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论文题目：Quantity or Quality? The Impact of Carbon Trading on Firms’ Green Innovation

Quantity or Quality? The Impact of Carbon Trading on Firms' Green Innovation

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Abstract: Given that firms' green innovation is important for their sustainable development, the role of carbon trading in this initiative is a key issue for social scientists. Although this practice has different impacts on the quantity and quality of green innovation, this distinction is rarely made in academic research, yielding inconsistent results and thus hampering the development of efficient policy instruments. To address this shortcoming, we conducted a quasi-experiment based on the carbon trading pilot scheme that commenced in China in 2011 and constructed a dataset of 9998 observed value of A-share listed industrial companies that took part in this initiative spanning the 2000–2021 period, to empirically test the effect of carbon trading pilots on firms' green innovation. The baseline results yielded by the staggered Difference-in-Differences (DID) method show that carbon trading pilots increased the quantity of green innovation, while having a marginal effect on its quality. This finding prompted us to further explore the mechanisms underlying these effects through theoretical models and heterogeneity analysis. Specifically, we developed a theoretical model based on an input–output function to analyze corporates' decision-making processes leading to green innovation that differs in quality and quantity. The obtained results reveal that positive effects of carbon trading on the green innovation quantity are mainly explained by firms' financial constraints. Moreover, our industry-level heterogeneity analysis suggests that the effect is greater in those industries with large externalities. These observations highlight the necessity of carbon trading pilot programs, as well as collaboration between enterprises in order to advance the high-quality green innovation initiatives.

Keywords: Carbon Trading, green innovation, heterogeneity analysis, externalities

Contents

1. Introduction **3**

2. Background **5**

3. Data **7**

3.1 Independent Variable 7

3.2 Dependent Variable 8

3.3 Control Variables 8

4. Empirical Strategy and Results **10**

4.1 Baseline Results 11

4.2 Robustness Test 13

5. Theoretical Framework **15**

5.1 Baseline Model 16

5.2 Model with Externalities 20

6. Discussion **24**

7. Conclusions **26**

1. Introduction

Firms' green innovation is crucial for their sustainable development and is a significant concern within the context of climate change (Paraschiv et al., 2012; Zheng et al., 2022). Consequently, a substantial body of literature has emerged to explore the drivers behind firms' green innovation (Amore & Bennedsen, 2016; Hu et al., 2021; Liu et al., 2022), with carbon trading as a prominent perspective (Liu & Li, 2022; Liu et al., 2022; Yao et al., 2021). However, prior attempts at establishing a causal relationship between carbon trading and corporate green innovation were hampered by endogeneity problems due to the difficulty to account for all influential factors (Chen et al., 2021). As a result, extant research has yielded inconsistent results, precluding the development of effective policy instruments. Some scholars may argue that such regulations are not needed, as they would impose restrictions on firms, reducing their innovation potential (Dechezleprêtre & Sato, 2017). Others hold an opposing of view, suggesting that strict environmental regulations encourage innovation aimed at reducing costs and maintaining profits (Ambec & Barla, 2005; Leeuwen & Mohnen, 2017). These debates prompted us to further explore this issue by conducting a quasi-experiment involving China's A-share listed companies that have participated in a carbon trading pilot scheme since 2011 to empirically test the effect of this initiative on firms' green innovation.

China is the world's most populous country and the largest emitter of carbon dioxide (Nancy, 2015). To reduce carbon emissions, in 2011, Chinese government introduced the aforementioned carbon trading pilot scheme in the Shanghai, Beijing, Hubei, Guangdong, and Tianjin provinces. In 2016, the scheme expanded to include Fujian. As carbon trading refers to the trading of carbon emission rights, in the context of this program, the Chinese government determines the total carbon emission targets and defines the carbon emission quotas for the participating emitters. To achieve these targets, the emitters need to be able to trade the carbon quotas freely in the secondary market. Therefore, carbon emission permits have become valuable assets that can be exchanged as commodities. This market dynamic provides a unique opportunity to examine the impact of carbon trading pilots on corporate green innovation.

