Carbon ETS and Trade Comparative Advantage of China's High-Emission Industries

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Abstract

Aiming at peaking and neutralizing carbon emissions, the Chinese government began implementing a Carbon Emission Trading Scheme (ETS) in 7 pilot provinces and cities in 2013. Using the industrial-level data from 2012 to 2016 in 32 provinces and municipalities in China, this study investigates the impact of ETS on the industrial-level trade comparative advantage of the high-emission industries. The difference-in-difference regression result shows that the ETS has a very weak positive impact on the trade comparative advantage of these high-emission industries. Among all the high-emission industries, the papermaking industry is most affected. Potential bias caused by the endogeneity problems embedded in the selection process of pilot areas is tested to be insignificant. The main result is tested to be robust to several robustness checks. Finally, the paper discusses the possible mechanism of the ETS impact through technology innovation. The overall results do not contradict Porter's hypothesis that ETS as an environmental regulation does not necessarily weaken the comparative advantage in trade.

Contents

List of Tables

List of Figures

1 Introduction

It has been a worldwide consensus since the Kyoto Protocol was signed that climate change has become one of the most urgent global crises. In order to pursue sustainable development, the Chinese government announced its own carbon goals in September 2020 — to peak carbon emissions before 2030 and achieve carbon neutrality before 2060. Despite traditional environmental regulations, China planned to set up a carbon emission trading scheme (ETS) in 2010 and began trading in Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen in 2013. Fujian followed up in September 2016. On July 16, 2021, national carbon trading started. Nowadays, China's economy has been deeply integrated with the world economy, and the products of the high-emission industries included in the trading scheme in the pilot areas have opened competition in the international market as well. The current study has confirmed the cost and benefit impact of the implementation of ETS on these enterprises' financial performance, investment decisions, and technological innovation at the firm level. So, how this will affect international comparative advantage at the industrial level is worth analyzing and testing, especially for those high-emissions that are included in the trading from the beginning stage.

Thus, this paper primarily aims to discover how the ETS impacts the trade comparative advantages of those high-emission industries.

There are two contradicting theories regarding how environmental regulations affect comparative advantage. Some early research supports the "constraint hypothesis" that environmental regulations weaken a country's comparative advantage in trade by increasing production costs and inhibiting technological innovation, that is, the "cost effect" of environmental regulations will hinder the improvement of international competitiveness (S. Yang, 2023). However, “Porter’s hypothesis” (Porter & Linde, 1995) believes that stringent environmental regulation will not necessarily weaken a country's comparative advantage in trade, but will encourage enterprises to increase investment in technological innovation, and in turn, it could offset the cost incurred by conforming to the environmental regulation and will conducive to enhancing a country's comparative advantage in trade. Hence, the exact type of effect of ETS remains to be determined.

Using the industrial-level panel data from 2012 to 2016 in 32 provinces and municipalities in mainland China, this study investigates the impact of ETS on the industrial-level trade comparative advantage of the high-emission industries by constructing a difference-in-difference model. The result shows that the ETS has a weak positive impact on the trade comparative advantage of these high-emission industries that conforms to Porter’s hypothesis. Potential bias caused by the endogeneity problems embedded in the selection process of pilot areas is tested to be insignificant. The main result is fairly robust and is not contradicted by the robustness checks. Additionally, this paper discusses the possible mechanism of the ETS impact through technology innovation. However, the empirical result is insignificant and fails to solidly support the theoretical explanation mainly due to the limitation of data.

Last but not least, this paper contributes to the current literature in two aspects. First, this paper focuses on the impact of ETS on the condition of China which contributes to the study of market-based environmental regulation. Second, this study enriches the literature on the factors that impact trade comparative advantage.

2 Literature Review

Previous literature has confirmed the promoting effect of the carbon emission trading scheme (ETS) on emission reduction and energy conservation (Hu, Ren, Wang, & Chen, 2020). However, there are opposite opinions about the consequent production and management performances. Some early research supports the “constraint hypothesis” that environmental regulations will weaken a country's comparative advantage in trade by increasing production costs and inhibiting technological innovation, that is, the "cost effect" of environmental regulations will hinder the improvement of international competitiveness (S. Yang, 2023). However, “Porter’s hypothesis” (Porter & Linde, 1995) believes that stringent environmental regulation will not necessarily weaken a country's comparative advantage in trade, but will encourage enterprises to increase investment in technological innovation, and in turn, it is conducive to enhancing a country's comparative advantage in trade. Hence, the exact type of effect of ETS remains to be determined.

