Effect of China's Carbon Emission Trading Scheme on Innovation

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Abstract

This paper investigates the impact of China's pilot for carbon emission trading schemes on innovation. Using number of patents as a proxy variable for innovation, I analyze firms' reactions to the implementation of the ETS pilots using the "propensity score matching difference in difference" approach. The results show that the ETS pilot has negative and statistically significant effect on firms' invention and utility patents,and the negative effect on number of utility patents is greater than on invention patents. Additionally, the impact of ETS pilots on different types of firms are heterogenous. For larger and private firms, the negative impact of the ETS pilot is greater than on small-scaled and government-owned firms.

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Section 1: Introduction

Human industrial activities are affecting greenhouse gas levels. According to the Fifth Assessment Report of Intergovernmental Panel on Climate Change, there is a 95 percent possibility that human-produced greenhouse gasses such as carbon dioxide, methane and nitrous oxide have caused much of the observed increase in Earth's temperatures over the past 50-plus years. And over the last century the burning of fossil fuels such as coal and oil has raised the concentration of atmospheric carbon dioxide from 280 parts per million to about 417 parts per million. Global climate change has already had observable effects on the environment. Glaciers have shrunk, ice on rivers and lakes is breaking up earlier, plant and animal ranges have shifted and trees are flowering sooner.

In recent years, countries have also been trying or considering using market-based means to reduce carbon dioxide emissions. For example, the European Union has established the European Union Emissions Trading System (EU ETS), and the United States has Regional Greenhouse Gas Initiatives (RGGI). Managing and reducing the intensity of national emissions became the basis for China’s mitigation pledges under the Global Climate Mitigation Frameworks. For example, in 2009, Premier Wen Jiabao solemnly pledged at the Copenhagen World Climate Conference to reduce carbon dioxide emissions per unit of GDP by 40 to 45 percent from 2005 levels by the year 2020. In May 2011, China proposed the *Twelfth Five-Year Plan* to gradually establish a carbon emissions trading market. The *Twelfth Five-Year Plan for Controlling Greenhouse Gas Emissions* established "innovative regional low-carbon development pilot demonstrations" and mentioned the future implementation of the "construction and operation of a national carbon emissions trading market", which indicates that China's ETS would gradually be piloted at the local level and then implemented nationwide. Leading up to the Paris Agreement in 2015, China updated its emissions intensity reduction commitment to 60–65 percent by 2030 and announced a fresh pledge to emission peak by 2030—albeit without specifying its level.

China's carbon emission trading market was first established as several pilots. In 2011, it was announced that there would be carbon emission trading pilots in seven provinces and cities, which are Beijing, Tianjin, Chongqing, Guangdong, Hubei, Shanghai and Shenzhen. The carbon trading pilots span northern China, central and western China and the southern coastal areas, covering a land area of 480,000 square kilometers, a population of 199 million, a total GDP of 1.85 trillion dollars, and an energy consumption of 762 million tons of standard coal. In 2013, this accounted nationally for 18% of the population, 30% of the GDP and 23% of energy consumption. In 2013 and 2014, these ETS pilots gradually officially launched, and in July 2021, the national carbon emission trading market was launched. As of December 31, 2021, the national carbon market has been running for 114 trading days, the cumulative trading volume of carbon emission allowances is 179 million tons, and the cumulative trading volume is 1.197 billion dollars, which accounted for 0.0067% of GDP in 2021.

As the primary productive driver of economic development, technological innovation is not only the core engine for economic growth, but also a key element in controlling environmental pollution and protecting the ecological environment. Under the carbon emission market, firms face the increase of production cost. Some may choose to invest more on technological innovations, which may improve the firm's productivity and offset the cost caused by environmental regulation. This is called the Porter Hypothesis. To identify whether China's carbon emission trading scheme follows this Porter Hypothesis, I investigated the impact of China's carbon emission trading pilot on innovation. Since there is limited data available for China's national carbon emission market, I choose to review the impact of pilots, which have been launched for more than 9 years now.

This paper used the PSM-DID method to alleviate the impact of endogeneity and try to identify if the effect of ETS on state-owned firms and private firms is heterogenous. The process of this approach is as follows:

First, through logit regression, for each company included in the policy I search for companies in the control group with similar propensity scores (that is, similar likelihood of being included in the policy based on the set guidelines the province used to choose companies for their pilots), to remove the original selection bias of the policy. This ensures that the processing group and control group companies are as similar as possible to meet the common trend assumption of DID. Then I calculate the change in outcome variable of each company before and after the launch of Carbon ETS, for both the companies in the pilot and their corresponding companies in the control group. The average treatment effect on the treated (ATT) is the difference between the change of companies included in the pilots and the change of companies excluded in the pilots.

Based on this, this paper uses the Propensity Score Matching-Difference in Differences method and the firm-level characteristics data from 2006 to 2020 to identify the effect of Carbon Emission Trading Scheme on innovation. The results show that the ETS pilot has a negative and statistically significant effect on firms' utility patent and invention patent numbers, with a greater impact on utility patents. Also, the impact of the ETS pilots on different types of firms are heterogenous. For larger and private firms, the negative impact of ETS pilot is greater than small-scaled and government-owned firms.

The contributions of this paper are as follows. First, current research is mostly focused on the country or sector level of environmental regulation, whereas here I examine firm level impact of ETS. Second, the identification of innovation. This paper used the "International Patent Classification Green List" launched by WIPO to divide the patents into seven categories.

Additionally, I also used the classification of patents by the Chinese Patent Office, which grants three types of patents: invention, utility, and design patents. Finally, the paper uses the PSM-DID method, an up-to-date method which helps solve the endogeneity problem and identify causality.

