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The Impact of Carbon Trading on Green Innovation–Based on China’s Inter-Provincial Panel Data

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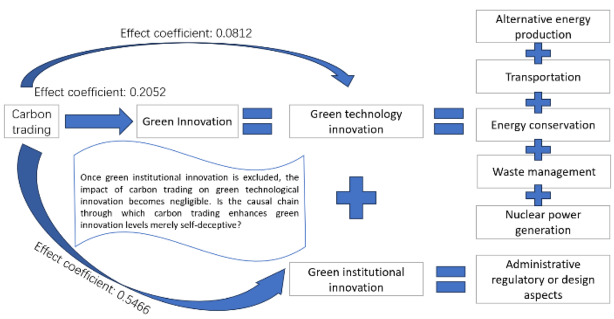
Graphical abstract



Abstract

Since 2012, China has implemented a series of carbon trading pilot programs across different regions. However, the impact of carbon trading policies on green innovation has not yet been fully discussed. This study utilizes nine-year panel data from 31 provinces and employs the Difference-in-Differences (DID) method to examine the differential effects of carbon trading policies on green innovation by categorizing green patents into six subsectors. The findings reveal substantial variations in policy impacts across different green innovation subsectors. Institutional factors emerge as crucial determinants in the influence mechanism. Specifically, carbon trading policies exhibit a significantly positive impact on green innovation when institutional innovation is incorporated; however, this positive effect is substantially diminished when institutional innovation factors are excluded and the focus shifts solely to pure green technology innovation.

Keywords: carbon trading, green innovation, institutional innovation, technology innovation

1. Introduction

Controlling anthropogenic climate change driven by fossil fuel consumption while balancing emissions mitigation with economic growth constitutes one of the most critical global policy challenges (Acemoglu *et al.* 2012). Effective climate policies must therefore simultaneously achieve decarbonization objectives and maintain economic vitality. To minimize growth disruptions, market-based mechanisms like carbon trading have emerged as prevalent policy instruments in climate governance. Currently operational in the European Union, New Zealand, China, South Korea, and other areas, carbon markets now regulate approximately 17% of global emissions[1]. These systems offer distinct advantages: By establishing market-driven trading rules, they enable enterprises to optimize emission reduction strategies through cost-benefit analysis. When abatement costs exceed carbon credit prices, firms may purchase allowances, while entities with lower mitigation costs can profit from selling excess reductions. This theoretically facilitates optimal resource allocation and cost-effective emissions control under capped pollution levels. However, this idealized market model faces practical implementation challenges. Transaction costs in carbon trading systems prove substantially higher than anticipated, while the administrative expenses required to establish and maintain market infrastructure often exceed those of conventional regulatory approaches.

As one of the world’s largest carbon emitters[2], China has implemented comprehensive measures to regulate its CO_2 emissions, with carbon emission trading serving as a particularly significant policy instrument. Eight pilot emissions trading systems (ETS) have been established across major Chinese cities and provinces: Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, Fujian and Shenzhen. Given the substantial variations in industrial structures among these pilot regions, each has developed distinct carbon trading mechanisms tailored to local conditions.

What impacts do carbon trading policies generate for enterprises and society? The Porter Hypothesis posits that properly designed environmental regulations can stimulate innovation. Consequently, innovation effects

[1] ICAP. Emissions Trading Worldwide Status Report 2023, 2023. https://icapcarbonaction.com/system/files/document/ICAP%20Emissions%20Trading%20Worldwide%202023%20Status%20Report_0.pdf

[2] World Bank. Word Bank Open Data,2023. https://data.worldbank.org.cn/

have emerged as a crucial metric for evaluating environmental policy effectiveness (Liu and Wang, 2017). Innovation can be categorized into green innovation and conventional innovation, with green innovation representing the essential pathway for addressing environmental challenges and achieving sustainable development. As a cornerstone environmental policy in China, understanding carbon trading's influence on green innovation is therefore paramount. Investigating this relationship enables us to: (1) assess whether carbon trading aligns with sustainable development principles, and (2) ensure its stimulative effects on clean technologies are properly acknowledged, rather than being overshadowed by potential crowding-out effects on conventional innovations.

To better understand the relationship between carbon trading and green innovation, this study sets out to examine the impact of carbon trading on green innovation. Based on provincial-level panel data from China and employing the DID methodology, the research focuses on addressing two core questions: (1) whether China's carbon trading pilot policies positively influence green innovation, and the magnitude of such effects; (2) how these impacts vary across different green innovation sectors, identifying which subsectors demonstrate more pronounced responses. The findings provide theoretical foundations for enhancing carbon trading mechanisms.