There is empirical evidence regarding the environmental regulations’ impacts on the trade comparative advantage. Du and Li (2020) find that the scale effect of environmental regulation might negatively impact the trade comparative advantage of some Chinese industries and reduce exports. Cole and Elliott (2003) used the sample data of 60 countries to analyze the influence that environmental regulations have on the comparative advantage of the trade of pollution-intensive products. They found that steel and chemical industries in capital-rich countries have comparative advantages, whereas, in developed countries with an abundant capital endowment, these industries do not shift, even if the intensity of environmental regulation is rising. Z.-b. Yang, Ma, and Pu (2015) use the revealed comparative advantage data from 2001 to 2012 in China's industrial sector to examine the relationship with environmental regulations. The result shows the impact of the intensity of the environmental regulation takes a U-shape. Liao and Xie (2017) discover a similar U-shape dynamic impact of environmental regulation trade comparative advantage based on the perspective of value added. Therefore, ETS as a typical market-based environmental policy should also impact the trade comparative advantage in some ways.

On the other hand, current studies cover the impacts of carbon pricing on many aspects of trade. No significant impact of ETS in the short-term with relatively low carbon prices or free allowances is found by Ellis, Nachtigall, and Venmans (2019) on the country-level competitiveness in trade in the electricity and industrial sectors, including net imports, FDI, turnover, value added, employment, employment, etc. According to the review of Verde (2020), some literature studies the competitiveness, among them, there are special concerns about the negative impact of unilateral carbon pricing where the international trade indicators, such as import and export, are highly relevant. Hence, other than competitiveness, carbon leakage is another issue that happens in international trade that scholars investigate as a consequence of carbon emission trading, especially in the context of EU ETS (Dechezleprêtre, Gennaioli, Martin, Muûls, & Stoerk, 2022;

Naegele & Zaklan, 2019). There is also further study examining the Carbon Border Adjustment Mechanism (CBAM), a complementary policy to the carbon trading scheme, and its effects on reducing the overall carbon leakage in international trade (Ambec, Esposito, & Pacelli, 2024).

However, China has not developed to the stage to consider and implement policies on preventing carbon leakage. Hence, focusing on the case of China, implementing ETS which only restricts domestic carbon emissions, Qi, Zhou, Li, and Tang (2021) find a significant positive impact on the low-carbon international competitiveness (LCIC) in the pilot areas by using the data of 30 industries and 30 provinces in China from 2009 to 2016 using the difference-in-difference-in-difference (DDD) model. Although the LCIC is different from the trade comparative advantage, the improvement of LCIC might contribute to the trade comparative advantage according to Porter's hypothesis.

3 Data Description & Model

3.1 Sample and Data

The sample consists of 32 provinces and municipalities in mainland China. According to the first-time pilot industries assessed to be included in the ETS by each pilot province and city, 6 high-emission industries are covered: the petrochemical industry, the chemical industry, the building materials industry, the iron and steel industry, the non-ferrous metal industry, and the papermaking industry. The original industrial-level export data of China is sourced from China Customs. To aggregate the world industrial-level data according to the industrial classification in China, one should first figure out each industry consists of what commodities, then search the corresponding world export data of every product and add them up. By checking the codes of the products belonging to each industry following the Industrial Classification of National Economic Activities China, this paper aligns the codes between the 2011 criterion (GB/T 4754—2011) and the 2017 criterion (GB/T 4754—2017), and then finds the matching product codes in the International Standard Industrial Classification of All Economics Activities (ISIC Rev.4) referring to the official document issued by Standardization Administration of China in 2017. After transforming all product codes from ISIC Rev.4 to Harmonized System (HS), the world export data is searched and downloaded from the United Nations Comtrade database, a database that compiles detailed global annual and monthly trade statistics by the United Nations Statistics Division. The industrial-level control variables are collected from the EPS database of which the data is originally collected from the China Industrial Statistics Yearbook, the China Labor Statistics Yearbook, and the Statistics Yearbook of each province and municipality issued by the National Bureau of Statistics. Additionally, the provincial-level macroeconomic data is sourced from the China Statistics Yearbook. In terms of the total number of patents of the A-share listed companies, they are originally sourced from the China National Intellectual Property Administration and matched with the firm's industry information to aggregate the number of the annually applied patents at the industrial level. Due to the industrial provincial export data missing too much before 2012 and after 2016, the time range of the data is limited. Also, the observations with missing values in export are replaced by 0. At last, all variables are winsorized at 1% and 99% levels to eliminate the impact of extreme values. After the above processing and because carbon ETS earliest started in 2013, the sample consists of high-emission industries' trade and production, and macroeconomics information in 32 provinces of mainland China from 2012 to 2016. The observation number totals 919.