The remainder of this paper is organized as follows. Section 2 introduces the institutional background and policy setting, and also introduces literature review. Then, Section 3 introduces the data and the research methodology used, and Section 4 presents the empirical results and analysis. Section 5 focuses on heterogeneity and robustness tests. Finally, Section 6 provides conclusions and limitations.

Section 2: Background and Literature Review

China's carbon emission trading market was first established at a local level. On October 29, 2011, China's National Development and Reform Commission issued a "Notice on Carrying out the Carbon Emissions rights Trading Pilot Work" and announced plans for a pilot for carbon trading, selecting seven regions to launch this policy experiment. In 2013 and 2014, these carbon emission trading pilots were rolled out successively.

The seven regions span Northern China, Central and Western China and the Southern coastal areas, and the economic development of different regions are diverse, so it is not surprising that the policy settings in each region are also region-specific. For example, the Hubei pilot focuses on market liquidity, while the Shenzhen pilot is more market performance oriented. The standards for selecting the companies in the pilot also differ between regions. In the Guangdong pilot, companies in electricity, cement, steel, petrochemical, and non-ferrous or paper industries and whose yearly carbon emission exceeds 20 thousand tons in any year between 2011 and 2014 are included in the pilot, but in the Shanghai pilot, the time period is limited to 2010 or 2011 for the above criteria. Overall however, most of the companies included in the pilots are large volume and are from heavy industry where their yearly carbon emission is 5 thousand tons or more, depending on the pilot (the Hubei province even has a minimum limit of 60 thousand tons in one year, which is a very high emission amount) . Therefore, China's pilot ETS mainly encompassed listed companies in the major high-carbon industries in the pilot areas.

The operation mode of the ETS has three steps. Step 1 is the determination of the free allocation quota. The government will investigate the historical emissions of regulated enterprises and then calculate the free quota for them, the amount of carbon they are allowed to release without paying. In step 2, free quotas will be issued to regulated enterprises in the pilot prior to the opening of the market. Then enterprises can purchase or sell quotas in the carbon emission trading market through carbon exchanges in step 3. To complete the quota settlement obligation implemented in the program, enterprises must own quotas equal to their amount of carbon emissions.

Reasonable environmental regulations can stimulate firm technological innovation, and the cost of compliance can be made up with product quality improvements from the extra innovation (Porter et al, 1995). This is called the "Porter Hypothesis". Jaffe and Palmer (1997) state three different Porter Hypotheses to avoid ambiguity. The narrow version of the hypothesis is that certain types of environmental regulation stimulate innovation. The "weak" version of the hypothesis is that environmental regulation places constraints on the profit opportunities of firms that were not there before. And the "strong" version of the hypothesis is that firms under normal operating circumstances do not necessarily find or pursue all profitable opportunities for new products or processes. Lanioe et al (2007) uses OECD databases and found strong support for the "weak" version, qualified support for the "narrow" version, and qualified support for the "strong" version as well.

The empirical analysis of emissions trading schemes sometimes has controversial results. Schmidt et al. (2012) found that EU ETS had limited effects on the rate and direction of corporate research, development, and demonstration as well as technology adoption, but long-term emission reduction targets are still an important determinant of corporate innovation activities. Qi and Zhang (2019) found that EU ETS significantly promotes renewable energy technological innovation in member countries. Calel (2012) found evidence that the EU ETS accounts for nearly a 1% increase in European low-carbon patenting compared to a counterfactual scenario.

To reduce the carbon emissions and reach the goal of carbon-neutral by around 2060, China also launched seven regional pilots of carbon emission trading schemes from 2013. And in 2020, the national carbon emission trading scheme is established. The ETS naturally created a pre-policy and post-policy comparison, and considering the accessibility of data, this paper analyzes the impact of China's pilot carbon emission trading scheme on firm innovation.

Similar to analysis on EU ETS, papers on China's carbon emission trading scheme also present diverse results. There are papers supporting the Porter Hypothesis, whose results show that China's Carbon Emission Trading Scheme is predicted to have a positive impact on the low carbon innovation of enterprises, and that there exists firm heterogeneity (Qi et al, 2021; Hu et al, 2020; Cui et al, 2017). But Chen et al (2021) and Lu et al (2019) explore the "weak" version of the Porter hypothesis. Based on green patent data, they found limited evidence of any influence of China's carbon emission trading scheme pilot policy on green innovation.

Section 3: Data and Empirical Strategy

To identify the effect of the pilot carbon emission trading scheme on innovation, I collected the initial data including all publicly listed firms in mainland China from 2006 to 2020. The economic characteristic data of listed companies is from Wind Database, and the patent data come from China’s National Knowledge Infrastructure (CNKI). The following is the process of dealing with the raw data.

First, the ETS pilot mainly covers eight industries, including electricity, architecture, aviation, chemical, building materials, paper, steel and petrochemical. In this paper, I only choose listed firms in these industries. Firms from the seven pilots including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong and Shenzhen are in the treatment groups. Firms in other provinces are in the control groups. Next, the initial data is from 2006 to 2020. For firms founded in this period, there will not be any data before establishment. Therefore, the panel data used in this paper is unbalanced. In the end, a total of 761 listed firms, together with 4933 observations are included in the model.

Technological innovation is intangible, thus it is difficult to estimate its change analytically. One way to measure innovation is through a proxy indicator, i.e., patents. In 2010, The World Intellectual Property Organization (WIPO) launched an online tool designed to facilitate the retrieval of patent information related to environmentally friendly technologies, the "International Patent Classification Green List", which is based on the "United Nations Framework Convention on Climate Change" for green patents. Seven major categories were developed: transportation, waste management, energy conservation, alternative energy production, administrative regulation or design aspects, agriculture or forestry and nuclear power generation. Besides the seven categories of patents, I also focus on invention patents versus utility patents. Compared with invention patents, utility patents don’t contain higher technological advances and may not require long-term R&D investment.

