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Research article

The environmental and economic effects of the carbon emissions trading scheme in China: The role of alternative allowance allocation ☆

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ABSTRACT

This paper examines the impact of China's carbon emission trading scheme (ETS) on carbon emissions reduction and economic performance with a focus on the role of alternative allowance allocation. Using the industry-by-province panel data during the 2008-2016 period, the empirical strategy employs a difference-in-difference-in-difference model. Some novel findings emerge. First, the ETS leads to a reduction in carbon emissions and emission intensity, in particular, for those adopting the benchmarking allowance allocation. Second, the reduction in carbon emissions arises from an increase in energy efficiency. Moreover, the adjustment of energy structure is more favorable to ETS regions adopting the benchmarking allocation rule compared with ETS regions using the grandfathering one. Third, the ETS has muted impacts on employment and returns on assets. A further comparison between the benchmarking and grandfathering rules reveals that the former is associated with a rise in employment, while the latter leads to an increase in returns on assets. In line with the findings, it is recommended that the government should further develop the benchmarking value of the sub-sectors, and gradually transform the allowance allocation methods into the benchmarking-dominated method for China ETS.

1. Introduction

Carbon ETS has been widely considered as an effective instrument to curb carbon emissions. China has become the largest energy consumer and carbon emitter in the world after its 33 years of high economic growth (Zhang et al., 2020a). As an active participant of combating global climate change, China has set a series of more ambitious targets for energy conservation and carbon emissions reduction. For example, carbon dioxide emissions per unit of GDP in 2030 is targeted to be reduced more than 60–65% compared with that in 2005. Additionally, China will peak its carbon emissions before 2030, and reach its carbon neutrality by 2060. To meet this international commitment to reducing carbon emissions, the Chinese government has resorted to the carbon ETS regional pilots to tackle climate change. From 2013 to 2014, China launched two provinces and five municipalities as the ETS pilots covering Hubei province, Guangdong province, Beijing, Shanghai, Shenzhen, Tianjin, and Chongqing. These regional pilots emit about 20% of national total carbon emissions and cover carbon-intensive sectors including ferrous metals, non-ferrous metals, manufacture of paper, chemical industry, steel, electricity, aluminum electrolysis (Munnings et al., 2016). The designs of ETS pilots differ greatly, including the three key elements of coverage, cap, and allowance allocation methods. From the point of view of allowance allocation, most pilots use free allocation, while Guangdong explores a combination of free and auction allocation. Of the free allocation, alternative allowance allocation, i.e., emission-based grandfathering, benchmarking, and historical carbon intensity method are used in different industries in the pilots (Duan et al., 2014). Most ETS-covered sub-sectors are allocated allowances by emission-based grandfathering, some by benchmarking and few by historical carbon intensity. Although some existing literature has examined the environmental impacts of China ETS, little is known about whether the environmental gains are at the expense of economic costs, and what is the role of carbon allowance allocation rules implemented across regional ETS pilots.

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Nomenclature

Symbols

i	Provinces
j	Sub-sectors
t	Years
ETS	Dummy variable of ETS pilots
$Post$	Dummy variable of ETS implement years
$Sector$	Average energy consumption per industrial revenue for sub-sector which is covered by ETS, otherwise it equals to 0
X	Control variables
Y	Dependent variable indicating environment, energy indicators or economic performance
α_{it}	Province linear trend
δ_{jt}	Industry linear trend
μ_{ij}	Province-industry fixed effect
ε_{ijt}	Error term
β	Regression coefficients
$Post_{2012}$	Dummy variables of year 2012
$ETSf$	Dummy variable of sub-sector adopting the emissions-based grandfathering
$ETSb$	Dummy variable of sub-sector adopting the benchmarking method
$ETSi$	Dummy variable of sub-sector adopting the historical carbon intensity method
$Rincome$	GDP per capita
$Rpop$	Population
$Rpatent$	Granted patents
$IndRD$	Industrial research and development investment
$Indfix$	Industrial investment in fixed assets
$Indcoal$	Industrial energy structure

Abbreviations

CO2	Carbon emissions
CO2 Intensity	Carbon emissions per industrial revenue
Energy Intensity	Energy consumption per industrial asset
Energy Structure	Coal consumption relative to all energy consumption
Labor	Number of workers
ROA	Returns on assets
DDD	Difference-in-difference-in-difference
DID	Difference-in-difference
ETS	Emission trading scheme

To fill this gap, this paper examines the dual impact of China carbon ETS on carbon emission and economic development. The former is measured by total carbon emissions and emission intensity, while the latter is proxied by labor employment and returns on assets (ROA). Moreover, we are interested in exploring the adjustment of energy efficiency and energy structure in response to ETS. Following some general guidelines of the National Development Reform Commission of China, each regional ETS pilot has its discretion to implement specific allowances allocation rules, such as the grandfathering rule or benchmarking rule (Duan et al., 2014). We further examine the role of the main alternative carbon allowance allocation rules, i.e., emission-based grandfathering, historical carbon intensity method and benchmarking in the environmental and economic assessment of China regional ETS pilots.

We have assembled the industry-by-province panel data during the 2008-2016 period. The empirical strategy employed in this paper is a difference-in-difference-in difference (DDD) model, offering a comparison of environmental and economic outcome variables of interests between the ETS regions and the non-ETS regions, between the covered sectors and the non-covered sectors, and between the pre- and post-ETS periods. Empirical findings reveal that the ETS leads to a decline in carbon emissions and emission intensity for the covered sectors in the ETS regions compared with the non-covered sectors in the non-ETS regions. This carbon reduction arises from the corresponding adjustment in energy intensity and energy structure. The latter is proxied by the fraction of coal consumption in all energy consumption. Moreover, the ETS has muted impacts on employment and returns on assets (ROA). A further comparison between the benchmarking and grandfathering rules of carbon allowance suggests that the former leads to a rise in employment, while the latter contributes to an increase in ROA.

This paper makes the following contributions to the existing literature. Whereas existing literature has examined the environmental impacts of the ETS, an important departure of this paper centers around the mechanism investigation. We seek to reveal that the declining carbon emissions mainly arises from an adjustment in energy structure and energy efficiency in response to the ETS. Another important departure is to further examine whether the environmental gains from the ETS is at the expense of economic slowdown and unemployment. Moreover, carbon allowance allocation rules implemented by the ETS regions capture the stringency of ETS. Which allowance allocation method performs better, and is appropriate to be applied to China's national ETS is concerned, but little is known from previous literature. This paper explores how the environmental and economic gains from the ETS are related to emission-based grandfathering, historical carbon intensity method and benchmarking for carbon allowance allocation.

The rest of the paper is arranged as follows. Section 2 reviews the related literature. Section 3 introduces the data source, variables definition, and the baseline empirical strategy. Section 4 presents the empirical findings, mechanism discussion, and the heterogeneous effect of alternative allowance allocation rules. Section 5 concludes the paper.