2. Literature review

Research on carbon trading can be divided into three general categories. The first category examines the scheme itself, such as studies conducted by Jiang *et al.* (2016) and Munnings *et al.* (2016). The most important uncertain variable in a carbon trading scheme is the carbon price, meaning that research on carbon prices is relatively extensive, including studies by Chevallier (2011) and Fan and Todorova (2017). The second category investigates antecedent variables of the schemes and carbon prices, i.e., what causes fluctuations in carbon prices; for example, research by Alberola *et al.* (2008). The third category explores consequence variables of the scheme and carbon prices, namely, what social and economic effects are brought about by carbon trading schemes. The topic of this paper belongs to the third category. Scholars have conducted substantial relevant research in this category. For example, Cong and Wei (2010) established an agent-based model to study the potential impact of introducing CET (Carbon Emission Trading) on China's power sector and discussed the impact of different allowance allocation options. Wu *et al.* (2016) used a CGE model to assess the economic impact of ETS policies in Shanghai. Cao *et al.* (2017) studied the impact of carbon trading policies and low-carbon subsidy policies on manufacturers' production and carbon emission reduction levels.

The research on technology innovation can also be divided into these three categories: research on technology innovation itself, such as Acemoglu (2002); research on antecedent variables of technology innovation; and research on the consequence variables of technology innovation. The topic of this paper belongs to the second category. Scholars have done a lot of relevant research on this category. For example, Shu *et al.* (2016) studied whether green management in firms operating in China fosters radical product innovation; Chakraborty and Chatterjee (2017) studied the indirect impact of environmental regulation on innovation activities of upstream firms in India; and El-Kassar and Singh (2019) developed and tested a holistic model that depicts and examines the relationships between green innovation and its drivers.

As for the relationship between carbon trading and technology innovation, there are also many studies focusing on this topic. Lin *et al.* (2017) estimated the potential influence of China's future nationwide carbon market on clean technology innovation. Because the national trading market had not been built yet, this paper used energy prices as a shadow price of carbon prices. The results indicate that the redirection effect overwhelms the crowding-out effect. Zhu *et al.* (2019) employed firm-level data and a quasi-experimental design to study how carbon trading affects low-carbon innovation in China, finding that China's pilot programs increased low-carbon innovation among ETS firms by 5–10% without crowding out other technological innovations, and this increase accounted for approximately 1% of the growth in regional low-carbon patents. Wang and Hao (2024) used panel data from 2007 to 2017 for 30 Chinese provinces and found that the carbon-trading policy significantly contributed to the coordinated advancement of green technologies across provinces while exhibiting a local siphoning effect. Zhao *et al.* (2024) based on panel data from 284 Chinese cities, examine the impacts of ETS on green innovation and find that ETS can significantly promote green innovation. In addition to examining the impact of carbon trading on regional green innovation, some scholars have also explored its effects on corporate green innovation. For example, Feng *et al.* (2017) used carbon emissions trading pilot policy as a quasi-natural experiment and found that the implementation of carbon emissions trading policies significantly reduced enterprise innovation in general, while promoting green technological innovation and inhibiting non-green technological innovation. Wang i (2024) explored the mechanisms of carbon trading in green innovation efficiency using a sample of A-share listed manufacturing enterprises in China, finding that carbon trading can significantly promote the green innovation efficiency of manufacturing enterprises. Jia *et al.* (2024) used DID to investigate the effect of carbon emission trading on green technology innovation in energy enterprises, suggesting that carbon emission trading has a positive impact on green technology innovation in energy enterprises. Hou (2024) using A-share listed firms in Shanghai and Shenzhen, analyzes the impact of China's carbon trading policy on green innovation and finds that the policy stimulates green innovation.The literature review shows that empirical evidence on the impact of carbon trading on green technology innovation is insufficient. There is no further subdivision of green innovation to explore the impact of carbon trading on different subsectors of green technology innovation. Green innovation involves different subsectors. By studying the impact of carbon trading on different subsectors, we can better understand its heterogeneous effects on green innovation across subsectors. This paper will make some attempts in this aspect.