3.2 Variable Definition

3.2.1 Carbon Emission Trading Scheme (ETS)

Carbon ETS started trading in December 2013 in 6 pilot provinces and cities: Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen. Among them, Shenzhen is included in Guangzhou province geographically, therefore, high-emission industries located in Shenzhen are treated to be the same as in Guangzhou in the sample. High-emission industries in the rest 25 provinces are included in the control group. Specifically, because Fujian began trading in mid-2016, the high-emission industries there are held in the control group in the simple difference-in-difference baseline model.

3.2.2 Revealed Comparative Advantage (RCA) Index

The concept of revealed comparative advantage was first introduced by Balassa (1965) to illustrate the relative trade performance of individual countries in particular commodities. In terms of industrial provincial export, the RCA index is defined as the ratio of the export of a province in an industry, divided by the ratio of the export of that industry in the world. If the RCA index is greater than 1, then the province exports in an industry relatively more than the rest of the world, in other words, it specializes in this industry. If the RCA index is lower than 1, then the province does not have a trade comparative advantage in this industry. If the RCA equals 1, the province is exporting at the global average level in this industry.

3.2.3 Control Variables and Technology Innovation

There are several commonly used industrial-level control variables that represent the primary factors that affect trade competitiveness. First, physical capital (*pc*) reflects the degree of capital endowment that an industry has in a province. In accordance with the Heckscher-Ohlin model, the intensity of capital endowment strongly impacts the export of an entity (Feenstra & Taylor, 2008). An entity with capital abundance will export more and hence gain a trade comparative advantage. Therefore, *pc* is calculated by the total assets divided by the annual average labor in an industry. Second, labor productivity (*lp*) reflects the average value of production produced by the employees of an industry during the year. Theoretically, a higher level of labor productivity supports more efficient production, which is more conducive to the formation and expansion of the industry's comparative advantage in international competition, and thus has higher international competitiveness. Labor productivity is calculated by the annual sales divided by the total average labor in an industry in a year. Third, research and development (*rd*) represents the technological and innovation strength of a certain industry in a province. Improvement of technology level contributes to the promotion of productivity and thus positively affects the trade comparative advantage. The R&D is evaluated by the ratio of total R&D expense to the gross industrial output (Liu & Xie, 2020). At the macro level, this paper controls the regional GDP per capita (*gdp*) as the economic development level of a province reflects and influences the overall local production, trade, and administration conditions.

To examine the possible mechanism through technology innovation, this paper uses the annual sum of applied patents (*sumpatent*) of the listed company in an industry to represent the innovation level. Compared to directly using R&D, the number of patents applied further reflects the transformation of R&D investment.

3.2.4 Descriptive Statistics

Table 1. Summary Statistics

Pilot	Variable	N	Mean	Min	Max	SD
N	*RCA*	739	0.4434	0.0000	6.7672	1.0422
	lnRCA	606	-2.3541	-8.4015	2.1057	2.2461
	lnpc	736	4.9268	3.4770	6.6954	0.6249
	lnlp	736	4.9474	3.5868	7.3889	0.6930
	lnrd	437	0.2462	-3.2189	1.8710	1.2599
	gdp	739	4.0349	2.1141	9.2658	1.3855
	sumpatent	739	27.0974	0	907	88.1842
Y	*RCA*	180	0.6226	0.0000	5.5152	1.1082
	lnRCA	164	-1.4646	-4.6533	1.7075	1.5204
	lnpc	180	4.9946	3.8137	6.5737	0.5501
	lnlp	180	5.1737	4.0099	7.2334	0.7241
	lnrd	106	0.7298	-3.2189	1.8710	1.0081
	gdp	180	7.3565	3.9149	12.1369	2.5387
	sumpatent	180	61.0056	0	917	169.0564

Note: This table shows the summary statistics of revealed comparative advantages and the control variables in the pilot area (treatment group) and non-pilot area (control group) separately.

Table 1 shows the descriptive statistics of the main variables. *lnRCA* is the natural log of the RCA index of each high-emission industry in each province or municipality per year. The number of observations is less after taking the natural log because the observations with 0 exports are eliminated. Overall, the average RCA in both groups is less than 1, which means that China does not have a comparative advantage in these high-emission industries in international trade. Meanwhile, the average level of industrial trade comparative advantage is higher in the pilot areas than in the non-pilot areas. This difference is not statistically significant at the 10% level by the *t*-test on the equality of the means (p=0.0414). However, whether this phenomenon is caused by the

ETS remains uncertain, so the parallel trend test and difference-in-difference regression should be conducted to figure this out. All the industrial-level control variables are taken log when used in the regression. All of these industrial production factors and the regional GDP per capita are higher in the pilot areas than in the non-pilot areas as well. This conforms to the fact that those selected areas are among the most developed areas with better administration, and abundant capital and technical resources. Therefore, it is not surprising that the average number of annually applied patents, which represents the technology innovation level, is higher in the pilot areas than in the non-pilot areas.