2. Literature Review

This paper is related to the existing literature on the efficiency of ETS construction, mainly from the perspectives of the dynamic behavior of carbon prices, trading volume, market liquidity, information transparency, and the rationality of allowance allocation (Zhao et al., 2017; Yi et al., 2018; Fan et al., 2019). For example, Zhao et al. (2016) analyzed the market efficiency of ETS pilots from four aspects: carbon price, trading volume, market liquidity, and information transparency. The market structure in the ETS also needs to be considered in the market efficiency evaluation, as most covered firms come from industries with high market concentration. Wang et al. (2018) incorporated transaction costs (monitoring, reporting, and verification (MRV) costs and trading costs) and market structure into a partial equilibrium model to study their effect on the reasonable coverage of the ETS. Their findings suggested that the MRV costs became the main factor of the breakdown inefficiency of the ETS and there seemed to be no inherent relationship between the market structure and the efficient coverage of the allowance market. The carbon allowance allocation is the core problem of ETS design, and most previous studies evaluated the regional allocated allowances based on equality and efficiency. Cai and Ye (2019) used zero-sum gains data envelopment analysis to allocate emissions allowances over China's 30 provinces and emphasized the effect of industrial structure on CO_2 emissions. A comparison between the results and official reduction goals showed that the government should increase CO_2 emissions allowances appropriately for most provinces with high proportions (more than 40%) of the second industry increment in GDP.

Another strand of literature centers around the empirical investigations for environmental effects of ETS. In terms of the carbon emissions reduction effect of ETS policy, many previous studies employed the computable general equilibrium (CGE) model to pre-estimate the possible contribution to carbon emissions reduction of ETS (Hübler et al., 2014; Lin and Jia, 2018). For example, Nong et al. (2020) conducted a CGE analysis of a multi-sector ETS to uncover the environmental and economic impacts of ETS, and found an ETS in Vietnam can be an effective policy with high emissions reduction and low costs. As for the post-estimation of ETS on carbon emission, some studies used the difference-in-difference (DID) method at the region level and find the ETS policy has pronounced impacts on carbon emissions. For example, Dong et al. (2019) apply the DID approach and provincial panel data to investigate whether ETS brings environmental dividends. Their findings indicated that the ETS significantly decreased carbon emissions in China's pilot regions. Based on the panel data of China's 30 provinces during 2000-2013, Zhang et al. (2017) adopted the DID and propensity score matching (PSM) methods to evaluate the effect of China's ETS pilots on carbon emission reduction. They found that the ETS effectively reduced carbon emissions. Zhou et al. (2019) studied the effect and influencing channels of China's ETS pilots on carbon intensity, using the decomposition and PSM-DID approach. Their findings revealed that China's ETS pilots have driven a significant decline in the carbon intensity and reduced the carbon intensity by adjusting the industrial structure. Qi et al. (2021a) found the ETS policy had significantly reduced carbon emission in the ETS areas compared with the non-ETS areas, and the Beijing carbon market performed the best among all pilots in terms of achieving targets of carbon reductions, followed by the Hubei carbon market.

Some studies further explored the carbon mitigation effects from ETS at the industry level. For example, based on panel data of 30 provincial industries from 2006 to 2015, Zhang et al. (2019a) employed a DID model to explore the effect of the ETS pilots on industrial carbon emissions and carbon intensity. The results showed that the ETS pilot policy had significant negative effects on industrial carbon emissions and intensity. Based on the data of industrial sub-sectors in China's 26 provinces from 2005 to 2015, Zhang et al. (2019b) explored the causal impact of China's ETS pilots on reducing carbon emissions at the initial stage (2013–2015) and analyzed the path of emission reductions, by applying the PSM and DID method. The results suggested that China's ETS pilots have reached carbon emission reductions in the covered sectors. Hu et al. (2020) used the DID approach to study the effects of China's ETS pilots on energy conservation and emission reduction based on the panel data of industry at the province level from 2005 to 2015. They found that carbon ETS decreased the carbon emissions of the covered industries in the ETS regions by 15.5% compared to those in the non-ETS regions. Employing a time-series econometric model of CO_2 emissions from electricity generation in Ireland for each half-hour over the period 1 January 2015 through 17 April 2018, Forbes and Zampelli (2019) found that carbon emissions would have been 6% higher in the absence of the European Union (EU) ETS. Calculating the production-based and consumption-based emissions of 28 industries in 30 provinces in China during 2005-2015, Gao et al. (2020) established the DDD models to evaluate the effect of ETS, and found that ETS pilots have greater effect on the mitigation of production-based emissions than consumption-based emissions.

This paper is also related to another strand of literature that examined the effect of ETS on economic performance, competitiveness, and technological progress (Demailly and Quirion, 2008). For example, Rogge et al. (2011) investigated the impact of the EU ETS on research, development, and demonstration. They found that the innovation impact of the EU ETS was muted because the scheme initially lacked stringency and predictability. Moreover, the impact varied significantly across technologies, firms, and innovation dimensions. Commin et al. (2011) examined how firms in different sectors were affected by the EU ETS, using a large number of European firms from 1996 to 2007. The results indicated that the effect of EU ETS on productivity and profits were negative, while the effect on labor and investment was statistically insignificant. In light of China's ETS, Zhang et al. (2020b) found sectoral trading (ST), and sectoral-and-temporal trading (STT) schemes may create potential gains of 268.02 and 612.26 trillion Yuan in the whole industrial during 2006–2015, by employing the data envelopment analysis (DEA) based optimization models. Zhang et al. (2020c) employed the DID-based propensity score matching model to evaluate the effect of ETS on technology innovation. The empirical results indicated that the effect of China's ETS on the technology innovation of related enterprises presented evident industrial heterogeneity. Specifically, the ETS policy helped 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 implied that China's ETS policy still had great potential for promoting the technology innovation of related enterprises. Based on the panel data of the listed firms in the seven high energy-consuming industries in China during 2010–2017, Zhang and Liu (2019) found the impact of ETS on firms' financial performance presented obvious industrial heterogeneity. The ETS policy reduced the financial performance of firms in the nonferrous metal industry but improved that in the power industry. Qi et al. (2021b) found evidence of a significant positive influence of a carbon trading pilot policy on the low-carbon international competitiveness of industries covered by the pilot programs, by a DDD approach.

To sum up, although previous studies investigated the effect of China's ETS on the carbon emissions reduction, economic or financial performance, technological innovation, etc., finding the consistent results on curbing carbon emissions and the heterogeneous results on economic performance or technological innovation, there are still several aspects that we feel compelled to compensate. First, a rare amount of the literature on studying the emissions reduction effect of ETS focuses on the carbon mitigation channels of ETS-covered sub-sectors in response to the ETS policy. Second, which allowance allocation method performs better in ETS pilots, or which one is appropriate to be applied to China's national ETS is concerned, but little is known from previous literature. To mitigate these concerns, this paper investigates the carbon mitigation channels of ETS-covered sub-sectors, and discloses the differences in the effectiveness on carbon mitigation and economic performance in response to allowance allocation alternatives.

3. Methodology and Data

3.1. Data Sources

This paper adopts the panel data of 39 industrial sub-sectors in 30 provinces (except Tibet, Hong Kong, Taiwan, and Macao) during 2008-2016. Carbon emissions, energy consumption, various fossil fuel consumption are obtained from Shan et al. (2017). The economic characteristics including total assets, revenue from the principal business, operating profits, and the average number of employed persons of industrial enterprises above designated size are provided by China Provincial Statistical Yearbooks. China Statistical Yearbooks supply GDP per capita, population, and the number of granted patents. The industrial panel data of investment in fixed assets, research and development (R&D) investment, and the ratio of coal consumption to total energy consumption are from China Industrial Statistical Yearbooks.

It should be noted that there are two reasons why the most recent data are not included in this paper. For one thing, China's national carbon emission trading scheme has been launched since 2017, and it covers the power industry in its initial stage.