3. Theoretical model

"Institutions play a more fundamental role in society and are the primary determinants of long-term economic performance" (North, 1990). Drawing upon institutional economics theory, we recognize institutions as critical factors influencing economic development. Therefore, we incorporate institutional factors into the economic growth equation(Equation 1):

$$Y = F(K, L, I) \tag{1}$$

Furthermore, Write the above formula as Cobb Douglas production function(Equation 2):

$$Y = AK^{\alpha} L^{\beta} I^{\gamma} \tag{2}$$

Take logarithm on both sides of the equation(Equation3):

$$LnY = Ln(A) + \alpha Ln(K) + \beta Ln(L) + \gamma Ln(I) \tag{3}$$

Put Ln(A) on the left side of the equation(Equation 4):

$$Ln(A) = LnY - \alpha Ln(K) - \beta Ln(L) - \gamma Ln(I) \tag{4}$$

In economic development research, Ln(A) is conventionally employed to measure technological progress factors. Since technological progress stems from innovation, the above formulation suggests that institutional factors may exert significant influence on innovation outcomes. Given that patent counts serve as a key metric for innovation, this study adopts green patent applications as a proxy for green innovation. Consequently, we posit that institutional arrangements targeting green development may significantly affect green patent outputs. Currently, China's primary institutional mechanism for green development is its carbon trading scheme. Therefore, this paper investigates the scheme's impact on green innovation. Building on the preceding analysis, we formulate the following hypotheses:

Hypothesis 1: The carbon trading scheme positively promotes regional green innovation.

Hypothesis 2: The scheme's promotional effects exhibit significant variation across different green innovation subsectors.

4. Model specification and variable declaration

4.1. model specification

This paper intends to employ the DID method to assess the net effects of carbon trading on green innovation. Treating the implementation of carbon trading as a quasi-natural experiment, the study defines a dummy variable for "whether a region is a carbon trading pilot" to divide the sample into treatment and control groups, and another dummy variable for "before and after the operation of the carbon market" to categorize the sample into before and after carbon market operation. By constructing an interaction term between these two dummy variables, the paper evaluates the net impact of the carbon market's operation. The baseline DID model is specified in Equation (5).

$$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 P_t + \beta_3 T_i P_t + \mu_{it} \tag{5}$$

Here, T_i is the grouping dummy variable. If individual i belongs to a carbon emissions trading pilot, it is assigned to the treatment group with T_i=1; otherwise, it is assigned to the control group with T_i=0. P_t is the policy implementation dummy variable, taking the value **0** before the policy is enacted and **1** afterward. The interaction term $T_i P_t$ combines the grouping and policy implementation dummy variables, and its coefficient β_3 captures the net effect of the policy.

Among China's provincial-level administrative units, seven provinces and municipalities launched carbon markets starting in 2013, providing a suitable quasi-natural experiment for applying DID. Specifically, seven provinces and cities had established carbon trading pilots, forming the treatment group, while the remaining provinces without carbon trading policies served as the control group. The carbon markets in these pilot regions began operating at different times: Beijing, Shanghai, Tianjin, and Guangdong started in 2013, Chongqing and Hubei in 2014, and Fujian in 2016. Accordingly, we construct a dummy variable CT, which takes the value 1 for pilot regions in the years when their carbon markets were operational and 0 otherwise. Based on this, we establish a two-way fixed effects econometric model (Eq. 6) to implement the DID approach and examine the net effects of carbon emissions trading on the outcome variables.

$$Y_{it} = \alpha_0 + \alpha_1 CT_{it} + \beta X_{it} + \vartheta_t + \mu_i + \varepsilon_{it} \tag{6}$$

Here, Y_{it} denotes the dependent variable, for this study is the number of green patents. The subscripts i and t represent the i-th province/municipality and the t-th year, respectively. ϑ_t captures time-fixed effects, μ_i represents province-level individual fixed effects, and X_{it} denotes other control variables. In the model above, the estimated coefficient α_1 is the primary focus of this study, as it measures the net impact of carbon emissions trading on dependent variable.

4.2. variable declaration

This study utilizes panel data from 31 provincial-level administrative regions (including municipalities and autonomous regions) in mainland China for the period 2009-2017. The variable specifications are presented as follows:

Dependent Variable: The dependent variable is green patent output. We identify green patents using the International Patent Classification (IPC) Green Inventory developed by the World Intellectual Property Organization (WIPO). The patent data were collected from the PatSnap database (https://www.zhihuiya.com/) between October and December 2019. Considering the typical 18-26 months publication lag for patent data (Zhu *et al.* 2019), our dataset covers patents granted through 2017.