3.3 Model

Based on the natural experiment of ETS, the difference-in-difference model of industrial-level trade comparative advantage, $lnRCA_{ijt}$, for each province i and industry j in yearly period t is specified as

$$lnRCA_{ijt} = \beta_0 + \beta_1\, pilot_{ij} * time_t + \beta X_{ijt} + \varepsilon_{ijt} + v_t + u_i \qquad (1)$$

where the dependent variable $lnRCA_{ijt}$ is the natural log of the revealed comparative advantage index. $pilot_{ij}$ is the treatment of ETS, which equals 1 if the high-emission industry is in the pilot areas and equals 0 otherwise. $time_t$ is a dummy variable denoting the policy implementation, which equals 1 after 2013 and equals 0 otherwise. X_{ijt} is a vector of control variables for province i and high-emission industry j and in period t. u_i and v_t are provincial and year fixed effects and ε_{ijt} is a stochastic error term.

The coefficient of the interaction term, β_1, indicates the percent difference of the RCA index in the pilot areas compared to the RCA index in the non-pilot areas after the ETS began, on average, and holding other variables constant. If the sign of β_1 is positive, ETS will be said to promote trade comparative advantage of high-emission industries, which would be consistent with Porter's hypothesis. But if the sign of β_1 is negative, the constraint hypothesis will be justified.

4 Main Results

4.1 Test for Parallel Trends

It is essential for the industrial trade comparative advantage level in the pilot areas and the other areas to conform with the parallel trend assumption so that the difference-in-difference model is valid for the estimation of the treatment effect of ETS. Thus, the industrial trade comparative advantage level in the pilot areas must have a similar trend as that of the non-pilot areas before the policy was implemented. One typical approach to test the parallel trend is to construct a time trend variable and regress the interaction term of the time trend and treatment on the dependent variable during the periods prior to the implementation of the policy (Wang, Cao, & Ye, 2018). The value of the trend equals 1 in 2012 and adds 1 for the following year 2013. The regression is as follows:

$$lnRCA_{ijt} = \beta_0 + \beta_1\, pilot_{ij} * trend_t + \beta_2\, pilot_i + \beta_3\, trend_t + \beta X_{ijt} + \varepsilon_{ijt} + v_t + u_i \qquad (2)$$

where the coefficient of the interaction term $pilot_{ij} * trend_t$, β_1, should not be significant if the industrial trade comparative advantage level of the pilot areas and the non-pilot areas have a parallel trend before the ETS begins. The result shown in Table 2 confirms this assumption and can, thus, predict that both the control and treatment groups would perform parallelly in the post-treated period without the treatment group being treated. Additionally, the trends of RCA in both the pilot group and treatment group in 2012 and 2013 are parallel, as shown in Figure 1. Hence, the difference-in-difference model is appropriate to be used in this case.

Table 2. Parallel trend test

	(1) OLS	(2) FE
*pilot*trend*	-0.2468	-0.0712
	(0.5808)	(0.0837)
pilot	0.0547	
	(0.9248)	
trend	-0.1145	
	(0.2493)	
Controls	Y	Y
Province FE	N	Y
Year FE	N	Y
_cons	-5.0800***	-0.4585
	(1.2238)	(2.5803)
r2_a	0.3469	0.0225
F	20.0959	1.0990
N	194	194

Note: This table reports the result of the parallel trend test. Column (1) and (2) report the OLS estimation and fixed effects results with the control variables. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

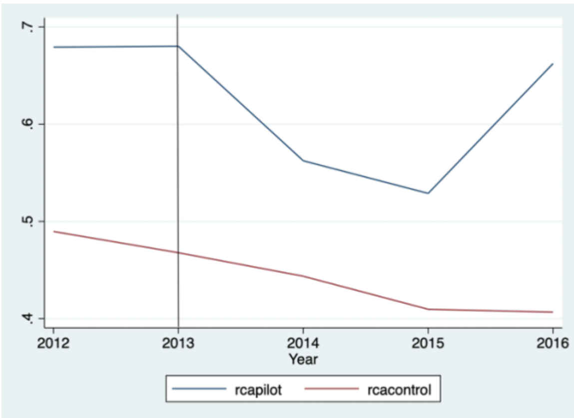

Figure 1. Parallel trends

4.2 Baseline Regression

Table 3 shows the result of the baseline regression. As shown in column (4), on average, the RCA index of the high-emission industry in the pilot areas is indeed 0.05 percent higher than that in the non-pilot areas after the ETS was implemented, holding other variables constant. The positive impact is extremely small in magnitude but statistically significant at a 1% level. This result generally does not conflict the Porter's Hypothesis that ETS as an environmental regulation, although could incur higher production costs for the high-emission industries, will not necessarily weaken its trade comparative advantage.