Specifically, more than 1,700 power enterprises that reach the emission threshold have been covered in the national carbon emission trading throughout the country. In addition, other covered industries in the ETS pilots are still in operation. With the co-existence of ETS pilots and national ETS, the identification of effects on emission reduction and economic performance in response to ETS pilots will be confusedly disturbed by the national ETS after 2017. Because there will be no regional/industrial treatment group or control group for the power industry after 2017. For another, the industry-by-province panel data of economic indicators such as return on assets, number of labor force, etc., are not updated to the latest year, or lack a large number of observations, which would cause spurious regression results.

Given the revision of industrial classification for China's economic activities in 2011, this paper merges the sub-sectors "Manufacture of Rubber" and "Manufacture of Plastics" before 2012 as the "Manufacture of Rubber and Plastics", and merges the sub-sectors "Manufacture of Automobiles" and "Manufacture of Railway, Shipping, Aerospace and Other Transport Equipment" after 2012 as the "Manufacture of Transport Equipment". Since Shenzhen city is part of Guangdong province, Shenzhen pilot is not considered in this paper. Besides, this paper obtains 18 industrial sub-sectors covered in China's ETS pilots, through combining the covered sub-sectors in each ETS pilot and their corresponding two-digit industrial sub-sectors. Table 1 provides a summary of alternative carbon allowance allocation methods adopted by different covered sub-sectors across ETS pilot regions.

3.2. Variable Constructions

This paper analyzes whether the ETS pilots promote carbon emissions reduction and affect the economic performance of industrial sub-sectors. Dependent variables include two sets of measures: one is carbon emissions and the other is economic characteristics. First of all, we use total carbon emissions and carbon emissions intensity to measure the environmental effects of the ETS. The latter is measured by emissions per revenue. To further explore the mechanism, energy intensity and energy structure and accounted for. The former is defined by energy consumption per unit of asset, while the latter is measured by coal consumption divided by total energy consumption. Provincial economic performance indicators include the number of employed labor and returns on assets measured by operating benefits divided by total assets. All dependent variables are defined in the logarithm fashion (Table 2).

This paper considers a series of provincial and industrial covariates that may play substantial roles in carbon emissions and economic performance. Specifically, we use regional GDP per capita to proxy economic growth, denoted by Rincome. Regional population is captured by Rpop. In line with Ozturk and Acaravci (2013), industrial investment in fixed assets is captured by Indfix. The number of regional granted patents denoted by Rpatent and industrial R&D investment captured by IndRD are adopted to measure technological progress at the province level (Lee and Min, 2015; Churchill et al., 2019). Lastly, energy structure, denoted by Indcoal, is proxied by the industrial ratio of coal consumption (Zheng et al., 2019; Yu et al., 2018).

3.3. Empirical Strategy

The DID strategy has an advantage in investigating the effectiveness of a certain policy by comparing the differences in the effects of a certain policy between the treatment group and the control group. In order to evaluate whether the China ETS pilots have reduced the carbon emissions or influenced the economic performance for the covered industries, the DDD method is used to compare the impact difference between the ETS and non-ETS regions, between covered and non-covered sectors, and between pre- and post-ETS periods. This paper introduces the ETS covered sub-sectors with different energy intensity to identify the differences between the covered sub-sectors (treatment group) and non-covered sub-sectors (control group) between ETS pilots and non-pilots areas before and after the ETS policy implementation. To estimate the treatment effect of ETS policy on carbon emissions and economic performance, the baseline DDD model is proposed as follows,

$$Y_{ijt} = \beta_1 ETS_i \times Sector_j \times Post_t + \beta_2 ETS_i \times Sector_j + \beta_3 ETS_i \times Post_t + \beta_4 Sector_j \times Post_t + X\theta + \alpha_{it} + \delta_{jt} + \mu_{ij} + \varepsilon_{ijt} \quad (1)$$

Table 1
ETS Covered Industries and Allowance Allocation Methods.

Sub-sectors with benchmarking	Sub-sectors with emissions-based grandfathering
Guangdong Mining and Processing of Ferrous Metal Ores	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Extraction of Petroleum and Natural Gas
Guangdong Manufacture of Paper and Paper Products	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Mining and Processing of Non-Ferrous Metal Ores
Guangdong Manufacture of Non-Metallic Mineral Products	Beijing/Tianjin/Chongqing/Shanghai/Hubei Mining and Processing of Ferrous Metal Ores
Guangdong Smelting and Pressing of Ferrous Metals	Beijing/Tianjin/Chongqing/Shanghai/Hubei Manufacture of Paper and Paper Products
Guangdong Manufacture of Transport Equipment	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Printing, Reproduction of Recording Media
Guangdong Production and Distribution of Electric Power and Heat Power	Beijing/Tianjin/Chongqing/Shanghai Manufacture of Non-Metallic Mineral Products
Hubei Manufacture of Non-Metallic Mineral Products	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Manufacture of Chemical Fibers
Hubei Production and Distribution of Electric Power and Heat Power	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Manufacture of Raw Chemical Materials and Chemical Products
Shanghai Manufacture of Transport Equipment	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Smelting and Pressing of Non-Ferrous Metals
Shanghai Production and Distribution of Electric Power and Heat Power	Beijing /Tianjin/Chongqing/Shanghai/ Hubei Smelting and Pressing of Ferrous Metals
Tianjin Production and Distribution of Electric Power and Heat Power	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Processing of Petroleum, Coking, Processing of Nuclear Fuel
	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Manufacture of Metal Products
Subsectors with historical carbon intensity method	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Manufacture of General Purpose Machinery
Beijing Production and Distribution of Electric Power and Heat Power	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Manufacture of Special Purpose Machinery
Beijing Production and Distribution of Water	Beijing/Tianjin/ Chongqing/Hubei Manufacture of Transport Equipment
Shanghai Production and Distribution of Water	Chongqing Production and Distribution of Electric Power and Heat Power
	Beijing/Tianjin/Chongqing/Shanghai/Hubei/ Guangdong Production and Distribution of Gas
	Tianjin/Chongqing/Hubei/Guangdong Production and Distribution of Water

Table 2
Descriptive Statistics.

Variables	Observations	Means	Std. Dev.	Minimum	Maximum
CO_2	9158	3.296	2.497	-3.554	10.433
CO_2 Intensity	8026	-2.093	1.876	-10.745	4.926
Energy Intensity	8404	-2.179	1.479	-11.253	5.803
Energy Structure	9640	0.224	0.310	0.000	0.999
Labor	8573	5.393	2.030	-2.813	10.408
ROA	7928	-2.682	1.070	-9.156	5.567
Rincome	10,530	10.534	0.506	9.196	11.680
Rpop	10,530	8.184	0.740	6.317	9.306
Rpatent	10,530	10.229	1.254	6.066	12.761
IndRD	10,140	0.182	0.277	0.000	3.800
Indfix	9,420	7.692	1.244	2.495	10.027
Indcoal	9,750	4.244	1.707	-5.116	7.502

Notes: CO2 intensity is Carbon emissions per industrial revenue, energy intensity is Energy consumption per industrial asset, energy structure is Coal consumption relative to all energy consumption, ROA is Returns on assets, Rincome is GDP per capita, Rpop is Population, Rpatent is Granted patents, IndRD is Industrial R&D investment, Indfix is Industrial investment in fixed assets, and Indcoal is Industrial energy structure. All variables are defined in the logarithm fashion.