To achieve this objective, we have compiled a dataset spanning the 2000–2021 period, covering 9998 observed value of A-share listed industrial companies operating across 14 industrial sectors in China. To examine this dataset, we adopted the staggered Difference-in-Differences (DID) model, as our aim was to compare the changes in the quantity of green innovation in firms located in provinces taking part in the carbon trading pilot scheme to those located in provinces that are not included in this initiative. Our baseline results showed that, while carbon trading pilots increased the quantity of green innovation, they had a marginal effect on innovation quality. We examined these findings further by performing three sets of robustness checks to address the omitted variables problem, whereby (1) we included additional firms' characteristics as control variables, (2) we conducted propensity score matching, and (3) we compared the historical and the benchmark method for permit allocation. The initially obtained results remained robust in all three tests.

We argue that the observed patterns are driven by externalities, i.e., the knowledge spillover effects (either positive or negative) that arise from economic activities in which the examined firms are not directly involved. We explore this problem through a model based on game theory where each firm participating in the market aims to maximize their profit. Accordingly, the competing firms need to choose the optimal quality and quantity of green innovation to maximize their carbon emission reductions, while adhering to the innovation budget which is modeled as a constraint. Our results show that the optimal level of innovation quality and quantity depends on their relative price and marginal effects on emission reduction. Externalities or spillover effects are also incorporated in the model as firms' final green innovation depends on their own performance and that of other participants in the same industry. Specifically, our model indicates that, the greater the externalities, the greater the increase in the green innovation quality. Moreover, inspired by the work of Popp (2002) and others, in our empirical analyses, we use the electric power industry as a proxy for high externalities. According to our industry-level heterogeneity analysis, the effect of carbon trading policy on the quality of innovation is greater in the electric power industry than in other sectors, which is consistent with our model's expectations.

Collectively, these findings have two major contributions to this field of study. First, innovation quality is rarely segregated from its quantity (typically proxied by the number of green patents), precluding accurate assessment of the level of green innovation.

Second, by considering externalities, we were able to quantify the variations in the influence of carbon trading pilots on the extent of green innovation across diverse industries. For this purpose, we assigned the firms included in the analyses into electric power or non-electric power industry category. In uncovering changes in the relationship between carbon trading pilots and the level of green innovation in these industries, this work further contributes to the understanding of the structural differences across industries as well as the effect of carbon trading pilots in each industry. The obtained findings thus highlight the necessity of piloting carbon trading, along with a close collaboration among enterprises, in order to promote green innovation.

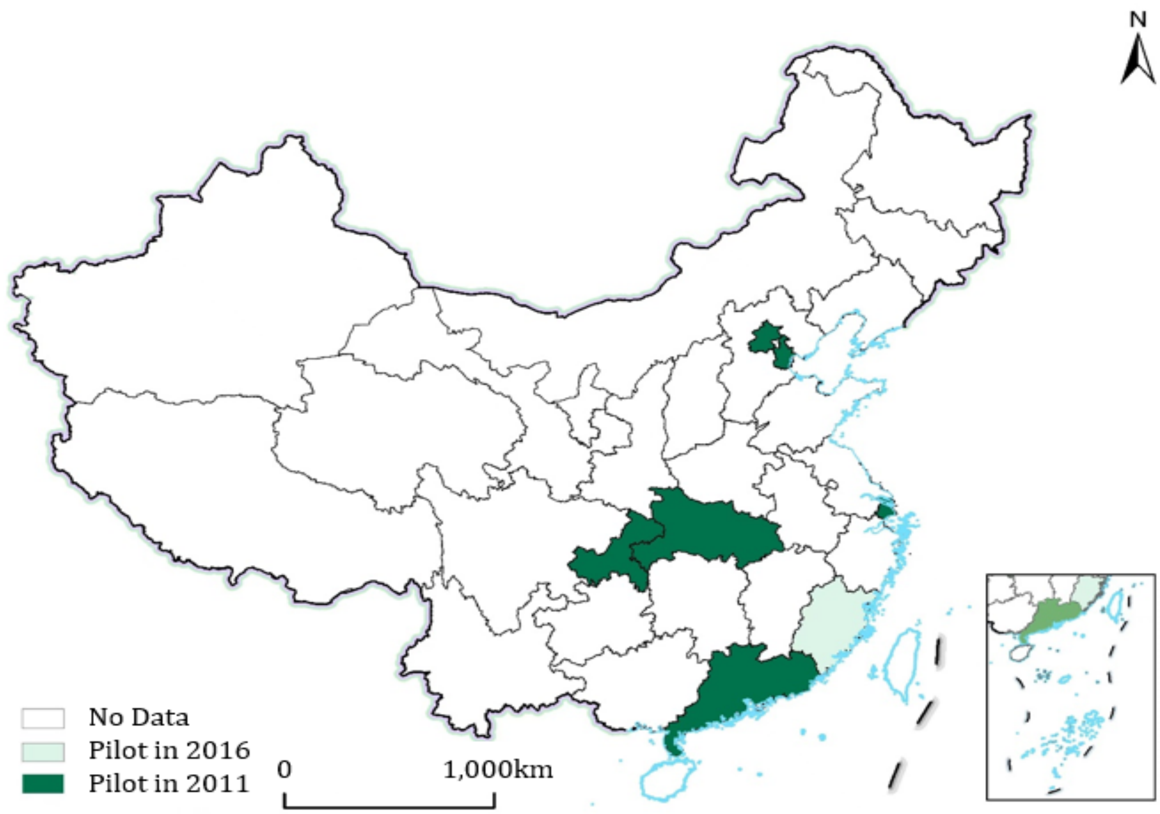
The remainder of this paper is structured into six sections. In Section 2, we provide an overview of carbon trading pilot initiatives in China and outline the data utilized in this study in Section 3. In Section 4, we elaborate on our empirical approach and present the outcomes of our analysis. The influence of externalities on green innovation is examined in Section 5, the key results are discussed in Section 6, and our concluding remarks are provided in Section 7.