The control variables in this study are mainly enterprise-level economic characteristics. Firstly, it is necessary to control the company size because the innovation level can be influenced by scale expansion. Compared to a small company, a large company can invest more on research and development, thus having a higher innovation level. In this study, I use the natural logarithm of the company's total asset and total number of employees to measure the firm size. Other control variables are return on equity and return on asset, which measure the profitability of an enterprise, as well as firm attributes. Firm attributes are divided into two categories. The compared group in the regression is "government-owned enterprise", which includes stated-owned enterprise, central enterprises and public enterprise. The other group is "private enterprise".

$$Patent_{i,j,t} = \alpha_{i,j,t} + \beta \cdot Post_{i,t} \cdot Treat_{i,j} + \gamma_1 \cdot Control_{i,j,t} + u_j + v_t + \varepsilon_{i,j,t}$$

Where the subscripts i, j and k stand for the firm, province and year, respectively. $Patent_{i,j,t}$ is the patent number of firm i located in province j in year t. $Post_{i,t}$ is a time variable and binary variable, which equals 1 if it is after 2014, and equals 0 if it is before 2014. $Treat_{i,j}$ is a policy variable and a binary variable, which equals 1 if firm i is in one of the seven pilots, i.e., the firm is in the treatment group, and equals 0 if firm i is in other provinces. $Control_{i,j,t}$ is a matrix containing the firm size, firm attribute, return on equity (ROE), return on assets (ROA), log of total assets and log of the number of employees. Because the patent number of enterprise varies between provinces and years, I need to control for province fixed effect as well as time fixed effect, which are u_j, v_t in the equation, respectively. $\varepsilon_{i,j,t}$ represents a disturbance term.

β is the coefficient of interest in this study, which represents how much this emission trading pilot affects innovation on average, holding other variables constant.

Table 1 shows the definition of the main variables, and Table 2 shows the descriptive statistics of the main variables. From Table 2, the mean of utility patents and invention patents of 761 listed firms in 2006-2020 are 0.49 and 0.33, respectively. The statistics for seven green patents classified by WIPO are also listed in Table 2. The mean of energy conservation, waste management, alternative energy production patents and transportation patents are successively declined, which are 0.38, 0.16, 0.13 and 0.09 respectively. The mean of administrative regulation or design aspects, agriculture or forestry and nuclear power generation patents are pretty small. And the maximum value of agriculture or forestry patents and nuclear power generation patents are 8 and 7, respectively.

Section 4: Regression Result

4.1 Propensity Score Matching

This paper uses a nearest neighbor within-caliper matching strategy to 1:2 match the samples of the treatment group and the control group. Matching to the nearest neighbor consists of simply finding the untreated observation with the closest propensity score to the propensity score of each treated observation. A caliper for matching is a maximum distance within which matches are allowed, and this paper used a caliper of 0.25 standard deviations of the logit of the propensity score.

First, because the data I used is panel data from 2006-2020, I used logit models to find comparable control groups for the treatment groups in each year. The variables used during matching period including sectors that firms belong to. And then I appended the matched samples of each year together and got the final data samples. Table 3 shows the PSM Logit regression results of the sample in 2014. Graph 1 shows the bias across covariates in 2014 for utility patents after matching. As shown in the graph, the deviation of the control group and the treatment group before and after matching was significantly reduced. In the case of good matching quality, the deviation should be reduced to within 10%. The percent bias of all covariates are less than 10%, and all are significantly smaller than the percent bias before matching. From Graph 2, it is clear that the distribution of treated and untreated groups in 2014 for utility patents after matching are consistent and are within the common value range.

I also examined whether there is a difference between the two groups of propensity score values before and after matching, which is visualized using the kernel density maps as shown in Graph 3 and 4. If the deviation of the nuclear density curves between the two groups before matching is relatively large, and the nuclear density curves after matching are relatively close, it means that the matching effect is good. As can be seen from Graph 3 and 4, the deviation of the two kernel density curves before and after matching is large, but the two curves are closer after matching, which can be seen from the reduction of the mean distance. The mean distance is measured by the distance between the two vertical lines. The navy line perpendicular to the horizontal axis in the figure is the sample of the treatment group mean line of propensity score values, the maroon line is the mean line for the control group. Therefore, to a certain extent, it can be shown that the matching is effective and has good matching quality.

4.2 Difference-in-Differences Results

Table 4 shows the estimation results of the effect of the carbon emission trading scheme pilot on the green patents. The results from column (1) to (9) are based on different dependent variables under fixed effects. The estimated coefficients of the interaction terms of interest are negative and statistically significant at 5% for utility patents, invention patents and energy conservation patents. But the estimated coefficients for other green patents, such as nuclear generation patent and administrative patent, are not statistically significant. Column (1) in Table 4 implies that the emission trading scheme pilot has reduced the utility patent by 0.5358 on average. Column (2) in Table 4 implies that the emission trading scheme pilot has reduced the invention patent by 0.5046 on average. So the ETS pilot has a larger effect on utility patents than on invention patents.

Overall, the regression results refute the Porter hypothesis, which implies that proper environmental regulation can trigger innovation, which will result in more efficient production (Porter and van der Linde 1995). This could be partly explained by the fact that the empirical findings also show that the estimated effect of environmental regulation is quite inconsistent, and it varies when the regulation, industry, estimation approach or timespan is different (Ambec et al. 2013, Galeotti, Marzio, et al. 2014). Other research focusing on the impact of the ETS pilot on innovation also has inconsistent results. For example, Hu et al. (2020) find that the CETS has a positive effect on the innovation quantity and the innovation quality using data from 2006-2016. And Z. Chen et al. (2021) found that the ETS pilot policy significantly decreased the proportion of green patents of enterprises by 9.3%. The findings in this paper also added to the empirical literature by providing evidence of the negative effect of ETS on innovation.