where i, j, t represent provinces, sub-sectors, and years, respectively. Y_{ijt} is the dependent variable indicating environment, energy indicators or economic performance. ETS_i is the dummy variable of ETS pilots: $ETS_i = 1$ if the province i is the ETS pilots, i.e., Beijing, Shanghai, Guangdong, Hubei, Tianjin, and Chongqing, otherwise $ETS_i = 0$. $Post_t$ is the dummy variable of years, taking $Post_t = 1$ if year t is equal to or after the launching year of ETS policy, $Post_t = 0$ otherwise. It should be noted that China ETS pilots is launched starting from 2013. We use the year 2013 as the policy implementation year. $Sector_j$ is the energy intensity for sub-sector j which is covered by ETS, otherwise $Sector_j$=0. The energy intensity is calculated by the average energy consumption per industrial revenue during 2008-2016. X denote control variables, consisting of GDP per capita (Rincome), granted patents (Rpatent), population (Rpop), industrial R&D investment (IndRD), industrial investment in fixed assets (Indfix), and industrial energy structure (Indcoal). ε_{ijt} is the error term. Besides, we control the province linear trend (α_{it}), industry linear trend (δ_{jt}), and province-industry fixed effect (μ_{ij}), province fixed effect, industry fixed effect, and year fixed effect, in order to control for time-varying and time-invariant provincial characteristics and industrial characteristics, and time-invariant differences for industries in different provinces (Shi and Xu, 2018). The coefficient β_1 of the interaction term $ETS_i \times Sector_j \times Post_t$ is the DDD estimator measuring the effects of the ETS pilot policy on the carbon emissions, energy indicators and economic performance for ETS-covered sectors in ETS pilots after the policy implementation.

4. Empirical Results and Discussion

4.1. Impacts of ETS on carbon emissions and economic performance

ETS covered enterprises may use cleaner energy with smaller emission coefficient (change energy structure), close down the backward production capacity and adopt low-carbon technologies (improve energy efficiency) to curb carbon emissions (Curtis and Lee, 2019). Whether these happen to China's ETS covered sub-sectors needs to be verified by the empirical evidence. According to Eq. (1), adopting the DDD approach, we first examine whether ETS pilots policy reduces carbon emissions of covered sub-sectors, then we test if ETS covered sub-sectors achieve emissions reduction by energy substitution or energy efficiency improvement. Finally, we investigate whether the ETS pilots policy damages the economic performance of covered sub-sectors. The results are shown in Tables 3-5, respectively.

Table 3
The Main Effect of ETS pilots on Carbon Emissions.

	CO_2		CO_2 Intensity	
	(1)	(2)	(3)	(4)
$ETS_i \times Post_t$	-0.107	-0.086	-0.028	-0.072
	(0.120)	(0.120)	(0.139)	(0.122)
$ETS_i \times Sector_j$	-0.128	-0.173*	-0.125	-0.170*
	(0.116)	(0.091)	(0.093)	(0.086)
$Sector_j \times Post_t$	0.101	0.029	0.023	0.008
	(0.086)	(0.075)	(0.091)	(0.078)
$ETS_i \times Sector_j \times Post_t$	-0.240***	-0.214***	-0.214**	-0.144*
	(0.085)	(0.077)	(0.092)	(0.075)
lnRincome	0.939*	0.598	-0.438	0.027
	(0.533)	(0.612)	(0.740)	(0.790)
lnRpop	-0.273	0.144	0.296	0.039
	(0.860)	(0.947)	(1.257)	(1.105)
lnRpatent	0.024	0.059	0.021	0.060
	(0.024)	(0.065)	(0.035)	(0.071)
lnIndcoal	0.007	0.002	0.010	0.004
	(0.018)	(0.021)	(0.019)	(0.021)
lnIndfix	0.044	-0.073	-0.402***	-0.166*
	(0.095)	(0.082)	(0.072)	(0.093)
lnIndRD	0.047	-0.056	-0.200***	-0.118**
	(0.043)	(0.064)	(0.057)	(0.055)
Observations	7,702	6,547	7,063	6,520
R^2	0.117	0.150	0.297	0.328
Province Fixed Effect (FE)	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province-Industry FE		Y		Y
Province linear trend		Y		Y
Industry linear trend		Y		Y

Note: Dependent variables: CO_2 denotes carbon emissions, while CO_2 Intensity is carbon emissions per revenue. ETS_i is the dummy variable of ETS pilot. ETS_i=1 if province *i* is the ETS pilot, otherwise ETS_i=0. $Post_t$ is the dummy variable of ETS implementation year. $Post_t$=1 if year *t* is after the ETS policy implementation in 2013, otherwise $Post_t$=0. $Sector_j$ is the energy intensity (energy consumption/revenue) if *j* is the ETS covered sub-sector, otherwise $Sector_j$=0. The clustered standard errors are reported in parentheses. *, ** and*** denote the significance at the 10%, 5% and 1% level, respectively.

The province, industry and year fixed effects are controlled in the former column of every dependent variable, while the time trend of provinces and industries, and province-industry fixed effect are also controlled in the latter column. The standard errors are clustered at the provinces level in all regressions. The results in Tables 3-5 indicate that,

First of all, the ETS pilots reduce carbon emissions and carbon intensity of the covered sub-sectors. The results in the columns (1) and (3) in Table 3 do not control the time trend of provinces and industries, and province-industry fixed effect. The DDD estimators are significantly negative. Furthermore, in the case of controlling the time trend of provinces and industries, and province-industry fixed effect in columns (2) and (4), the coefficients of the interaction term $ETS_i \times Sector_j \times Post_t$ are significant at the 10% level. This indicates the ETS pilots policy does effectively reduce the total and relative amount of carbon emissions of covered sub-sectors. The ETS pilots policy makes the total carbon emissions, the carbon intensity of covered sub-sectors decline 24.1% and 14.4% compared with non-covered sub-sectors in non-ETS regions.

Second, the covered sub-sectors in ETS pilots mainly reduce carbon emissions through the way of energy efficiency improvement, rather than energy substitution. The coefficients of the interaction term in columns (1) and (2) in Table 4 are significantly negative at the 10% level, which suggests the ETS pilots reduce the energy intensity of covered sub-sectors. Compared with the non-ETS sub-sectors, the covered sub-sectors in ETS pilots decrease their energy consumption per unit of the asset by 38.7%. Therefore, the implemented ETS pilots policy effectively improves the energy efficiency of energy-intensive sub-sectors. It also can be seen that the co-

Table 4
The Effects of ETS Pilots on Energy Consumption.