On the other hand, the extremely small magnitude of impact implies that a single policy has limited power to change the overall situation.

Table 3. Baseline regression

	(1) OLS	(2) OLS	(3) FE	(4) FE
*pilot*time*	0.0514	-0.1190	0.0006^{***}	0.0005^{***}
	(0.1049)	(0.1234)	(0.1234)	(0.0002)
pilot	-1.0e+02	239.1697		
	(211.1857)	(248.4671)		
time	-0.1103^{*}	-0.1873^{***}		
	(0.0650)	(0.0620)		
Controls	N	Y	N	Y
Province FE	N	N	Y	Y
Year FE	N	N	Y	Y
_cons	219.7736^{*}	370.6452^{***}	-2.6832^{***}	-0.8615
	(130.8757)	(124.7354)	(0.2079)	(0.8342)
r2_a	0.0296	0.3334		
F	12.7954	51.5539		
N	770	510	770	510

Note: This table reports the result of baseline regression. Column (1) and (2) reports the OLS estimation results without and with the control variables. Column (3) and (4) reports the estimation results without and with the control variables where the year fixed effect and provincial fixed effect are controlled. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

There are possible reasons that lead to this result. First, there could be bias caused by the endogeneity problems embedded in the selection process of the pilot area. As discussed in the previous section, all the statistics of the industrial and provincial level characteristics appear to be higher in the pilot area than in the non-pilot area. It is reasonable that all the pilot provinces and cities have abundant capital and production resources, vibrant markets, easier access to technology, and, most importantly, better regulatory administration. Thus, this is not a random selection. However, the result in the test on the equality of mean and the parallel pre-trends implies that this bias is not too significant to negate the estimate.

Second, unlike the previous literature which studies the impact of the overall stringency of environmental regulations on the trade comparative advantages, ETS is a single policy with limited impact, and the construction of the difference-in-difference model cannot reflect the precise stringency of the ETS in different pilot areas.

Last but not least, not all products in each high-emission industry are included in ETS at the beginning stage, and the detailed list is different province from province to some extent. So, aggregating all the commodities at an industrial level to calculate the RCA index of an industry is not very accurate. The impact of different products might not be great enough to be reflected at an industrial aggregate level.

In addition to the baseline regression in all the high-emission industries, Table 4 shows the estimation results of six industries each. The individual results of these industries are generally consistent with the main result at an aggregated level, while only the papermaking industry has a 1% statistically significant and moderately higher increase, that is 0.16%, in the RCA index after implementing the ETS compared to the prior period, on average and holding other variables constant. In other words, the papermaking industry is more influenced by carbon emission trading than other high-emission industries. This could be explained from one perspective, that is, firms in the papermaking industry tend to take risks by choosing illegal pollutant strategies if the profit is large when encountering environmental regulation (Zhang, Qin, Wang, Cheng,

& Tian, 2021). Thus, the papermaking industry is less likely to be negatively affected by the implementation of ETS.

Table 4. Regression by each industry

	(1) PC	(2) CH	(3) BM	(4) IS	(5) NFM	(6) PM
*pilot*time*	0.0009	0.0005	0.0002	0.0005	0.0002	0.0016***
	(0.0011)	(0.0003)	(0.0004)	(0.0005)	(0.0004)	(0.0007)
Controls	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
_cons	11.8941	-1.7361	3.0428	1.7805	-3.9361*	-2.3087
	(16.5219)	(1.4348)	(2.0774)	(2.4362)	(2.2334)	(3.9544)
N	35	134	96	96	95	51

Note: This table reports the regression result of each industry. Column (1), (2), (3), (4), (5), and (6) reports the fixed effects estimation results of the petrochemical industry (PC), the chemical industry (CH), the building materials industry (BM), the iron and steel industry (IS), the non-ferrous metal industry (NFM), and the papermaking industry (PM), respectively. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

5 Mechanism

Most current research believes that environmental regulations affect the comparative advantage in the form of cost effect and offset effect (Costantini & Mazzanti, 2012). The increase in the cost of emission control and trading could inhibit investment in R&D in the short term caused by the potential liquidity problem and thus reflected by the decrease in the innovation output. Another possible situation is that the policy could stimulate technology innovation, especially focusing on green technology which aims at reducing carbon emissions permanently saving money, and surviving in the long-run competition. Either of these is the case in the ETS problem remains uncertain.