The WIPO IPC Green Inventory categorizes green technologies into seven subsectors: Alternative energy production (ae), Transportation (tr), Energy conservation (ecs), Waste management (wm), Administrative regulatory or design aspects (ar), Nuclear power generation (npg). We aggregate patent counts for each subsector and calculate total green patents (gp) to examine both the overall and subsector-specific effects of carbon trading on green innovation. As China's carbon trading pilots currently exclude the primary industry, our dataset accordingly excludes patents classified under the agriculture/forestry sector. For the remaining six subsectors, we add a value of 1 to all patent counts before logarithmic transformation to address zero values. Regarding patent classifications spanning ranges (e.g., H01M4/86-4/98), we collect data at the subgroup level or higher due to the impracticality of manual collection for all individual IPC codes within these ranges.

Explanatory variable: The explanatory variable is a binary indicator representing the implementation status of carbon trading schemes. It takes the value of 1 for regions and years where the carbon trading policy was implemented, and 0 otherwise. The implementation data were obtained from official policy documents issued by the seven pilot regional governments in China.

Control variables: include gross domestic product (GDP), R&D funds of industrial enterprises above designated size (RD), energy industry investment (EI), local fiscal expenditure for environmental protection (GE), and coke production (CP). GDP represents the level of economic development of a region and is an important variable that affects the level of science, technology, and innovation, and thus the level of green innovation in a region; generally, the higher the GDP, the higher the level of green innovation. The GDP data used in this paper are real values adjusted to 2005 constant prices. R&D expenditure of industrial enterprises above designated size is used to measure the innovation capital investment of key enterprises in the province, and generally this variable is proportional to the level of green innovation. Energy industry investment measures the capital investment used for fossil energy development and production, which has a crowding-out effect on the green development of energy and is inversely proportional to green innovation. Local fiscal expenditure on environmental protection measures a regional government's support for environmental protection and is directly proportional to green innovation.

Table 1. Result of the descriptive statistics of variables.

variables	Mean	Median	Maximum	Minimum	Std. Dev.
GP	3793.54	1888.50	31864.00	25.00	5385.91
AE	430.83	261.00	3419.00	5.00	546.39
TR	179.03	142.50	799.00	1.00	183.34
ECS	1855.02	991.00	15639.00	7.00	2709.67
WM	245.57	133.00	1703.00	5.00	309.61
AR	1030.16	365.50	12528.00	1.00	1793.07
NPG	58.93	17.50	381.00	1.00	91.80
RD	3579610.00	1970481.00	16762749.00	77940.00	4444303.00
GDP	16 681.98	12 748.05	69 075.06	996.10	13 588.80
EI	1110.56	976.11	2998.27	232.10	607.33
GE	128.87	111.75	458.44	32.24	73.00
CP	1780.11	1278.19	6677.74	133.00	1634.17

Based on the resource curse hypothesis, this paper adds coke production as a control variable. It should be noted that this curse may not be reflected in GDP, because resource-rich regions can obtain higher GDP and per capita income by selling resources, but the number of green patents related to sustainable development and technological innovation is likely to be affected, and the future development of these regions may be constrained. Energy production rather than reserves or extraction was chosen to characterize the resource curse hypothesis because changes in reserves are more random and sudden, while extraction data are not easily available. Coke production was chosen over petrol, diesel, natural gas, etc., for energy production because China's coal resources can be developed by each province, while oil and gas resources are developed centrally. The data for the control variables are all from the official website of the National Bureau of Statistics of China (http://data.stats.gov.cn/). This section uses panel data from 2011 to 2017 for 29 provincial administrative units in mainland China (excluding Tibet and Hainan), and **Table 1** presents descriptive statistics for all the data used in this section.

5. Result

The estimated results of the equations are reported in **Table 2**. It can be seen that for the overall number of green patents, the impact of carbon trading on it is significantly positive at the 1% significance level, the overall equation passes the F-test, with an adjusted R-squared of 87.47%, indicating that the operation of the carbon market has a significantly positive effect on enhancing regional green innovation levels. This conclusion is consistent with Calel and Dechezlepretre (2016) and Feng *et al.* (2017).

Table 2. The estimation results.