	Energy Intensity		Energy Structure	
	(1)	(2)	(3)	(4)
$ETS_i \times Post_t$	0.034	0.030	-0.011	-0.012
	(0.122)	(0.097)	(0.017)	(0.016)
$ETS_i \times Sector_j$	-0.029	0.023	-0.015***	-0.022***
	(0.132)	(0.161)	(0.007)	(0.008)
$Sector_j \times Post_t$	-0.054	0.026	-0.003	-0.011
	(0.071)	(0.058)	(0.006)	(0.009)
$ETS_i \times Sector_j \times Post_t$	-0.295*	-0.387**	0.003	0.009
	(0.127)	(0.153)	(0.007)	(0.010)
Observations	7,372	6,795	8,033	6,797
R^2	0.255	0.325	0.082	0.086
Province Fixed Effect (FE)	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province-Industry FE		Y		Y
Province linear trend		Y		Y
Industry linear trend		Y		Y

Note: Dependent variables: Energy Intensity is the logarithm energy consumption per industrial revenue, while Energy Structure is the logarithm ratio of coal consumption to total energy consumption. ETS_i is the dummy variable of ETS pilot. ETS_i=1 if province i is the ETS pilot, otherwise ETS_i=0. $Post_t$ is the dummy variable of ETS implementation year. $Post_t$=1 if year t is after the ETS policy implementation in 2013, otherwise $Post_t$=0. $Sector_j$ is the energy intensity (energy consumption/revenue) if j is the ETS covered sub-sector, otherwise $Sector_j$=0. All columns control the provincial and industrial economic variables, including provincial GDP per capita, population, granted patents, and industrial investment in fixed assets, R&D investment and ratio of coal consumption. The clustered standard errors are reported in parentheses. *, ** and *** denote the significance at the 10%, 5% and 1% level, respectively.

Table 5
The Effect of ETS Pilots on Economic Performance.

	Labor		ROA	
	(1)	(2)	(3)	(4)
$ETS_i \times Post_t$	-0.050	0.004	0.111*	0.009
	(0.073)	(0.053)	(0.067)	(0.017)
$ETS_i \times Sector_j$	0.040	0.075	-0.017	-0.027
	(0.051)	(0.076)	(0.086)	(0.027)
$Sector_j \times Post_t$	0.093***	0.088***	0.056	-0.004
	(0.019)	(0.017)	(0.057)	(0.014)
$ETS_i \times Sector_j \times Post_t$	-0.021	-0.073	-0.002	0.017
	(0.050)	(0.075)	(0.089)	(0.025)
Observations	6,371	5,855	6,908	6,908
R^2	0.086	0.177	0.103	0.952
Province Fixed Effect (FE)	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province-Industry FE		Y		Y
Province linear trend		Y		Y
Industry linear trend		Y		Y

Note: Dependent varaibles: Labor is the logarithm number of wokers, while ROA denotes returns to assets. ETS_i is the dummy variable of ETS pilot. ETS_i=1 if province i is the ETS pilot, otherwise ETS_i=0. $Post_t$ is the dummy variable of ETS implementation year. $Post_t$=1 if year t is after the ETS policy implementation in 2013, otherwise $Post_t$=0. $Sector_j$ is the energy intensity (energy consumption/revenue) if j is the ETS covered sub-sector, otherwise $Sector_j$=0. All columns control the provincial and industrial economic variables, including provincial GDP per capita, population, granted patents, and industrial investment in fixed assets, R&D investment and ratio of coal consumption. The clustered standard errors are reported in parentheses. *, ** and*** denote the significance at the 10%, 5% and 1% level, respectively.

efficients of the interaction terms in columns (3) and (4) are insignificant, which illustrates the ETS pilots policy does not significantly decrease the ratio of coal consumption of energy-intensive sub-sectors. Thus, the covered energy-intensive sub-sectors do not reduce carbon emissions by the channel of energy substitution in a short time.

Finally, the ETS pilots policy does no damage to their labors and returns of assets (ROA). The results in Table 5 show that, among the proxy variables of economic performance, all the coefficients of the interaction term are not significant. This indicates that the ETS pilots policy does not affect the labors and ROA of covered sub-sectors. From the perspective of Porter Hypothesis, environmental regulation does not undermine competitiveness but acts as an incentive for companies to innovate, which, in turn, enhances productivity (Brandi et al., 2020). The ETS policy is expected to push covered firms to develop more low-carbon technologies, thereby prompting innovations that compensate or even surpass the costs of complying with ETS policy. Thus, the labor and ROA of covered sub-sectors have not been influenced.

4.2. Robustness Checks

The empirical results of the basic model demonstrate the ETS pilots policy has great impacts on carbon emissions reduction while has no damage to economic performance, and ETS covered sub-sectors reduce emissions mainly by the way of improving the energy efficiency. To further ensure the treatment effect is really from the ETS pilots policy, instead of other policies that influence the changes in dependent variables, this paper next compares the significant difference in the treatment effects before and after the ETS pilots policy implementation to do the robust test, shown as follows,

$$Y_{ijt} = \beta_0 ETS_i \times Sector_j \times Post_{2012} + \beta_1 ETS_i \times Sector_j \times Post_t + \beta_2 ETS_i \times Sector_j + \beta_3 ETS_i \times Post_t + \beta_4 Sector_j \times Post_t + X\theta + \alpha_{it} + \delta_{jt} + \mu_{ij} + \varepsilon_{ijt} \quad (2)$$

where$Post_{2012}$ is the dummy variables of year 2012, and $Post_{2012} = 1$ if year is 2012, otherwise $Post_{2012} = 0$. Other variables have the same meanings with the Eq. (1). If the coefficient β_1 of the interaction term $ETS_i \times Sector_j \times Post_t$ is significant, and the coefficient β_0 of the interaction term $ETS_i \times Sector_j \times Post_{2012}$ is not significant, this indicates before the ETS policy implementation, there are no obvious changes in dependent variables, while there are significant changes in dependent variables after the ETS policy implementation. Thus, the changes in dependent variables do date from the ETS pilots policy, instead of other policies.

According to the 2012 year dummy variable and Eq. (2), we can analyze whether the effectiveness of carbon emissions reduction is really from the ETS pilots initiated in 2013. If the carbon emissions in covered sub-sectors in 2012 have a significant difference compared with non-ETS covered sub-sectors, carbon emissions reduction does not result from ETS policy. Instead, if the carbon emissions in covered sub-sectors in 2012 have no difference compared with non-ETS covered sub-sectors, but have a significant difference in 2013 compared with non-ETS covered sub-sectors, the carbon emissions reduction is caused by ETS policy.

The results of robust test are shown in Table 6, we can find the coefficients of the interaction terms in carbon emissions, carbon intensity, and energy intensity are not significant before 2013, while they are significant after 2013. The coefficients of the interaction terms in energy structure, labor and ROA are insignificant both before and after 2013. The results indicate the reduction in the total and relative amount of carbon emissions is derived from the ETS pilots policy initialed in 2013 by the channel of energy efficiency improvement. Besides, the insignificant impacts of ETS pilots on labor and ROA are also robust.

4.3. Heterogeneity in Alternative Allowance Allocation

EU ETS has adopted the free allocation of emission allowance in the first and second phases. In the first phase, 95% of initial allowances were freely allocated to firms based upon the grandfathering rule, while in the second phase, 90% of initial allowances

Table 6
Robustness Check.