4.3 Parallel Trend Assumption

One of the assumptions of the Difference in Difference method is Parallel Trend assumption, which requires that in the absence of treatment, the difference between the treatment and control group is constant over time. Graph 5 shows the parallel trends. Before 2014, the trends of treatment and control groups for patents are consistent, and the levels of patents are basically the same. After 2014, the number of patents increased in the control group, while the trend for the treatment group flattened. Overall, it is shown in the graph that the difference between the treatment and control group before treatment is constant over time.

Section 5: Heterogeneity and robustness test

The above regression results show that the carbon emission trading scheme pilot has significant impact on innovation. But is the impact on innovation different among enterprises of different nature, such as company attributes and sizes? Becker et al. (2013) find that firms’ responses to environmental regulation vary by firm types and spending on pollution abatement operating costs per unit of output increases with establishment size. To further explore the impact of the ETS, I divided enterprises based on their nature and ran several sub-sample regressions. The estimated results are in Table 5 and 6.

Table 5 shows the estimation result of sub-sample regression for small-scaled and large-scaled enterprises. The dependent variables for the first two columns and last two columns are utility patents and invention patents, respectively. The effect of ETS pilot on utility patents of small-scaled enterprises is statistically insignificant. And the effect of ETS pilot on utility patent and invention patent of large-scaled enterprises is negative and statistically significant at 5% level. Compared to utility patents, the effect of ETS on utility patents is deeper, resulting in reduction by -0.5493. The reason for this heterogeneity effect of ETS could be that the pollution abatement operating costs per unit of output increases with the firm size. Therefore, a large-scaled enterprise faces a higher pollution abatement cost due to the environmental regulation than a small-scaled enterprise.

Table 6 shows the estimation result of sub-sample regression for government-owned and private enterprises. The dependent variables for the first two columns and last two columns are utility patents and invention patenst, respectively. The effect of the ETS pilot on utility patents and invention patents of government-owned enterprises are heterogenous. For utility patents, the effect on government-owned enterprises is negative but statistically insignificant at 5% level, while its effect on the invention patents of government-owned enterprises is negative and statistically significant at 5% level. The effect of the ETS pilot on utility patents and invention patents of private enterprises is negative and statistically significant at 5% level. Compared to government-owned firms, the effect of ETS on utility patents of private firms is deeper, resulting in reduction by -0.9844. The reason for this heterogeneity effect of ETS on different types of firms could be that the government-owned firms have lower pollution cost abatement than private firms due to the natural attribute.

Then I conducted a placebo test as the robustness test on the main regression results. First, I excluded the data from 2013 to 2020 in the model, and then took 2009 as the starting time of the carbon emission trading scheme pilot. Second, I repeated the process of PSM-DID method estimation and got the results of the robustness test in Table 7. The estimated coefficients of interest become insignificant at 10% level for utility patent and invention patent. Therefore, it passed the robustness test.

Section 6: Conclusion

In 2013 to 2014, China's carbon emission trading scheme pilot was officially launched, aiming at achieving emission peak by 2030 and carbon neutrality by 2060. Using this ETS pilot as a quasi-natural experiment, I construct a PSM-DID framework to investigate the impact of China's carbon emission trading scheme pilot on innovation. Using patents as a proxy variable for innovation, I found that the results didn't support the Porter Hypothesis. The results show that the ETS pilot has a negative and statistically significant effect on firms' utility patent and invention patent. And the negative effect on utility patents is greater than invention patents. Besides this, the impact of ETS pilots on different types of firms are heterogeneous. For larger and private firms, the negative impact of ETS pilot is greater than small-scaled and government-owned firms.

This is against the Porter hypothesis, which implies that proper environmental regulation can trigger innovation, which will result in more efficient production. (Porter and van der Linde 1995). The empirical findings of other papers also show that the estimated effect of environmental regulation is quite inconsistent, and it varies when the regulations, industry, estimation approach or timespan is different (Ambec et al. 2013, Galeotti, Marzio, et al. 2014). Using data from 2006-2016, Hu et al. (2020) found that the CETS has a positive effect on the innovation quantity and quality. Z. Chen et al. (2021) found that the ETS pilot policy significantly decreased the proportion of green patents of enterprises by 9.3%. The findings in this paper added to the empirical literature by providing evidence of the negative effect of ETS on innovation.

Based on the above findings, the carbon emissions trading market established to reduce carbon emissions affects the development of enterprises to a certain extent. From the affected performance of different enterprises, private and large-scaled enterprises should further strengthen emission performance management, optimize the incentive mechanism, and promote technological innovation in reducing carbon emissions. On the road of carbon emission reduction and carbon trading market, China still needs to continue to explore and balance the relationship between ecology and development, and find a sustainable development path.

There are still some shortcomings in this paper. First, the mechanism is unclear. Due to the lack of trading information about the participation of specific enterprises in the carbon market, the mechanism by which policies affect innovation cannot be further explored. Secondly, there are many control variables at the enterprise level, but too few control variables at the city level, resulting in unbalanced variables after matching, and there may be some endogeneity problems.