2. Background

As greenhouse gas (GHG) concentrations are at their highest level in human history, various attempts are being made across the globe to reduce CO_2 output in order to prevent further climate change, which would lead to more intense droughts, rising sea levels, and extinction of many species. One of the most prominent international policies aimed at arresting global warming was the Kyoto Protocol, which laid the foundation for the modern GHG emission reduction schemes. Ratified in 2005 with the participation of 192 parties, the protocol targeted an average 5% emission reduction during the 2008−2012 period relative to the 1990 levels. The Kyoto Protocol was amended in 2012, initiating the second commitment period which ended in 2020. Unlike other GHG emission reduction schemes, the Kyoto Protocol was market-oriented and featured flexible market mechanisms (UNFCCC, 1992). In particular, Article 17 of the Kyoto Protocol allowed countries that have not used all their permitted emission units to sell those permits to countries that have exceeded their capacity (UNFCCC, 1992). Such mechanism boosted the cost-effectiveness of GHG emission abatement as well as encouraged green investment in the private sector along with the development of cleaner infrastructure. It also led to the establishment of the world's first carbon trading market—the Emission Trading System in the European Union, which has remained the largest despite the emergence of other carbon trading markets (European Commission, 2005).

China, being the world's most populous country and the largest CO_2 emitter (Nancy, 2015), also initiated a carbon trading pilot scheme in 2011 with the aim of reducing carbon emissions. The Chinese National Development and Reform Commission was responsible for this program, which initially included Shanghai, Beijing, Hubei, Guangdong, Shenzhen, and Tianjin provinces. In 2016, the scheme was expanded to include Fujian province, as shown in Figure 1.

Figure 1 The Carbon Trading Pilots in Provinces



3. Data

For the present study, the data spanning the 2000–2021 period pertaining to 9998 observed values of A-shared listed companies operating across 14 industrial sectors in China was analyzed to elucidate the effect of carbon emission permit trading on green innovation. The information on green patents (as a measure of innovation quantity) was sourced from Chinese Research Data Service (CNRDS), while other relevant the data was taken from CSMAR.

3.1 Independent Variable: Carbon Trading Pilot Participation

In the model developed as a part of this study, participation in the carbon trading pilot initiative was considered an independent variable. As Shanghai, Beijing, Hubei, Guangdong, and Tianjin provinces were initially selected for this initiative and were joined in 2016 by

Fujian province, companies operating in pilot cities that were included in the carbon trading program in 2011 or 2016 were coded as 1 and others were coded as 0.