	CO_2 (1)	CO_2 Intensity (2)	Energy Intensity (3)	Energy Structure (4)	Labor (5)	ROA (6)
$ETS_i \times Sector_j \times Post_{2012}$	-0.080	-0.080	0.023	0.005	-0.075	0.014
	(0.143)	(0.143)	(0.065)	(0.009)	(0.121)	(0.016)
$ETS_i \times Sector_j \times Post_t$	-0.284*	-0.284*	-0.384**	0.014	-0.073	0.019
	(0.154)	(0.154)	(0.154)	(0.013)	(0.075)	(0.026)
Observations	6,547	6,547	6,795	6,797	5,855	6,908
R^2	0.150	0.565	0.325	0.086	0.177	0.952
Province FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province-Industry FE	Y	Y	Y	Y	Y	Y
Province linear trend	Y	Y	Y	Y	Y	Y
Industry linear trend	Y	Y	Y	Y	Y	Y

Note: ETS_i is the dummy variable of ETS pilot. ETS_i=1 if province *i* is the ETS pilot, otherwise ETS_i=0. $Post_t$ is the dummy variable of ETS implementation year. $Post_t$=1 if year *t* is after the ETS policy implementation in 2013, otherwise $Post_t$=0. $Post_{2012}$=1 if year *t* is 2012, otherwise $Post_{2012}$=0. $Sector_j$ is the energy intensity (energy consumption/revenue) if *j* is the ETS covered sub-sector, otherwise $Sector_j$=0. All columns control the provincial and industrial economic variables, including provincial GDP per capita, population, granted patents, and industrial investment in fixed assets, R&D investment and ratio of coal consumption. The clustered standard errors are reported in parentheses. *, ** and*** denote the significance at the 10%, 5% and 1% level, respectively.

are freely allocated using the benchmarking rule. In line with the EU ETS, China's ETS pilots mainly adopt the free allocation, among which most of the sub-sectors use the emissions-based grandfathering, some use the benchmarking, and few adopt the historical carbon intensity method. This allows us to use DID approach to evaluate the actual and heterogeneous effects on the carbon mitigation and economic performance in response to the allowance allocation alternatives, for the covered sub-sectors. To analyze the heterogeneous effects of different allowance allocation methods on carbon emissions reduction and economic performance, this paper further establishes the DID models to investigate the heterogeneous effects, to provide the experience for the allowance allocation of China's national ETS policy, shown as follows,

$$Y_{ijt} = \beta_0 ETSf_{ij} \times Post_t + \beta_1 ETSb_{ij} \times Post_t + \beta_2 ETSi_{ij} \times Post_t + X\theta + \alpha_{it} + \delta_{jt} + \mu_{ij} + \varepsilon_{ijt} \tag{3}$$

Given that the allowance allocation method of a certain sub-sector may be different in different pilots, we set the dummy variables $ETSf_{ij}$, $ETSb_{ij}$ and $ETSi_{ij}$ to represent the allowance allocation methods. $ETSf_{ij} = 1$ if the sub-sector j in province i adopts the emissions-based grandfathering, and zero otherwise. $ETSb_{ij} = 1$ if the sub-sector j in province i adopts the benchmarking method, and zero otherwise. $ETSi_{ij} = 1$ if the sub-sector j in province i adopts the historical carbon intensity method, and zero otherwise. Other variables have the same meanings with Eq. (1). Comparing the coefficients of the interaction terms of $ETSf_{ij} \times Post_t$, $ETSb_{ij} \times Post_t$ and $ETSi_{ij} \times Post_t$ can identify the heterogeneous effects of the allowance allocation methods on carbon emissions reduction and economic performance of covered sub-sectors.

According to Eq. (3), the differences in the impacts of emissions-based grandfathering, benchmarking and historical carbon intensity method on carbon emissions reduction and economic performance are shown in Tables 7–9. The columns (1) (2) and (3) in every dependent variable only list the results that regress the corresponding samples adopting emission-based grandfathering, or benchmarking, or historical carbon intensity method, respectively, while column (4) list the results that regress all the samples adopting the three allowance allocation methods at the same time. It can be seen that the results of columns (1), (2) and (3) are very close to the results of column (4).

First, the sub-sectors adopting benchmarking are reduced more carbon emissions and emission intensity, compared with those adopting the emissions-based grandfathering and historical carbon intensity method. From the columns (4) and (8) in Table 7, the coefficients of $ETSf_{ij} \times Post_t$ and $ETSi_{ij} \times Post_t$ are not significant, which suggests the carbon emissions reduction is ineffective of sub-sectors adopting the emissions-based grandfathering and historical carbon intensity method. However, the coefficient of $ETSb_{ij} \times Post_t$ is significantly negative at the 10% level, which denotes the great effectiveness on carbon emissions reduction of sub-sectors adopting benchmarking. Therefore, the sub-sectors adopting benchmarking have a better effect on carbon emissions compared with the other two allowance allocation methods. This is because the emissions-based grandfathering and historical carbon intensity method are based on the historical carbon emissions or intensity, assuming the enterprises are keeping emitting the carbon emissions as the past levels. Thus, it is ignored that enterprises have taken emission reduction actions before the ETS and enterprises will take further emission reduction actions under the influence of the ETS mechanism after the policy. Besides, the emissions-based grandfathering may result in "whipping the fast and hard-working" and the embarrassing situation where enterprises with more carbon emissions get more emissions allowances (Xiong et al., 2017). Hence, this phenomenon is not benefited to motivating enterprises to develop and introduce advanced low-carbon and energy conservation technologies and drives little to reduce carbon emissions for covered enterprises.

Second, sub-sectors adopting benchmarking and historical carbon intensity method mainly depend on optimizing energy structure to achieve carbon emissions reduction, compared with sub-sectors using the grandfathering one. The column (8) in Table 8 shows that, the coefficient of $ETSf_{ij} \times Post_t$ is not significant, while the coefficients of $ETSb_{ij} \times Post_t$ and $ETSi_{ij} \times Post_t$ are significantly negative at the 5% level, indicating sub-sectors adopting benchmarking and historical carbon intensity method decrease their ratio of coal consumption compared with other sub-sectors, while emissions-based grandfathering does not have this effect.

Although the energy structure of covered sub-sectors is not significantly changed on the whole, the sub-sectors adopting benchmarking and historical carbon intensity method can optimize their energy structure. Under the benchmarking method, the baseline emissions of the industry are set, either the industrial average baseline of carbon intensity, or the industrial advanced baseline of carbon intensity, which encourages the advanced and spurs the backward. The benchmarking method can avoid the problem of purposely increasing emissions to obtain extra allowances, and can result in more equitable allowance allocations. Hence, it provides enough motivation for enterprises to use cleaner energy or phase out the inefficient equipment. The historical carbon

Table 7
The Heterogeneous Effects of Allowance Allocation Methods on Carbon Emissions.

	CO_2				CO_2 Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETSf_{ij} \times Post_t$	-0.034			-0.037	-0.009			-0.013
	(0.119)			(0.119)	(0.115)			(0.115)
$ETSb_{ij} \times Post_t$		-0.148*		-0.153*		-0.160*		-0.162*
		(0.085)		(0.087)		(0.087)		(0.091)
$ETSi_{ij} \times Post_t$			0.195	0.181			0.132	0.122
			(0.162)	(0.155)			(0.161)	(0.155)
Observations	6,551	6,551	6,551	6,551	6,520	6,520	6,520	6,551
R^2	0.029	0.029	0.029	0.029	0.220	0.220	0.220	0.503
Province FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Province linear tend	Y	Y	Y	Y	Y	Y	Y	Y
Industry linear trend	Y	Y	Y	Y	Y	Y	Y	Y

Note: $ETSf_{ij}$, $ETSb_{ij}$, and $ETSi_{ij}$ denote binary indicators for sector j in ETS region i that adopts the emission-based grandfathering allocation, benchmarking allocation, and the historical carbon intensity rule, respectively. $Post_t$ is the dummy variable of ETS implementation year. $Post_t$=1 if year *t* is after the ETS policy implementation in 2013, otherwise $Post_t$=0. $Sector_j$ is the energy intensity (energy consumption/revenue) if *j* is the ETS covered sub-sector, otherwise $Sector_j$=0. All columns control the provincial and industrial economic variables, including provincial GDP per capita, population, granted patents, and industrial investment in fixed assets, R&D investment and ratio of coal consumption. The clustered standard errors are reported in parentheses. *, ** and*** denote the significance at the 10%, 5% and 1% level, respectively.