	Ln(gp)(1)	Ln(gp)(2)	Ln(gp)(3)
ct	0.2052***(3.9301)		
parallel		-0.0349(-1.0085)	
ct-advance 2			0.0695(1.1808)
Ln(gdp)	0.3767***(9.5117)	0.3244***(8.3713)	0.3408***(8.9453)
Ln(rd)	0.5918***(13.6409)	0.6469***(15.1169)	0.6193***(17.4954)
Ln(ei)	-0.1456***(-4.8455)	-0.1685***(-5.5082)	-0.1572***(-4.4453)
Ln(ge)	0.5079***(7.3193)	0.5335***(7.8792)	0.5405***(8.2206)
Ln(cp)	-0.1560***(-25.0593)	-0.1735***(-18.3224)	-0.1622***(-20.7520)
const	-4.8880***(-7.4865)	-4.9973***(-7.4117)	-4.9624***(-7.5520)
Time effect	Control	Control	Control
Regional effect	Control	Control	Control
N	203	203	203
Adjusted R2	0.8747	0.8728	0.8730
Prob(F-statistic)	0.0000	0.0000	0.0000

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively; the square brackets are t statistics*

An essential assumption in employing the DID approach to assess the impact of carbon trading on green innovation is that, in the absence of carbon trading intervention, the development trends of green innovation in both treatment and control groups would remain consistent without systematic divergence over time—that is, the trends should exhibit parallel patterns between the two groups. The parallel trend assumption test was performed following the methodologies outlined in Zhou and Chen (2005) and Liu and Zhao (2015). Specifically, we construct a dummy variable parallel to indicate whether a provincial-level administrative unit belongs to the treatment group (assigned a value of 1, regardless of whether carbon trading was implemented in a given year) or the control group (assigned 0). By replacing CT with parallel as the explanatory variable in the regression, we examine whether the grouping itself (rather than the policy) significantly affects green innovation.

If parallel proves statistically significant, it would suggest that the classification into treatment and control groups inherently influences green innovation, violating the parallel trend assumption and undermining the credibility of the original DID estimates. Conversely, if parallel is statistically insignificant, it confirms no systematic pre-existing differences between the groups, validating the parallel trend assumption for the baseline model. The results of this test are presented in Column 3 of **Table 2**. The empirical findings show that parallel is statistically insignificant, confirming that the original DID specification satisfies the parallel trend hypothesis.

To further verify the robustness of the estimation results, we conduct a counterfactual test by altering the policy implementation timeline, following methodologies employed by Zhou and Chen (2005) and Liu and Zhao (2015). Changes in green innovation might stem from other policy interventions or random factors beyond carbon trading policies. To rule out such possibilities, we uniformly advance the carbon trading launch year by two years for all pilot regions, creating a counterfactual dummy variable labeled ct-advance2. This modified variable replaces the original ct in our baseline regression. If ct-advance2 shows a statistically significant positive effect on green innovation, it would suggest that the observed changes likely originated from factors other than carbon trading implementation. Conversely, if ct-advance2 proves insignificant, it confirms that the changes in green innovation are indeed attributable to the carbon trading policy rather than other random factors. The results of this counterfactual test are presented in Column 4 of **Table 2**. Empirical findings demonstrate that ct-advance2 is statistically insignificant, indicating that our estimation results successfully pass the counterfactual test and maintain robust validity.

From the empirical results above, it is evident that the implementation of carbon trading has a significant positive driving effect on green innovation development. However, does carbon trading exert a substantial positive impact on every category of green innovation? How do its effects differ across subcategories of green innovation? This section will further discuss these issues.

Using the six subcategories of the IPC Green Inventory—alternative energy production (ae), transportation (tr), energy conservation (ecs), waste management (wm), administrative regulation or design (ar), and nuclear power generation (npg)—as dependent variables, we estimate Equation (6). Additionally, considering that administrative regulation or design falls under the category of institutional innovation, while the remaining five subcategories belong to technological innovation, we also estimate an equation with the aggregate of the five subcategories (excluding administrative regulation or design) as the dependent variable. This allows us to examine the differential effects of carbon trading on green institutional innovation versus green technological innovation. The estimation results are presented in **Table 3**.

Table 3. Regression Results with Green Patent Subcategories as Dependent Variables