3.2 Dependent Variable: Quantity and Quality of Green Innovation

In this study, the quantity of innovation, as a dependent variable, was measured by the number of green patents attained by companies. Using this approach has several advantages. First, compared with financial investment and input in research and development, green patents are much more specific and better reflect the level of corporations' innovation in the green technology sector. Second, using the number of green patents that had already been attained rather than those that had been filed allowed us to eliminate poor-quality innovations.

Nonetheless, this approach did not holistically account for the effect of corporate green innovation since the relative quality of attained patents was not considered. To mitigate this issue and measure the quality of green innovation, we adopted the method proposed by Zhang et al. (2022), allowing the quality of green patents to be based on the difference in the International Patent Classification (IPC) of patents attained by a company as indicated in the following equation:

$$quality_{xt} = 1 - \sum \alpha^2$$

$\alpha = the\ proportion\ of\ the\ number\ of\ patents\ in\ a\ category\ owned\ by\ company\ x\ in\ year\ t$

Accordingly, the greater the value of *quality*, the more diverse a company's patent portfolio is, which indicates higher quality of innovation.

3.3 Control Variables

Several factors could affect the level of green innovation, which could be classified into two categories: the scale of a firm and its financial indicators. The size and the age of a firm are typically adopted as the indicators of its scale, given that the size often affects the availability of resources and thus the development of new green technologies, while the age impacts the innovating capacity (Li et al., 2021). In the sample analyzed as a part of this study, the mean firm size is 22.214, and the mean age is 2.692.

We also controlled for Tobin's Q ratio, return on assets, and leverage, as they respectively indicate a firm's ability to create value (which is associated with its ability to innovate), to generate revenue (reflecting the efficiency and profitability), and financial risks. Table 1 summarizes the definitions of key variables.

Table 1: Definition of Key Variables

Variable	Definition	Reference
Pilot	If a firm takes part in carbon permit trading, the value is 1 and is 0 otherwise.	Xiao et al. (2022)
Scheme benchmark	If permits are allocated to a firm by the benchmark method, the value is 1 and is 0 otherwise.	Song et al. (2021)
Scheme history	If permits are allocated to a firm by the historical method, the value is 1 and is 0 otherwise.	Song et al. (2021)
Number	Natural logarithm of the number of green patents attained by a firm	Du et al. (2021)
Quality	The quality of green patents attained by a firm	Zhang et al. (2022)
Tobin Q	The ratio between the market value and the replacement value of physical assets	Shi and Wu (2022)
ROA	Return on assets	Li (2022)
Lev	Leverage	Li (2022)
Size	Size of a firm	Tang et al. (2022)

Firm age	The number of years since the firm was founded	Wang and Zhang (2022)

Table 2 provides the descriptive statistics of the dataset used in the analyses. As can be seen from the tabulated data, the number of green patents obtained by one company in one year ranges from 0 to 61, demonstrating significant variation in the level of innovation. In addition, the mean number of green patents was 0.155 while the mean quality of green innovation was only 0.107, showing an overall relatively poor innovation performance.

Table 2 Descriptive Statistics of Key Variables

Variable	Observations	Mean	Std. Dev.
Number	9,555	0.155	1.603
Quality	9,289	0.107	0.224
Tobin Q	9,433	1.697	1.071
ROA	9,554	0.037	0.057
Lev	9,555	0.480	0.204
Size	9,555	22.214	1.380
Firm age	9,555	2.692	0.489

4. Empirical Strategy and Results

The empirical strategy adopted in the present study follows the standard DID model, as the aim is to investigate the effect of carbon trading on corporate green innovation. The model specification takes the following form:

$$Innovation\ (number, quality)_{xt} = \alpha + \beta Participation_{xt} + \delta C_{xt} + \delta_x + \sigma_t + \varepsilon_{xt} \qquad (1)$$

The first model was developed to compare the relative changes in the quantity and quality of green innovation of companies participating in carbon trading with those of companies that were not part of this pilot program. Accordingly, in Equation (1), $Innovation_{xt}$ refers to the quantity and quality of green patents attained by company *x* in year *t.* The main explanatory variable is $Participation_{xt}$, which is a dummy variable that equals 1 if the company participated in carbon trading and takes the value of 0 otherwise. C_{xt} refers to all control variables incorporated into the model, including Tobin's Q, ROA, leverage, firm size, and firm age. As befits a fixed-effects model, δ_x captures the time-invariant regional characteristics for province *x* that may be associated with the reform, whereas σ_t controls for the temporal effects in our estimation, and ε_{xt} is the error term.