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Appendix

Table 1 Definition of main variables

Classification	Variable	Definition
	Treat	1 if firms are included in ETS, 0 otherwise
	Post	1 if after policy, 0 if before policy
Control Variables	firm_size	1 if firm size is small, 2 if middle, 3 if large
	firm_attr	0 if Public enterprise, 1 if Private Enterprise
	ROE	Return on Equity
	ROA	Return on Asset
	lasset	Log form of Total Asset in millions
	lemployee	Log form of the number of employees
	period	Period of existence
Dependent Variables	Engy_prod_pat	Alternative energy production patent
	Transport_pat	Transportation Patent
	Engy_conser_pat	Energy Conservation Patent
	Waste_manag_pat	Waste Management Patent
	Agri_pat	Agriculture/Forest Patent
	Adminis_gen_pat	Administrative, Regulatory or Design Patent
	Nuclear_pat	Nuclear Power Generation Patent
	Invention_pat	Invention Patent
	Utility_pat	Utility Patent

Table 2 Descriptive statistics of main variables

Variable	Observations	Mean	SD	Min	Max
Treat	4933.00	0.47	0.50	0.00	1.00
Post	4933.00	0.25	0.43	0.00	1.00
period	4933.00	2.79	0.44	1.00	3.00
Firm size	4933.00	0.45	0.50	0.00	1.00
Firm attributes	4933.00	9.46	7.00	0.00	28.00
Return on Equity	4933.00	9.67	9.39	0.00	188.30
Return on Asset	4933.00	7.05	5.57	0.02	165.13
$ln(asset)$	4933.00	8.56	1.49	2.37	14.82
$ln(employee)$	4933.00	7.69	1.42	0.00	13.22
Energy Conservation Patent	4933.00	0.13	1.67	0.00	86.00
Transportation Patent	4933.00	0.09	0.78	0.00	24.00
Energy Conservation Patent	4933.00	0.38	3.62	0.00	109.00
Waste Management Patent	4933.00	0.16	1.57	0.00	69.00
Agriculture/Forest Patent	4933.00	0.01	0.18	0.00	8.00
Administrative, Regulatory or Design Patent	4933.00	0.03	0.51	0.00	19.00
Nuclear Power Generation Patent	4933.00	0.02	0.22	0.00	7.00
Invention Patent	4933.00	0.33	3.22	0.00	101.00
Utility Patent	4933.00	0.49	3.55	0.00	131.00

Table 3 PSM Logit Regression Results of sample in 2014

VARIABLES	Coefficient	Standard Error	Z-value	P-value
Return on Equity	0.060***	0.018	3.36	0.001
Return on Asset	-0.067**	0.026	-2.55	0.011
$ln(asset)$	0.010	0.041	0.23	0.816
$ln(employee)$	-0.007	0.037	-0.19	0.847
period	-0.023*	0.013	-1.83	0.067
Constant	-0.385*	0.223	-1.73	0.085

*** p<0.01, ** p<0.05, * p<0.1

Pseudo R^2 = 0.0245, Log likelihood = -535.32263

Table 4 Regression Result of PSM-DID

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Utility patent	Invention patent	Energy production patent	Transportation patent	Energy conservation patent	Waste management patent	Agriculture patent	Administrative patent	Nuclear Generation patent
Post*Treat	-0.5358***	-0.5046***	-0.2608***	-0.0392	-0.5864***	-0.1094	-0.0158*	-0.0246	-0.0092
	(0.164)	(0.157)	(0.082)	(0.038)	(0.170)	(0.081)	(0.009)	(0.024)	(0.013)
ROE	-0.0028	-0.0004	-0.0010	0.0001	-0.0010	-0.0002	0.0001	-0.0008	-0.0003
	(0.006)	(0.006)	(0.003)	(0.001)	(0.006)	(0.003)	(0.000)	(0.001)	(0.000)
ROA	0.0091	-0.0038	-0.0000	0.0008	0.0046	0.0017	-0.0001	-0.0016	0.0003
	(0.010)	(0.010)	(0.005)	(0.002)	(0.011)	(0.005)	(0.001)	(0.002)	(0.001)
$ln(asset)$	-0.1397	-0.1260	-0.0242	-0.0093	-0.1845*	-0.0489	0.0045	-0.0023	-0.0073
	(0.094)	(0.090)	(0.047)	(0.022)	(0.098)	(0.047)	(0.005)	(0.014)	(0.007)
$ln(employee)$	0.1126	-0.0068	0.0382	-0.0161	0.0431	0.0583	0.0025	-0.0207*	0.0024
	(0.073)	(0.069)	(0.036)	(0.017)	(0.075)	(0.036)	(0.004)	(0.011)	(0.006)
period	0.0825***	0.0718***	0.0220**	0.0146***	0.0785***	0.0300***	0.0025**	0.0043	0.0034**
	(0.022)	(0.021)	(0.011)	(0.005)	(0.023)	(0.011)	(0.001)	(0.003)	(0.002)
Constant	0.0934	0.9184	-0.0735	0.1369	0.9108	-0.0870	-0.0858**	0.1991**	0.0409
	(0.695)	(0.665)	(0.346)	(0.162)	(0.718)	(0.344)	(0.037)	(0.101)	(0.054)
Observations	4,933	4,933	4,933	4,933	4,933	4,933	4,933	4,933	4,933
R-squared	0.017	0.013	0.011	0.008	0.013	0.010	0.007	0.006	0.004
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of stockcode	761	761	761	761	761	761	761	761	761

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Heterogeneity effect of different types of companies: firm size

	Utility patent		Invention patent	
VARIABLES	Small-scaled	Large-scaled	Small-scaled	Large-scaled
Post*Treat	-0.4101	-0.5493***	-1.1039*	-0.4119***
	(0.250)	(0.190)	(0.607)	(0.147)
ROE	-0.0070	-0.0068	-0.0077	0.0035
	(0.005)	(0.009)	(0.013)	(0.007)
ROA	-0.0040	0.0264	-0.0052	-0.0050
	(0.008)	(0.018)	(0.019)	(0.014)
$ln(asset)$	-0.1921	-0.1540	-0.2527	-0.1190
	(0.145)	(0.112)	(0.351)	(0.087)
$ln(employee)$	0.0401	0.1482*	0.1369	-0.0231
	(0.092)	(0.089)	(0.225)	(0.069)
period	0.1104***	0.0793***	0.1140	0.0652***
	(0.031)	(0.026)	(0.074)	(0.020)
Constant	0.8392	-0.1218	1.3289	0.9017
	(1.025)	(0.859)	(2.493)	(0.665)
Observations	951	3,982	951	3,982
R-squared	0.056	0.017	0.029	0.013
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes
Number of stockcode	209	552	209	552