	Ln(ae)	Ln(tr)	Ln(ecs)	Ln(wm)	Ln(ar)	Ln(npg)	Ln(nar)
ct	0.0427	-0.2782***	0.1563**	-0.0924	0.5466***	0.3948***	0.0812*
	1.2871	-3.1104	2.5123	-1.0413	5.7103	2.6416	1.6547
Ln(gdp)	0.2838**	0.1806**	0.5348***	0.1262**	0.4316***	0.4704***	0.3730***
	2.1279	2.1093	9.4996	2.5238	3.3069	3.2444	9.4502
Ln(rd)	0.5459***	0.7097***	0.5861***	0.6725***	0.6357***	0.4856***	0.5887***
	9.7803	16.2046	13.0213	15.4124	5.7815	3.5668	17.2575
Ln(ei)	-0.0730**	-0.3205***	-0.1752***	-0.0771	-0.1128*	-0.1533***	-0.1319***
	-2.5298	-3.7992	-6.2574	-0.9051	-1.7884	-3.0416	-4.2713
Ln(ge)	0.4205***	0.9351***	0.3038***	0.3707***	0.6875***	0.6282***	0.4164***
	6.3113	7.6137	4.9905	3.9305	3.6837	5.1397	8.6552
Ln(cp)	-0.1071***	0.0427	-0.1475***	-0.1722***	-0.2017***	-0.1808***	-0.1437***
	-8.8919	1.1982	-12.5742	-10.6582	-7.7321	-3.6798	-32.9304
const	-5.7406***	-9.9561***	-5.9826***	-5.9222***	-8.3869***	-9.2013***	-4.8098***
	-13.6074	-20.5201	-10.0004	-10.2415	-6.6857	-15.2378	-8.9128
Time effect	Control	Control	Control	Control	Control	Control	Control
Regional effect	Control	Control	Control	Control	Control	Control	Control
N	203	203	203	203	203	203	203
A-R2	0.8163	0.7361	0.8746	0.7383	0.7737	0.6395	0.8897
F-prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively; the square brackets are t statistics*

The average number of patents in the alternative energy production (ae) subcategory ranks third among the six subcategories. As a pivotal technology in green energy utilization, alternative energy production holds significant importance for achieving sustainable development. The estimation results for this subcategory as the dependent variable are presented in the "ln(ae)" column of **Table 3**. Empirical results show that the coefficient of the carbon trading implementation dummy variable fails to pass the significance test when using this subcategory as the dependent variable, indicating that carbon trading has no statistically significant impact on patent activity in alternative energy production. This may be because most enterprises participating in carbon trading belong to traditional energy industries with limited engagement in renewable energy sectors, leading to fewer innovation efforts directed toward alternative energy technologies. The equation overall passes the F-test, with an adjusted goodness-of-fit reaching 81.63%. All control variables exhibit statistically significant coefficients, and their signs align with prior theoretical expectations.

The average number of patents in the transportation (tr) subcategory ranks fifth among the six subcategories. The estimation results using this subcategory as the dependent variable are presented in the "ln(tr)" column of **Table 3**. Empirical findings reveal that the coefficient of the carbon trading implementation dummy variable is negative and passes the significance test at the 1% level, indicating that carbon trading exerts a negative impact on green innovation in the transportation sector. This may be attributed to the fact that, except for Shanghai, Shenzhen, and Beijing, China's carbon trading pilot programs do not cover the transportation sector, potentially creating a crowding-out effect on transportation-related green innovation. The equation overall passes the F-test, with an adjusted goodness-of-fit of 73.61%. All control variables except coke production show statistically significant coefficients, and their signs align with theoretical expectations.

Under the context of limited breakthroughs in alternative energy technologies, it is crucial to optimize existing energy utilization. The energy conservation (ecs) subcategory encapsulates such green innovation efforts, with its average number of green patents ranking first among the six subcategories. The estimation results using this subcategory as the dependent variable are presented in the "ln(ecs)" column of **Table 3**. Empirical findings demonstrate that the coefficient of the carbon trading implementation dummy variable is positive and statistically significant at the 5% level, indicating that carbon trading significantly stimulates innovation activities in energy conservation. However, the magnitude of this effect is smaller than carbon trading's overall promoting impact on green innovation. The equation passes the F-test with an adjusted goodness-of-fit of 87.46%. All control variables exhibit statistically significant coefficients, and their signs align with theoretical expectations.

The waste management (wm) subcategory focuses on the recycling and utilization of waste materials. Given current technological capabilities and energy reserves, waste management remains a critical component of green innovation, with its average number of patents ranking fourth among the six subcategories. The estimation results using this subcategory as the dependent variable are presented in the "ln(wm)" column of **Table 3**. Empirical results indicate that the coefficient of the carbon trading implementation dummy variable fails to pass the significance test when using this subcategory as the dependent variable, suggesting that carbon trading has no statistically significant effect on innovation activities in waste management. The equation passes the F-test with an adjusted goodness-of-fit of 73.83%. All control variables except energy industry investment exhibit statistically significant coefficients, and their signs align with prior expectations.