The model also features the main explanatory variable, $Scheme\_benchmark_{xt}$, which is a dummy variable that equals 1 if the carbon permit was allocated by the benchmark method and is set to 0 otherwise, and $Scheme\_history_{xt}$, another dummy variable that equals 1 if the carbon permit was allocated by the historical method and 0 otherwise. Under the historical method of allocation, the emission permits for firms are determined from their historical emission levels. On the other hand, under the benchmark method, the emission permits are determined from the average emission level for a particular industry. We expect the coefficient β to be positive.

4.1 Baseline Results

The empirical results obtained by applying Equation (1) to our dataset are reported in Table 3, whereby the effect of participation in carbon trading on the quantity of innovation (when control variables are included in the model) is shown in Column 2. As can be seen from the tabulated data, participation in carbon emission permit trading as well as firm age exerted a statistically significant and positive impact on the number of green patents. The strength of this relationship was stronger compared to that shown in Column 1 where the effects of control variables are excluded.

The effect of participation in carbon trading on the quality of innovation without/with control variables is shown in Column 3 and 4. It is evident that participation in carbon trading has marginal effect on the quality of green innovation, but this effect disappears after controlling for Tobin's Q, ROA, leverage, firm age, and firm size. To further explore this issue, we conducted a heterogeneity analysis in the later section of this paper by dividing the firms into two industry categories.

Table 3 The Impact of Carbon Trading Pilots on Green Innovation: Baseline

	Quantity of green innovation		Quality of green innovation	
	(1)	(2)	(3)	(4)
Pilot	0.035***	0.038***	-0.017*	-0.015
	(0.010)	(0.010)	(0.010)	(0.010)
Tobin Q		-0.004		0.003
		(0.003)		(0.003)
ROA		-0.059		-0.015
		(0.050)		(0.048)
Lev		0.031		-0.023
		(0.022)		(0.022)
Size		-0.006		0.043***
		(0.005)		(0.005)
Firm age		0.039**		0.017
		(0.019)		(0.018)
Constant	0.041***	0.068	0.111***	-0.881***
	(0.003)	(0.121)	(0.003)	(0.118)
Observations	9,502	9,379	9,234	9,115
R-squared	0.551	0.554	0.367	0.375

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In general, participation in the carbon trading pilot program had a positive influence on the number of green patents attained by companies, supporting the findings obtained by Song et al. (2021). This result also validated Porter's hypothesis suggesting that environmental policies lead to an increase in innovation. As Porter explained, there are multiple potential reasons behind this link, as environmental regulations make companies aware of resource inefficiencies and prompt them to seek technological improvements. Such regulations also reduce uncertainty in the necessity of environmental investment and generate pressure that urges innovation and progress (Ambec et al., 2013).

4.2 Robustness Test

We also conducted the PSM-DID analysis and the findings reported in Table 4 indicate that carbon pilot participation still significantly and positively affected the number of green patents (Column 2). Similarly, the relationship between carbon trading pilot participation and green patent quality remained statistically insignificant (Column 4). Thus, the robustness tests had no impact on the previously reached conclusions.

Table 4: The Impact of Carbon Trading Pilot on Green Patents: PSM

	Quantity of green innovation		Quality of green innovation	
	(1)	(2)	(3)	(4)
Pilot	0.030***	0.033***	-0.017	-0.015
	(0.010)	(0.010)	(0.010)	(0.010)
Tobin Q		-0.004		0.003
		(0.003)		(0.003)
ROA		-0.031		-0.009
		(0.050)		(0.049)
Lev		0.044**		-0.025
		(0.022)		(0.022)
Size		-0.009		0.042***
		(0.005)		(0.005)
Firm age		0.044**		0.019
		(0.019)		(0.019)
Constant	0.041***	0.105	0.112***	-0.876***
	(0.003)	(0.121)	(0.003)	(0.120)