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Heterogeneity effect of different types of companies: firm attributes

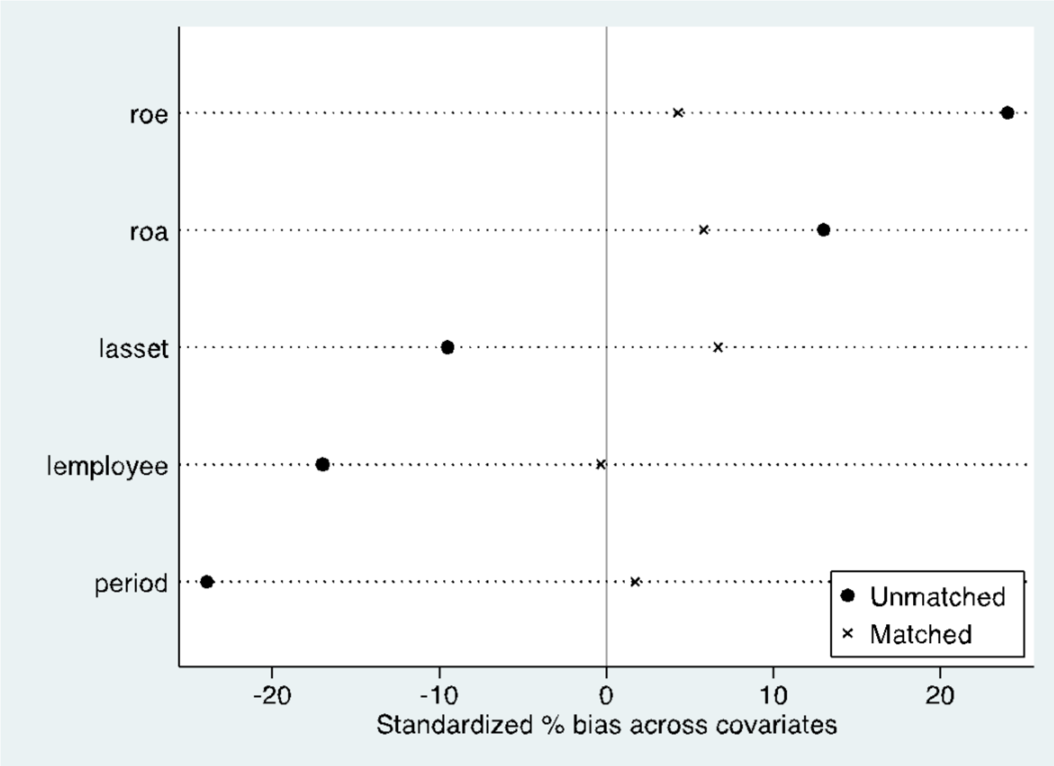
	Utility patent		Invention patent	
VARIABLES	Government-owned	Private Firm	Government-owned	Private Firm
Post*Treat	-0.2295*	-0.9844***	-0.4426**	-0.5737**
	(0.120)	(0.363)	(0.203)	(0.252)
ROE	-0.0008	-0.0072	-0.0021	-0.0005
	(0.004)	(0.012)	(0.008)	(0.009)
ROA	0.0027	0.0236	-0.0114	0.0146
	(0.007)	(0.024)	(0.012)	(0.017)
$ln(asset)$	-0.1892***	-0.1034	-0.0935	-0.2050
	(0.066)	(0.227)	(0.112)	(0.158)
$ln(employee)$	0.0205	0.2554	-0.1024	0.1725
	(0.052)	(0.167)	(0.088)	(0.116)
period	0.0881***	0.0896	0.0825***	0.0550
	(0.015)	(0.056)	(0.026)	(0.039)
Constant	0.9324*	-0.9110	1.1801	0.4506
	(0.528)	(1.507)	(0.890)	(1.047)
Observations	2,704	2,229	2,704	2,229
R-squared	0.038	0.017	0.016	0.017
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes
Number of stockcode	339	422	339	422