The nuclear power generation (npg) subcategory represents a critical opportunity for global energy systems, particularly amid severe pollution from fossil fuels, depleted hydropower resources, and the instability of wind and solar energy. The advancement of nuclear fusion technology may hold the key to a permanent solution to energy challenges. Paradoxically, the average number of patents in this subcategory ranks last among the six, likely due to the high technological entry barriers associated with nuclear research. The estimation results using this subcategory as the dependent variable are presented in the "ln(npg)" column of **Table 3**. Empirical findings reveal that the coefficient of the carbon trading dummy variable is positive and statistically significant at the 1% level, demonstrating that carbon trading significantly promotes patent activity in nuclear power generation. Notably, the magnitude of this positive effect ranks second among all six subcategories and exceeds the coefficient of carbon trading's overall impact on total green patents. The equation passes the F-test with an adjusted goodness-of-fit of 63.95%. All control variables exhibit statistically significant coefficients, and their signs align with prior theoretical expectations.

The administrative regulation or design (ar) subcategory falls under green institutional innovation, whereas the aforementioned five subcategories belong to green technological innovation. With the implementation of carbon trading, patent applications in the administrative regulation or design subcategory are inevitably amplified, as carbon trading itself constitutes an institutional framework for green development. Regions implementing carbon trading inevitably witness extensive policy and regulatory design efforts, leading to a substantial surge in patents within this subcategory. The average number of patents in the administrative regulation or design subcategory ranks second among the six subcategories. This remarkably high ranking for an institutional innovation subcategory—distinct from technological innovation—reflects, to some extent, the complexity of China's administrative system.

The estimation results using this subcategory as the dependent variable are presented in the "ln(ar)" column of **Table 3**. Empirical results show that the coefficient of the carbon trading dummy variable is positive and statistically significant at the 1% level, with its magnitude exceeding the coefficients of carbon trading's effects on the other five subcategories and overall green innovation. This raises a critical question: If the primary positive impact of carbon trading on green innovation stems from its direct influence on institutional innovation closely tied to its implementation, what is its true effect on technological innovation when institutional innovation is excluded?

To address this, we construct a new dependent variable nar (representing green technological innovation) by subtracting administrative regulation or design patents from total green patents. Re-estimating the original equation with nar yields results presented in the "ln(nar)" column of **Table 3**. The findings indicate that carbon trading exerts a statistically significant positive effect on green technological innovation at the 10% level. However, this effect is far weaker compared to its impact on green institutional innovation and overall green innovation.

Therefore, this paper answers the two hypotheses put forward above. Carbon trading can indeed promote regional green innovation, and its impacts vary across different sectors of green innovation.

6. Conclusion

In this paper, carbon trading is added as a dummy variable into the equation to explore the influencing factors of green innovation. It is found that carbon trading has a significant positive impact on green patent applications, and this impact is different for each subsector that makes up the green patent inventory. We also find that the exclusion of green institutional innovations substantially weakens carbon trading's role in promoting green innovation. This is a very important conclusion. In the previous assessment of the impact of carbon trading, this point was often been ignored: the green innovation inventory contains the institutional innovation itself. After removing institutional innovation, carbon trading obviously can not effectively promote the development of green technology innovation. Every new institutional arrangement we have made for carbon trading is actually strengthening the bubble that carbon trading can affect green innovation. Furthermore, this study reveals that carbon trading effectively promotes green innovation within the covered industries, yet this stimulative effect shows limited spillover to non-covered sectors. Consequently, this study recommends expanding the sectoral coverage of carbon trading, with priority given to incorporating waste management and transportation industries into the trading system at appropriate stages.

In the future, more attention should be paid to the impact of carbon trading policies on sustainable development. In the research process of this paper, there are still the following points that can be improved or further explored: 1. The control variables in this paper include two variables to verify the resource curse hypothesis - coal production and coke reserves - which are examined in the overall regression equation. This remains a meaningful and valuable topic for follow-up research; 2. The carbon trading scheme represents an elegant institutional arrangement, but its role in promoting sustainable development requires further examination. Could alternative policies achieve better emission reduction effects? Is the selection of this aesthetically appealing yet potentially ineffective policy driven by political and economic constraints? 3. Carbon trading policies originated from the sulfur dioxide emission trading market in the United States, which similarly assigned value to previously worthless pollutant emission rights. Why has the sulfur dioxide market been more successful? Is this due to the availability of substitutes for sulfur dioxide, lower treatment costs, or because the carbon market involves too many industries?