Table 8
The Heterogeneous Effects of Allowance Allocation Methods on Energy.

	Energy Intensity				Energy Structure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETSf_{ij} \times Post_t$	-0.011			-0.013	-0.001			-0.003
	(0.089)			(0.089)	(0.017)			(0.017)
$ETSb_{ij} \times Post_t$		-0.106		-0.108		-0.038**		-0.039**
		(0.088)		(0.092)		(0.017)		(0.018)
$ETSi_{ij} \times Post_t$			0.124	0.117			-0.178***	-0.180***
			(0.130)	(0.130)			(0.024)	-0.003
Observations	6,801	6,801	6,801	6,801	6,803	6,803	6,803	6,803
R^2	0.216	0.216	0.216	0.216	0.079	0.079	0.080	0.080
Province FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Province linear tend	Y	Y	Y	Y	Y	Y	Y	Y
Industry linear trend	Y	Y	Y	Y	Y	Y	Y	Y

Note: $ETSf_{ij}$, $ETSb_{ij}$, and $ETSi_{ij}$ denote binary indicators for sector j in ETS region i that adopts the emission-based grandfathering allocation, benchmarking allocation, and the historical carbon intensity rule, respectively. $Post_t$ is the dummy variable of ETS implementation year. $Post_t$=1 if year *t* is after the ETS policy implementation in 2013, otherwise $Post_t$=0. $Sector_j$ is the energy intensity (energy consumption/revenue) if *j* is the ETS covered sub-sector, otherwise $Sector_j$=0. All columns control the provincial and industrial economic variables, including provincial GDP per capita, population, granted patents, and industrial investment in fixed assets, R&D investment and ratio of coal consumption. The clustered standard errors are reported in parentheses. *, ** and*** denote the significance at the 10%, 5% and 1% level, respectively.

Table 9
The Heterogeneous Effects of Allowance Allocation Methods on Economic Performance.

	Labor				ROA			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETSf_{ij} \times Post_t$	-0.154			-0.144	0.027*			0.028*
	(0.103)			(0.107)	(0.015)			(0.015)
$ETSb_{ij} \times Post_t$		0.340***		0.311***		0.020		0.025
		(0.076)		(0.079)		(0.019)		(0.020)
$ETSi_{ij} \times Post_t$			-0.136	-0.164			0.098***	0.104***
			(0.133)	(0.158)			(0.030)	(0.030)
Observations	5,861	5,861	5,861	5,861	6,914	6,914	6,914	6,914
R^2	0.173	0.173	0.170	0.175	0.952	0.952	0.952	0.952
Province FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Province linear tend	Y	Y	Y	Y	Y	Y	Y	Y
Industry linear trend	Y	Y	Y	Y	Y	Y	Y	Y

Note: $ETSf_{ij}$, $ETSb_{ij}$, and $ETSi_{ij}$ denote binary indicators for sector j in ETS region i that adopts the emission-based grandfathering allocation, benchmarking allocation, and the historical carbon intensity rule, respectively. $Post_t$ is the dummy variable of ETS implementation year. $Post_t$=1 if year *t* is after the ETS policy implementation in 2013, otherwise $Post_t$=0. $Sector_j$ is the energy intensity (energy consumption/revenue) if *j* is the ETS covered sub-sector, otherwise $Sector_j$=0. All columns control the provincial and industrial economic variables, including provincial GDP per capita, population, granted patents, and industrial investment in fixed assets, R&D investment and ratio of coal consumption. The clustered standard errors are reported in parentheses. *, **, and *** denote the significance at the 10%, 5% and 1% level, respectively.

Table 10
The Comparison between the Results of This Paper and Literature.

Typical literature	Topic	Method	Results on carbon mitigation	Results on economic performance	Results on carbon mitigation channels	Roles of alternative allowance allocation
Zhang et al. (2020b)	Economic output and carbon mitigation	optimization model	Carbon emissions may decrease by 17.17 billion tons under sectoral trading scheme.	Sectoral trading may create potential gains of 268.02 trillion yuan in 2006–2015.	Sectoral trading decreased industrial carbon intensity by 19.80% during 2015–2020.	-
Chen et al. (2020)	Carbon mitigation and influencing mechanism	DID	China's pilot ETS had significant carbon reduction effects at both national and regional level.	-	Influencing channels of industrial upgrading and optimized resource allocation were verified.	-
Gao et al. (2020)	Carbon mitigation	DID	ETS had greater effect on the mitigation of production-based emissions than consumption-based.	-	-	-
Qi et al. (2020)	Environmental and economic effects	DID	China's pilot ETS policy had significantly reduced carbon emission in the ETS areas.	This emission reduction had not come at the cost of economic development.	The ETS policy led to a decline in carbon intensity and fossil fuel energy consumption relative to all energy types.	-
Zhang et al. (2019b)	Carbon mitigation and influencing mechanism	DID	China's pilot ETS had significantly promoted carbon emission reductions of the covered industrial sub-sectors.	-	The carbon emission reductions were achieved through the decreased outputs of industrial sub-sectors.	-
Hu et al. (2019)	Energy conservation and emission reduction	DID	ETS decreased the energy consumption of the regulated industries by 22.8% and the CO2 emissions by 15.5%.	-	-	-
Zhou et al. (2019)	Carbon mitigation and influencing channels	DID	China's emission trading pilots drove a significant decline in the carbon intensity.	-	Emission trading pilots reduced the carbon intensity by adjusting the industrial structure.	-
Zhang et al. (2018)	Impact of carbon allowance allocation on the electricity industry	CGE analysis	-	-	-	In the electricity sector, historical emission intensity could have better performance in commodity price, electricity supply, ETS price, GDP.
This paper	Carbon mitigation, influencing channels, Economic performance and Roles of alternative allowance allocation	DDD DID	The ETS leads to a reduction in carbon emissions and emission intensity.	The ETS has muted impacts on employment and returns on assets.	The reduction in carbon emissions arises from an increase in energy efficiency.	The benchmarking has a better effect on both the environmental and economic performance comparing with the other two.

intensity method is designed to encourage enterprises to at least keep or reduce their historical carbon intensity to avoid additional emission costs. Similar to the benchmarking method, this method also encourages covered entities to reduce emissions through energy substitution or improvement in energy efficiency. As Jin et al. (2020) stated, the difference among the alternative allocated allowances lies in the stringency of exogenous emission constrains for the covered specific sub-sectors. The benchmarking and historical carbon intensity methods tighten the emission constrains compared with the grandfathering one, which prompt technology and energy efficiency improvement faster owing to carbon reduction pressure.