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

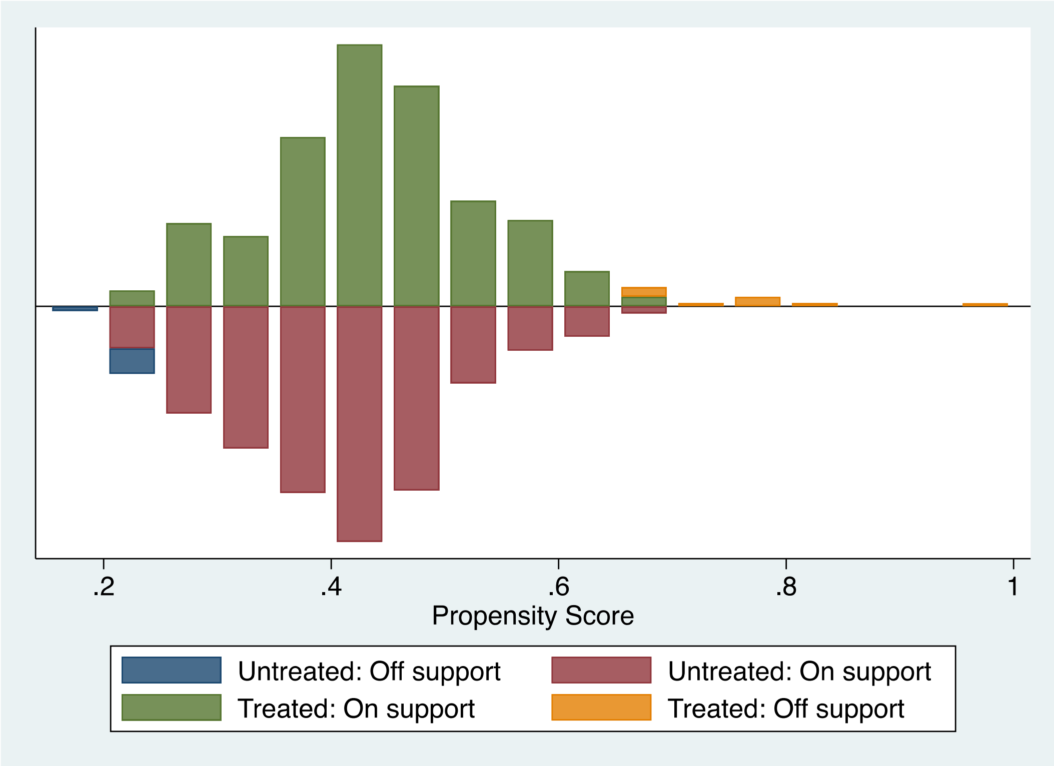
Table 7 Robustness Regression Result

VARIABLES	(1) Utility patent	(2) Invention patent	(3) Energy production patent	(4) Transportation patent	(5) Energy conservation patent	(6) Waste management patent	(7) Agriculture patent	(8) Administrative patent	(9) Nuclear Generation patent
Post*Treat	0.0436	-0.0212	-0.0041	0.0149	0.0563	-0.0274	-0.0020	-0.0172	0.0019
	(0.070)	(0.037)	(0.014)	(0.025)	(0.087)	(0.021)	(0.002)	(0.014)	(0.007)
ROE	-0.0101	-0.0031	0.0004	-0.0000	-0.0136	0.0000	0.0000	0.0002	-0.0002
	(0.009)	(0.004)	(0.001)	(0.001)	(0.012)	(0.001)	(0.000)	(0.000)	(0.000)
ROA	0.0299	0.0116	-0.0008	0.0053	0.0359	0.0002	-0.0001	0.0009	0.0001
	(0.019)	(0.010)	(0.001)	(0.004)	(0.026)	(0.001)	(0.000)	(0.001)	(0.000)
$ln(asset)$	0.0309	0.0033	0.0108	-0.0443	0.0861	-0.0092	0.0009	-0.0088	-0.0012
	(0.089)	(0.064)	(0.016)	(0.049)	(0.102)	(0.010)	(0.001)	(0.010)	(0.003)
$ln(employee)$	-0.0030	-0.0346	-0.0092	-0.0086	-0.0250	0.0071	0.0010	-0.0030	0.0001
	(0.026)	(0.030)	(0.007)	(0.018)	(0.040)	(0.007)	(0.001)	(0.002)	(0.001)
period	0.0340	0.0261	0.0110*	0.0231	0.0069	0.0106**	0.0000	0.0069	0.0016
	(0.031)	(0.022)	(0.006)	(0.019)	(0.034)	(0.005)	(0.000)	(0.005)	(0.002)
Constant	-0.4585	0.1082	-0.0509	0.2455	-0.5775	-0.0176	-0.0146	0.0586	0.0062
	(0.652)	(0.429)	(0.079)	(0.351)	(0.749)	(0.080)	(0.015)	(0.065)	(0.023)
Observations	1,683	1,683	1,683	1,683	1,683	1,683	1,683	1,683	1,683
R-squared	0.017	0.014	0.008	0.007	0.034	0.008	0.006	0.007	0.008
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of stockcode	480	480	480	480	480	480	480	480	480

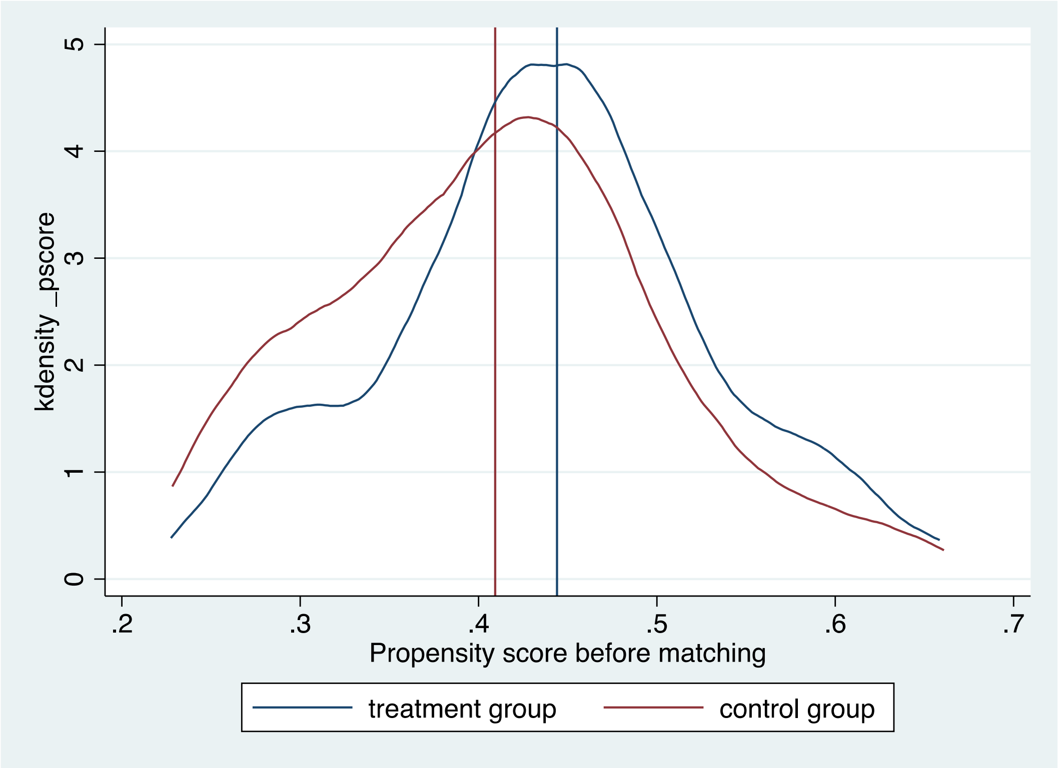
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1