References

Acemoglu D. (2002). Directed technical change. *Review of Economic Studies*, **69**, 781-809.

Acemoglu D., Aghion P., Bursztyn L. and Hemous D. (2012). The environment and directed technical change. *American Economic Review*, **102**, 131-166.

Alberola E., Chevallier J. and Cheze B. (2008). Price drivers and structural breaks in European carbon prices 2005-2007. *Energy Policy*, **36**, 787-797.

Calel R. and Dechezlepretre A. (2016). Environmental policy and directed technological change: Evidence from the European carbon market. *Review of Economics and Statistics*, **98**, 173-191.

Cao K., Xu X., Wu Q. and Zhang Q. (2017). Optimal production and carbon emission reduction level under cap-and-trade and low carbon subsidy policies. *Journal of Cleaner Production*, **167**, 505-513.

Chakraborty P. and Chatterjee C. (2017). Does environmental regulation indirectly induce upstream innovation? New evidence from India. *Research Policy*, **46**, 939-955.

Chevallier J. (2011). A model of carbon price interactions with macroeconomic and energy dynamics. *Energy Economics*, **33**, 1295-1312.

Cong R. G. and Wei Y. M. (2010). Potential impact of (CET) carbon emissions trading on China's power sector: A perspective from different allowance allocation options. *Energy*, **35**, 3921-3931.

El-Kassar A. N. and Singh S. K. (2019). Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technological Forecasting and Social Change*, **144**, 483-498.

Fan J. H. and Todorova N. (2017). Dynamics of China's carbon prices in the pilot trading phase. *Applied Energy*, **208**, 1452-1467.

Feng C., Shi B. and Kang R. (2017). Does environmental policy reduce enterprise innovation?—Evidence from China. *Sustainability*, **9**(6), 872.

Hou J. (2024). Does carbon emission trading affect China's green innovation? an exploration from the perspective of the enterprise lifecycle. *Sustainability,* **16**.

Jia L., Zhang X., Wang X., Chen X., Xu X., and Song M. (2024). Impact of carbon emission trading system on green technology innovation of energy enterprises in China. *Journal of Environmental Management,* **360.**

Jiang J., Xie D., Ye B., Shen B. and Chen Z. (2016). Research on China's cap-and-trade carbon emission trading scheme: Overview and outlook. *Applied Energy*, **178**, 902-917.

Lin S., Wang B., Wu W. and Qi S. (2017). The potential influence of the carbon market on clean technology innovation in China. *Climate Policy*, **18**, 71-89.

Liu R. M. and Zhao R. J. (2015). Do national high-tech zones promote regional economic development? Evidence from difference-in-differences method. *Management World*, **263**(08), 38-46.

Liu W. and Wang Z. (2017). The effects of climate policy on corporate technological upgrading in energy intensive industries: Evidence from China. *Journal of Cleaner Production*, **142**, 3748-3758.

Munnings C., Morgenstern R. D., Wang Z. and Liu X. (2016). Assessing the design of three carbon trading pilot programs in China. *Energy Policy*, **96**, 688-699.

North D. C. (1990). Institutions, institutional change and economic performance. *Cambridge University Press,* Cambridge.

Shu C., Zhou K. Z., Xiao Y. and Gao S. (2016). How green management influences product innovation in China: The role of institutional benefits. *Journal of Business Ethics*, **133**, 471-485.

Wang J. and Hao S. (2024). Will China's carbon-trading policy foster coordinated innovation in green technologies? *Data Science & Management*, **7**(4).

Wang M., Wang X., Liu Z., and Han, Z. (2024). How can carbon trading promote the green innovation efficiency of manufacturing enterprises? *Microelectronics Journal,* **53.**

Wu R., Dai H., Geng Y., Xie Y., Mosui T. and Tian X. (2016). Achieving China's INDC through carbon cap-and-trade: Insights from Shanghai. *Applied Energy*, **184**, 1114-1122.

Zhao Z., Zheng Y. and Ye S. W. T. (2024). The impact of carbon emissions trading system on regional green innovation: a perspective of foreign investment agglomeration. *Polish Journal of Environmental Studies.,* **33**(4), 4973-4982.

Zhou L. A. and Chen Y. (2005). The policy effects of rural tax and fee reform in China: Estimation based on a difference-in-differences model. *Economic Research Journal*, **08**, 44-53.

Zhu J., Fan Y., Deng X. and Xue L. (2019). Low-carbon innovation induced by emissions trading in China. *Nature Communications*, **10**(1).