.70
	CI	U	1.31	1.69	−15.20		−0.88	0.38
		M	1.28	1.47	−7.70	49.30	−0.59	0.56
	lnCI	U	−0.39	−0.54	10.70		0.72	0.47
		M	−0.47	−0.35	−8.20	23.50	−0.43	0.67
	lnGO	U	14.89	13.86	59.90		3.89	0.00
		M	14.75	14.80	−2.80	95.30	−0.16	0.87
	$[\ln GO]^2$	U	223.93	195.68	59.40		3.97	0.00
		M	219.73	221.39	−3.50	94.10	−0.19	0.85
	lnGOP	U	13.67	13.33	44.40		3.00	0.00
		M	13.62	13.59	3.70	91.60	0.21	0.83
	$[\ln GOP]^2$	U	187.29	178.21	43.50		2.98	0.00
		M	186.05	185.17	4.20	90.30	0.23	0.82
	SAR	U	0.56	0.44	36.30		2.34	0.02
		M	0.55	0.46	27.80	23.30	1.26	0.21
	FAR	U	0.32	0.36	−22.50		−1.72	0.09
		M	0.32	0.32	−0.10	99.50	−0.01	1.00
	PROF	U	0.07	0.08	−23.30		−1.55	0.12
		M	0.07	0.07	−11.70	49.60	−0.64	0.52
Kernel	lnCE	U	14.50	13.32	51.90		3.40	0.00
		M	14.45	14.33	5.30	89.80	0.30	0.76
	CI	U	1.31	1.69	−15.20		−0.88	0.38
		M	1.31	1.37	−2.40	84.30	−0.19	0.85
	lnCI	U	−0.39	−0.54	10.70		0.72	0.47
		M	−0.41	−0.42	1.00	90.70	0.05	0.96
	lnGO	U	14.89	13.86	59.90		3.89	0.00
		M	14.86	14.75	6.20	89.70	0.36	0.72
	$[\ln GO]^2$	U	223.93	195.68	59.40		3.97	0.00
		M	222.88	219.93	6.20	89.50	0.35	0.73
	lnGOP	U	13.67	13.33	44.40		3.00	0.00
		M	13.64	13.60	5.20	88.20	0.30	0.76
	$[\ln GOP]^2$	U	187.29	178.21	43.50		2.98	0.00
		M	186.65	185.52	5.40	87.60	0.31	0.76
	SAR	U	0.56	0.44	36.30		2.34	0.02
		M	0.55	0.47	26.40	27.20	1.27	0.21
	FAR	U	0.32	0.36	−22.50		−1.72	0.09
		M	0.33	0.32	2.80	87.80	0.14	0.89
	PROF	U	0.07	0.08	−23.30		−1.55	0.12
		M	0.07	0.07	−3.20	86.10	−0.20	0.84



(a) Trends in carbon emissions

(b) Trends in carbon intensity

Fig. C.1. Trends in dependent variables

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