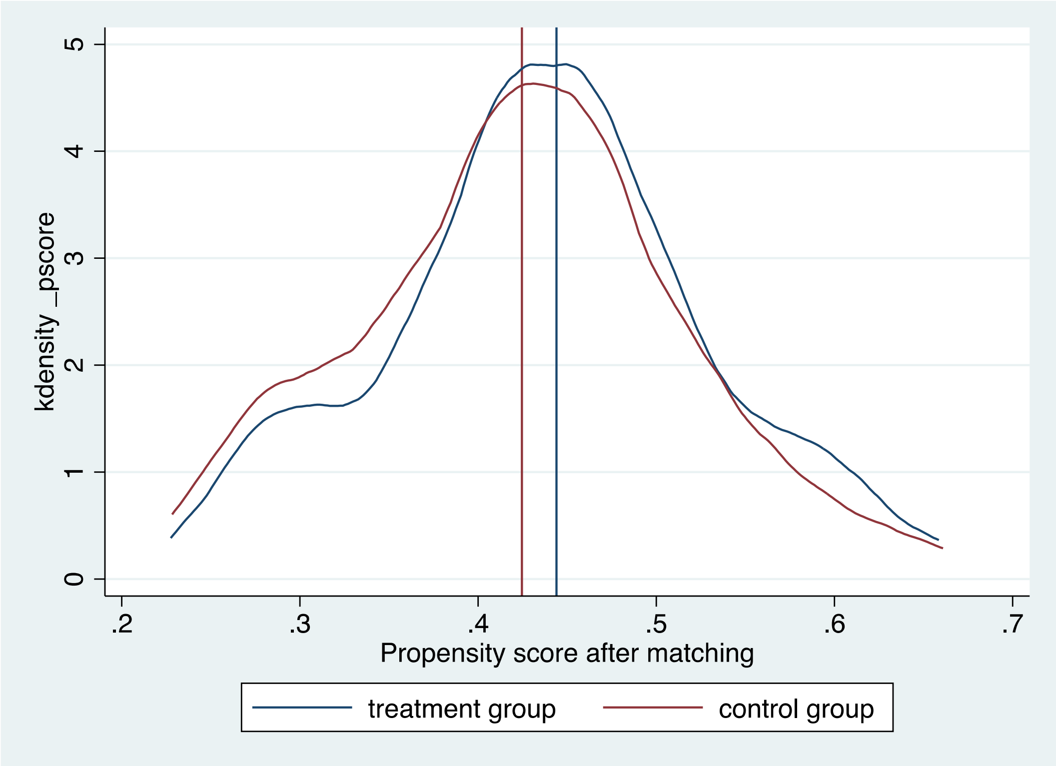
Graph 1 Bias across covariates in 2014 for utility patent



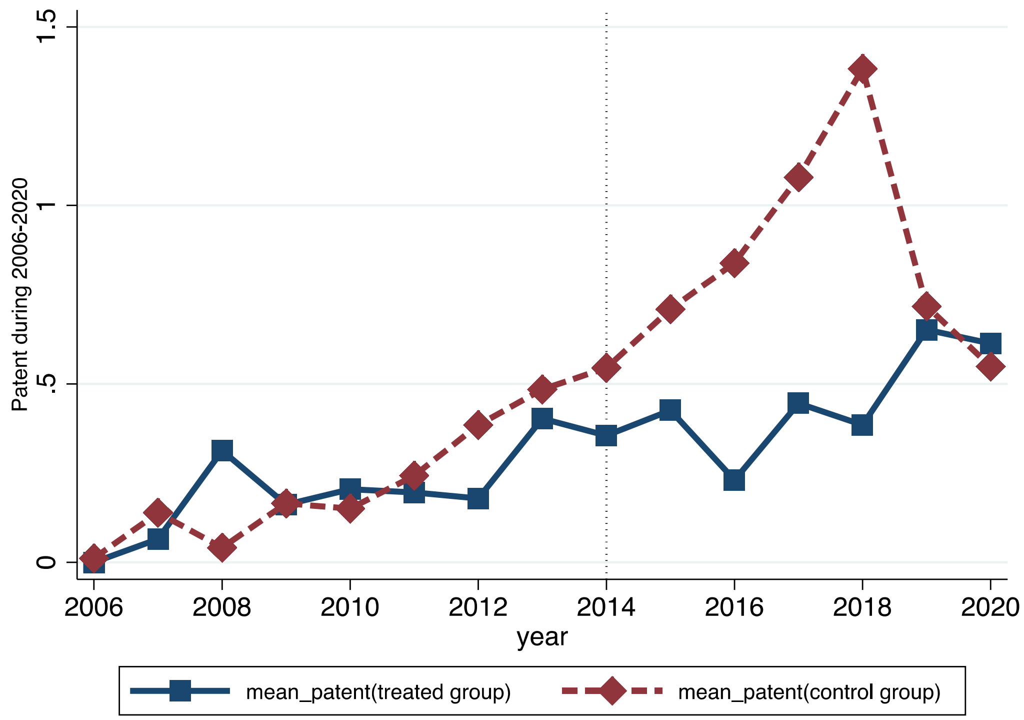
Graph 2 Distribution of treated and untreated group in 2014 for utility patent



Graph 3 Kernel density Graph before Matching



Graph 4 Kernel density Graph after Matching



Graph 5 Parallel Trend Test of DID