On the other hand, as discussed when introducing R&D as a control variable, the improvement of technology level contributes to the promotion of productivity and thus positively affects the trade comparative advantage. The technology innovation is a further manifestation of the R&D investment. It emphasizes the output of research and development that reflects an effect of the combination of R&D input and the efficiency of technology transformation. Hence, unlike previous literature that directly examines the technology level by using the R&D expense and technology introduction (Liu & Xie, 2020), this paper uses the annual sum of the number of patent applications as the measurement. Therefore, it is meaningful to investigate the empirical evidence of this mechanism.

Intuitively, a higher level of R&D investment will prospectively lead to more innovation output. Thus, to eliminate this endogeneity problem caused by R&D (*lnrd*) and patent (*sumpatent*), first, construct a new fixed effects model of *lnRCA* without controlling *lnrd* to reexamine the impact of ETS on the trade comparative advantage.

$$lnRCA_{ijt} = \alpha_0 + \alpha_1\, pilot_{ij} * time_t + \alpha X_{ijt} + \varepsilon_{ijt} + v_t + u_i \qquad (3)$$

The regression result of Model (3) is expected to be consistent with the baseline result given that, from Table 3 column (3) and (4), the fixed effects model with and without the control variables deviates not much.

Then, the difference-in-difference model of industrial-level aggregated patents application, $sumpatent_{ijt}$, for each province i and industry j in yearly period t is specified as

$$sumpatent_{ijt} = \gamma_0 + \gamma_1\, pilot_{ij} * time_t + \gamma X_{ijt} + \varepsilon_{ijt} + v_t + u_i \qquad (4)$$

where the coefficient of the interaction term, γ_1, indicates the unit difference in the number of patents applied by a high-emission industry in the pilot areas compared to the non-pilot areas after the trading began, on average, and holding other variables constant. The sign of γ_1 is expected to be negative if the ETS inhibits the innovation activities and vice versa.

Lastly, Model (5) is a difference-in-difference model of the trade comparative advantage for each province i and industry j in yearly period t with industrial total applied patents as an explanatory variable.

$$lnRCA_{ijt} = \delta_0 + \delta_1\ pilot_{ij} *\ time_t + \delta_2 sumpatent_{ijt} + \delta X_{ijt} + \varepsilon_{ijt} + v_t + u_i \quad (5)$$

If the sign of δ_2 is positive, then the technology innovation is said to partially promote the trade comparative advantage, and vice versa. However, only if both γ_1 and δ_2 are statistically significant that the mechanism of technology innovation will be proved to be empirically valid.

Table 5. Mechanism of technology innovation

	(1) *lnRCA*	(2) *sumpatent*	(3) *lnRCA*
*pilot*time*	0.0005***	-0.0004	0.0005***
	(0.0002)	(0.0096)	(0.0002)
sumpatent			0.0002
			(0.001)
Controls	Y	Y	Y
Province FE	Y	Y	Y
Year FE	Y	Y	Y
_cons	-1.1652	-10.6594	-1.1730
	(0.7942)	(24.9739)	(0.7940)
N	770	916	770

Note: This table reports the results of the mechanism of technology innovation. The control variables are the same as in the baseline regression except for the exclusion of *lnrd*. Column (1) reports the fixed effects estimation with control variables of the effect of ETS policy on trade comparative advantage. Column (2) reports the fixed effects estimation with control variables of the effect of ETS policy on technology innovation. Column (3) reports the fixed effects estimation with control variables of ETS and the technology innovation impact on the revealed comparative advantage. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