Third, sub-sectors adopting benchmarking increase their labors compared with emissions-based grandfathering and historical carbon intensity method. The column (4) in Table 9 shows the coefficients of $ETSf_{ij} \times Post_t$ and $ETSi_{ij} \times Post_t$ are not significant, while the coefficient of $ETSb_{ij} \times Post_t$ is significantly positive at the 1% level. This indicates the ETS pilots policy has no impact on the labors of sub-sectors adopting emissions-based grandfathering and historical carbon intensity method, while it increases the labors of sub-sectors adopting benchmarking. For one thing, the benchmarking method makes the allowance allocations more equitable, and provides more incentives for enterprises to reduce carbon emissions. To get more free allowances, not only the advanced but also the backward enterprises are motivated to research and develop or adopt the low-carbon technologies, improve the energy efficiency, introduce the advanced equipment, which can lead to more employment opportunities. For another, the benchmarking method is complex when setting the baseline benchmarking of the sectors, compared with the other two allocation methods. It has a higher requirement for data and needs to gather the benchmarks of sorts of products in the sectors, which may increase employment.

Finally, the sub-sectors adopting emissions-based grandfathering and historical carbon intensity increase their ROA. The column (8) in Table 9 shows the coefficients of $ETSf_{ij} \times Post_t$ and $ETSi_{ij} \times Post_t$ are positive at the 10% significance level, and the coefficient of $ETSb_{ij} \times Post_t$ is not significant. This denotes the sub-sectors adopting emissions-based grandfathering and historical carbon intensity increase their ROA while benchmarking does not have this effect. The historical methods often allocate more allowances to enterprises with more carbon emissions according to their historical emissions or intensity, which obeys the rule of polluter-pay-principle. Actually, the carbon emissions allowances are the valuable assets, but the enterprises emitting more carbon emissions gain the assets for free under the historical methods and need not pay for the emissions, or reach compliance without any effort (Qi and Cheng, 2018), which makes their financial performance better. Zhang et al. (2020b) also found the ETS policy increase the output of the covered sub-sectors. As they explained, if a sector's emissions exceed the mandatory limits, it needs to purchase a certain number of emissions allowances from other sectors which have surplus quotas, leading to an increase in its production costs. Those sub-sectors adopting grandfathering and historical carbon intensity method often get more allowances, which means they can pay less carbon emissions reduction cost, even get more revenue for selling extra carbon allowances. Because of the "windfall profits" under the historical allocation methods, some existing high-emission enterprises in bad economic conditions are still able to survive.

The difference between the allocated allowances lies in the stringency of exogenous emission constraints for the covered specific sub-sectors. Emission-based grandfathering enables the enterprises emitting more carbon emissions to gain more free allowances, suffer less pressure to reduce emissions or reach compliance with less effort. For the historical carbon intensity method, the enterprises with more carbon intensity gradually obtain less free carbon allowances according to the tightening historical carbon intensity baseline, which places more pressure on carbon emissions reduction. The benchmarking method can avoid the problem of purposely increasing emissions to obtain extra allowances and can result in more equitable allowance allocations, as advanced enterprises that work hard to achieve emission reductions will obtain more carbon allowances, while backward enterprises with less, or even no, emission reductions will obtain fewer carbon allowances. The benchmarking and historical carbon intensity method tightens the emission constraints compared with grandfathering. The roles of emission-based grandfathering, benchmarking, and historical carbon intensity method on the environmental and economic performance disclose that benchmarking have a better effect on both carbon mitigation and economic performance compared with the other two allowance allocation methods. Sub-sectors adopting the benchmarking reduce emissions at no expense of economic costs. Benchmarking is expected to be widely applied, and for emission-based grandfathering and historical carbon intensity, the carbon permits need to be further tightened due to their useless roles in carbon mitigation while gaining windfall profits.

4.4. Comparison of results with previous literature

In this section, this paper compares the effectiveness of China ETS pilots policy with previous literature on carbon emission reduction, economic performance, channels of carbon mitigation in response to China ETS pilots, and the roles of emission-based grandfathering, benchmarking, and historical carbon intensity. Table 10 shows the comparison between the results of this paper and previous literature about the effectiveness of China's ETS. First, the most previous studies evaluated the effects of China ETS pilots on carbon mitigation, and the results verified the effective role of ETS in emission reduction, which is consistent with our results on carbon mitigation. Second, previous literature reached no consensus on the channels of carbon mitigation and economic performance of China ETS pilots. This effect may exhibit the differences in terms of specific ETS pilots and cover sub-sectors because the policy design has differences in the ETS pilots, and each area and sub-sector has its specific economic and environmental characteristics. Our results disclose differences in the effects on carbon mitigation channels and economic performance for alternative allowance allocation. Finally, very little literature studied the impacts of alternative allowance allocation on the effectiveness of China ETS pilots. Used the CGE analysis to pre-estimate the impacts of allowance allocation in the electricity sector, indicating that historical emission intensity could have better performance in commodity price, electricity supply, ETS price, GDP. Our results arise from the actual and causal effects of China's ETS in all covered industries, disclosing that the benchmarking has better effects on both the carbon emission reduction and economic performance.

5. Conclusions and Policy Implications

Using China carbon ETS policy as a quasi-natural experiment, this paper employs the industry-by-province data to make a quantitative assessment regarding the environmental and economic impacts of the ETS. The empirical strategy resorts to the DDD model by comparing outcome variables of interests between the ETS regions and the non-ETS regions, between the covered sectors and the non-covered sectors, and between the pre- and post-ETS periods. Moreover, we further investigate the mechanism of how the adjustment of energy structure and energy efficiency responds to the ETS. Along this line, we explore the role of alternative emission allowance allocation rules in the environmental and economic impacts of the ETS.

We obtain some novel empirical findings. First, the ETS leads to a reduction in carbon emissions and emission intensity for the covered sectors in the ETS regions compared with the non-covered sectors in the non-ETS regions. The decline in carbon emission is more pronounced for the ETS regions adopting the benchmarking allowance allocation. Second, the reduction in carbon emissions arises from an increase in energy efficiency. The optimization of energy structure is more favorable to ETS regions adopting the benchmarking allocation rule compared with ETS regions using the grandfathering one. Third, the ETS has muted impacts on employment and returns on assets. A further comparison between the benchmarking and grandfathering rules reveals that the former is associated with a rise in employment, while the latter leads to an increase in returns on assets.

The empirical findings of this paper have profound policy implications. China regional ETS pilots have an effective impact on carbon emissions reduction while it does not seriously damage the economic performance of covered sub-sectors, suggesting that the ETS policy is initially successful, and can provide a rich experience and strong support for the national ETS construction. It is foreseeable that the progressive national carbon emission rights trading market policy is likely to achieve the expected effect in carbon emissions reduction. Second, the ETS policy mainly relies on improving energy efficiency to reduce carbon emissions, however, the driving force for energy substitution or energy structure optimization is not enough. Few sub-sectors adopting benchmarking and historical carbon intensity methods reduce their ratio of coal consumption. The ETS policy fails to promote energy structure optimization and clean energy development. This needs to perfect the design of the ETS system, concentrating on the allowance allocation method and market regulation to ensure the allocated allowance is appropriate and fair, and the carbon price is reasonable and moderate. Finally, the effectiveness in carbon emissions reduction and economic performance of sub-sectors adopting benchmarking is better than the other two allowance allocation methods to some degree. In the future, it is necessary to further refine the allowance allocation method of benchmarking, develop the benchmarking value of the sub-sectors, and gradually transform the allowance allocation methods into the benchmarking-dominated method.

As for the future work, there is still much to be done. For instance, on the one hand, some further research can be done to estimate the different effects on the environmental and economic performance of the sub-sectors adopting the allowance allocation of auction or free. On the other hand, more research can be concentrated on the effect of covered enterprises with alternative allowance allocation, not only at the regional or industrial level.

Declaration of Competing Interest

None

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