Table 5 column (1) shows the new estimation of the effect of ETS policy on trade comparative advantage without controlling *lnrd*. The result is fully consistent with the baseline regression as expected. Table 5 column (2) shows the regression result of Model (4). On average, a high-emission industry in the pilot area applies for 0.0004 patents less than the high-emission industry in the non-pilot area, on average, and holding other variables constant. The amount of missing value of the total patents in the original sample is relatively large which could cause a large bias and result in this statistical insignificance. The number of listed firms in the high-emission industries is not large and the difficulty in accessing and matching the patent with industry information through these listed companies causing this data restriction. However, the result appears different when regressing Model (4) by each industry. Results in Table 7 show that only the building materials industry has an average less patent applications in the pilot area than the non-pilot area after ETS was implemented, the other 5 high-emission industries all have more patents applied in the pilot areas after the trading began. Among them, the non-ferrous metals industry in the pilot area applies for 0.0276 patents more than this industry in the non-pilot area, on average, and holding other variables constant. This result is significant at the 5% level. Chen and Lin (2020)'s study confirms that technology innovation plays the most important role in the improvement of carbon emission performances in the non-ferrous metals industry in China. Lin and Chen (2020) find that technological innovation has a mediating effect on environmental regulation and green development in China's non-ferrous metals industry which conforms to Porter's hypothesis. Combining the result with above empirical evidence, it is reasonable that the impact of ETS on technology innovation stands out in the non-ferrous metals industry. In addition, the extremely small amount of change might indicate the internal technology innovation of these high-emission industries is not affected by the ETS in the early stage of the policy implementation. In other words, there could be a lag in the response of innovation output to the policy as the research and development of technology takes up a relatively longer term. The result in Table 5 column (3) shows the regression result of Model (5). A unit increase of patent applications in a high-emission industry leads to a 0.0002 percent decrease in the RCA index of this industry, on average, and holding other variables constant. This result although, the sign of which implies a positive impact conforms to prior theory and empirical discoveries, is also insignificant and extremely small with the restriction of observations. Thus, the above results cannot support a mechanism through technology innovation empirically.

Table 6. Regression of technology innovation by each industry

	(1) PC	(2) CH	(3) BM	(4) IS	(5) NFM	(6) PM
*pilot*time*	0.0023	0.0020	-0.0026	0.0046	0.0276**	0.0056
	(0.0030)	(0.0271)	(0.0286)	(0.0313)	(0.0112)	(0.0060)
Controls	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
_cons	9.4624	-58.2605	-45.3267	-1.3e+02	-31.8219	0.0929
	(9.2762)	(110.4522)	(68.6897)	(138.0172)	(102.5356)	(7.6184)
N	150	155	155	154	150	152

Note: This table reports the regression result of technology innovation of each industry. Column (1), (2), (3), (4), (5), and (6) reports the fixed effects estimation results of the petrochemical industry (PC), the chemical industry (CH), the building materials industry (BM), the iron and steel industry (IS), the non-ferrous metal industry (NFM), and the papermaking industry (PM), respectively. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

6 Robustness Checks

6.1 Alternative measurement of trade comparative advantage

Despite the natural log of the RCA index used in the baseline regression, there are other indices widely used to measure trade comparative advantages. According to Laursen (2015)'s study, there is an alternative measurement of trade comparative advantages that also eliminates the asymmetry problem of the RCA index other than the natural log of the RCA index. The revealed symmetric comparative advantage (RSCA) index equals (RCA-1)/(RCA+1) which neutralizes the value around 1 that precisely reflects the industrial specialization. The number of observations used in this robustness check regression is more than in the baseline regression because the observations with export equal to 0 could have an RSCA value while invalid under the natural log measurement. Therefore, this paper uses RSCA as an alternative measurement of the dependent variable to test the robustness of the main result. The result in Table 7 column (4) shows a weak positive policy impact, though it is insignificant. However, this result does not contradict the main conclusion.

Table 7. Regression with alternative measurement RSCA

	(1) OLS	(2) OLS	(3) FE	(4) FE
*pilot*time*	0.0026	-0.0472	0.0001*	0.0001
	(0.0281)	(0.0388)	(0.0000)	(0.0001)
pilot	-5.0998	94.9085		
	(56.5885)	(78.0852)		
time	-0.0121	-0.0471***		
	(0.0118)	(0.0128)		
Controls	N	Y	N	Y
Province FE	N	N	Y	Y
Year FE	N	N	Y	Y
_cons	23.6539	93.0855***	-0.6609***	-0.7103***
	(23.8417)	(25.6813)	(0.0366)	(0.1727)
r2_a	0.0124	0.3301		
F	4.6606	49.9437		
N	919	543	919	543

Note: This table reports the result of regression with alternative measurement *RSCA*. Column (1) and (2) reports the OLS estimation results without and with the control variables. Column (3) and (4) reports the estimation results without and with the control variables where the year fixed effect and provincial fixed effect are controlled. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

6.2 Exclusion of Fujian Province

In the baseline regression, Fujian province, as it started trading years after other pilot provinces and cities in mid-2016, is not included in the treatment group, but in the control group. Then, to enhance the robustness of the baseline result, Fujian province is removed from the sample. The result in Table 8 is consistent with the baseline regression result which also implies that the ETS impact on Fujian is too weak to influence the overall result. The robustness of baseline regression is confirmed in this case.

Table 8. Regression without Fujian province

	(1) OLS	(2) OLS	(3) FE	(4) FE
*pilot*time*	0.0622	-0.1209	0.0006***	0.0006***
	(0.1062)	(0.1242)	(0.0002)	(0.0002)
pilot	-1.2e+02	243.1633		
	(213.8820)	(250.2385)		
time	-0.1211*	-0.1801***		
	(0.0671)	(0.0646)		
Controls	N	Y	N	Y
Province FE	N	N	Y	Y
Year FE	N	N	Y	Y
_cons	241.5710*	355.9332***	-2.7489***	-0.9819
	(135.1618)	(130.0567)	(0.2143)	(0.8669)
r2_a	0.0345	0.3364		
F	14.1024	51.5317		
N	740	485	740	485

Note: This table reports the result of regression without Fujian province. Column (1) and (2) reports the OLS estimation results without and with the control variables. Column (3) and (4) reports the estimation results without and with the control variables where the year fixed effect and provincial fixed effect are controlled. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

6.3 PSM-DID

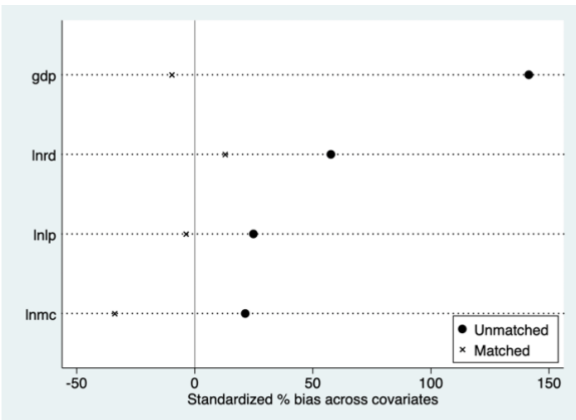

Figure 2. Propensity score matching result

Table 9. PSM-DID

	(1) OLS	(2) OLS	(3) FE	(4) FE
*pilot*year*	0.0253	-0.1697	0.0810	0.0083
	(0.0976)	(0.1169)	(0.0711)	(0.1110)
pilot	-50.0145	341.3186		
	(196.5382)	(235.3790)		
year	-0.2815	-0.4445***		
	(0.1752)	(0.1665)		
Controls	N	Y	N	Y
Province FE	N	N	Y	Y
Year FE	N	N	Y	Y
_cons	-2.1854***	-6.1617***	-48.1693	-11.2229
	(0.1353)	(0.8120)	(40.0411)	(84.9269)
r2_a	0.0289	0.3301	0.0289	0.1727
F	12.8439	51.0307	1.5358	1.7001
N	770	510	325	72

Note: This table reports the result of PSM-DID regression. Column (1) and (2) reports the OLS estimation results without and with the control variables. Column (3) and (4) reports the estimation results without and with the control variables where the year fixed effect and provincial fixed effect are controlled. Robust standard errors are reported in parentheses. ***, **, and * respectively denote the statistical significance of a two-tailed test at the 1%, 5%, and 10% level.

The propensity score matching method is adopted to eliminate the bias caused by the significant differences in corporate characteristics between those in the non-pilot areas and the pilot areas (Heckman, Ichimura, & Todd, 1998). The covariates used in predicting the propensity scores are all control variables that reflect the industrial production characteristics and GDP per capita. According to Figure 2, the propensity score matching generates a better-matched control group which could provide better counterfactual outcomes for the treatment group. By regressing with the matched sample, the result shown in Table 9, although it is still positive, the magnitude of the coefficient is greater than the baseline result and is not significant. The inconsistency is very likely caused by the sharply reduced number of observations due to the propensity score matching process. However, this result generally does not contradict the conclusion of the very weak positive and nearly no impact of ETS on the trade comparative advantage of the high-emission industries.

7 Conclusion

Aiming at peaking and neutralizing carbon emissions, the Chinese government began implementing a Carbon Emission Trading Scheme (ETS) in 7 pilot provinces and cities in 2013. Using the industrial-level data from 2012 to 2016 in 32 provinces and municipalities in China, this study investigates the impact of ETS on the industrial-level trade comparative advantage of the high-emission industries. The difference-in-difference regression result shows that the ETS has a very weak positive impact on the trade comparative advantage of these high-emission industries which supports Porter's hypothesis. The main result is fairly robust and is not contradicted by the robustness checks. Additionally, this paper discusses the possible mechanism of the ETS impact through technology innovation. However, the empirical result is insignificant and cannot solidly support the theoretical explanations mainly due to the limitation of data. Above all, the conclusion of this study shows that the ETS does not threaten the trade comparative advantage of those high-emission industries. Therefore, it should not become a primary concern when promoting this policy nationwide and in more industries. However, due to the limitation of data, the result generated from a short period does not necessarily reflect the long-term impact. Thus, it is still worth further analyzing with more comprehensive data and a longer time range.

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