R-squared	0.557	0.560	0.368	0.375
Observations	9,255	9,134	8,996	8,879

Note: Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Next, we analyzed the effect of different permit allocation methods on the quantity and quality of green innovation reported in Table 4.[1] For this purpose, we used *Scheme benchmark* as the proxy variable for the benchmark method of allocation, while *Scheme history* was the proxy variable for the historical method of allocation. Based on the results presented in Column 1 of Table 5, the benchmark allocation method did not have a statistically significant effect on the number of patents, whereas the historical allocation method had a statistically significant and positive effect on the number of patents. This finding aligns with the baseline result. When the effect of different permit allocation methods on the quality of green innovation were analyzed, as shown in Column 3 and Column 4, neither method exhibited a statistically significant effect on the quality of green innovation, corresponding with the baseline result of having a marginal effect on the quality of green innovation.

Table 5 The Impact of Carbon Trading Pilots on Green Innovation: Different Methods

	Quantity of green innovation		Quality of green innovation	
	(1)	(2)	(3)	(4)
Scheme benchmark	-0.019		0.020	
	(0.021)		(0.020)	
Scheme history		0.113***		-0.018
		(0.014)		(0.014)
Tobin Q	-0.003	-0.004	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)

[1] For the analyses presented in this section, data related to the Chongqing were excluded as the methods of allocation were self-reported in this province.

ROA	-0.022	-0.025	-0.013	-0.012
	(0.049)	(0.049)	(0.049)	(0.049)
Lev	0.046**	0.043*	-0.024	-0.023
	(0.022)	(0.022)	(0.022)	(0.022)
Size	-0.009	-0.008	0.042***	0.042***
	(0.005)	(0.005)	(0.005)	(0.005)
Firm age	0.037*	0.049***	0.023	0.020
	(0.019)	(0.019)	(0.019)	(0.019)
Constant	0.125	0.059	-0.884***	-0.875***
	(0.121)	(0.120)	(0.119)	(0.119)
Observations	9,169	9,169	8,914	8,914
R-squared	0.559	0.563	0.375	0.375

Note: Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5. Theoretical Framework

The empirical findings reported in the preceding section confirmed that carbon trading increased firms' quantity of green innovation while having a marginal effect on its quality. Nevertheless, the exact mechanism behind this phenomenon remains ambiguous. In addition, the extent of this effect in different industries has not been sufficiently explored. To address these shortcomings, we analyzed corporates' decision making related to both quantity and quality of green innovation, aiming to identify the impact of carbon trading on this process. For this purpose, a theoretical model that takes into consideration the externality effects is proposed. Externalities are of great importance for innovation success, which depends on collaborative potential within the industry and the relationships among suppliers (Acemoglu et al., 2023).

5.1 Baseline Model

When developing the model, we assumed that all market participants make production and innovation decisions with the goal of maximizing their profits. In the carbon trading context, this implies that green innovation is motivated by the need to reduce carbon emissions, while considering the cost of such initiatives.

Accordingly, the traditional profit function of a typical firm can be expressed as:

$$\pi = pq - cq \tag{1}$$

where p refers to product price, q denotes the quantity produced, and c is the cost of producing one product. However, under the carbon trading scheme, firms can gain additional revenue by selling their unused permits. Therefore, the revenue R_C the firm could gain by reducing emissions can be expressed as:

$$R_c = qmrv \tag{2}$$

where m refers to the carbon emissions generated by producing each product, v represents the carbon permit market price, and r represents the Emission Reduction Coefficient due to green innovation, where $r \in [0,1]$, indicating that greater r corresponds to a greater carbon emission reduction. To examine and compare the investment strategies aimed at improving the quantity and quality of green innovation, respectively, we distinguished the costs associated with each aspect, as expressed below:

$$c_{GI} = w_1 x + w_2 y \tag{3}$$

where c_{GI} refers to the cost of developing green innovation, x denotes the quantity of green innovation developed by a firm, y represents the quality of green innovation developed by a firm, w_1 refers to the per unit average cost of increasing the quantity of green innovation without considering the quality, and w_2 refers to the per unit average cost of increasing the quality of green innovation. Therefore, the profit function of a firm in the carbon trading context can be expressed as:

$$\pi = pq + cq + qmrv - w_1 x - w_2 y \tag{4}$$

The effect of firms' green innovation on carbon emission reduction is measured by *r*. Since *r* represents the proportion of emissions that are reduced, its maximum value is 1. In addition, as *r* approaches 1, the marginal effect of each additional green innovation gradually decreases. As these properties of *r* correspond to the characteristics of an s-curve, the differential equation for calculating *r* could be expressed as:

$$\frac{dr}{dx} = \theta(1 - r) \tag{5}$$

where *x* refers to the total number of green innovations while θ represents the output coefficient per green innovation. Moreover, the $0 \leq r \leq 1$ constraint is consistent with the definition of *r* as the proportion of a firm's total emissions that are reduced. After solving the differential equation, it could be expressed as follows:

$$r = 1 - e^{-\theta x} \tag{6}$$

Since the output coefficient per green innovation θ is also related to the quality of green innovation, θ could be defined as:

$$\theta = a + by \tag{7}$$

where a refers to the output coefficient of the green innovation quantity while b denotes the output coefficient of the green innovation quality as they are positively related. *r* can be expressed as:

$$r = 1 - e^{-ax-bxy} \tag{8}$$

After substituting *r* with this expression, the profit function is given by:

$$\pi = pq - cq + qmv(1 - e^{-ax-bxy}) - w_1x - w_2y \tag{9}$$

In addition, we assumed that each firm has a fixed budget for green innovation development, where:

$$w_1x + w_2y = k \tag{10}$$

To determine the optimal quantity and quality of green innovation under these financial constraints, and to solve the maximization problem with constraints, we adopted the following Lagrange function:

$$L = pq - cq + qmv(1 - e^{-ax-bxy}) - w_1x - w_2y + \lambda(k - w_1x - w_2y) \tag{11}$$

By taking a derivative with respect to x_1, y_1, and λ, we obtain:

$$\frac{dL}{dx} = (qmv)(e^{-ax-bxy})(a + by) - w_1 - w_1\lambda = o$$
$$\frac{dL}{dy} = (qmv)(e^{-ax\ -bxy})(bx) - w_2 - w_2\lambda = o$$
$$\frac{dL}{d\lambda} = k - w_1x - w_2y = 0$$

By solving this system of three equations, we arrive at the optimal value of *x* and *y*:

$$x = \frac{k}{2w_1} + \frac{aw_2}{2bw_1} \tag{12}$$

$$y = \frac{k}{2w_2} - \frac{a}{2b} \tag{13}$$

The optimal value of *x* and *y* reflects the relationship that innovation quantity and quality, as two important innovation factors, have with other related variables. As the two terms comprising *x* are positive, *x* must also be positive, which indicates that carbon trading will increase the quantity of green innovation. In addition, this increase is proportional to k, a, and w_2, while it is inversely proportional to w_1 and b. In other words, as a firm's budget increases, so will the number of green innovations. In addition, firms have to find an optimal balance between innovation quantity and quality, depending on the relative price ($\frac{w_1}{w_2}$) and the relative marginal effect ($\frac{a}{b}$). If the relative price of innovation quantity increases (decreases), the optimal level of innovation quantity decreases (increases). If the relative marginal effect of innovation quantity increase (decrease), the optima level of innovation quantity increase (decrease). The same arguments apply to the optimal level of quality.

In Section 1, we defined the quality of innovation according to the difference in the International Patent Classification (IPC) of patents attained by a company, the value of which ranges from 0 to 1. Nevertheless, according to Equation (13), *y* could be negative when k is smaller than $\frac{w_2 a}{b}$. To better align the model with our empirical results, we designed a piecewise function based on the value of k, where:

$$y = \begin{cases} 0 & when\ k < \frac{w_2 a}{b} \\ \frac{k}{2w_2} - \frac{a}{2b} & when\ k \geq \frac{w_2 a}{b} \end{cases} \tag{14}$$

These conditions are set because when k is smaller than $\frac{w_2 a}{b}$ and *y* is negative, firms have no incentives to invest in the quality of innovation and will only focus on increasing its quantity (Jia et al., 2019). Conversely, when k is greater than $\frac{w_2 a}{b}$ and y is positive, firms will invest in efforts aimed at improving the innovation quality according to Equation (13).

The equation for x is similarly modified as a piecewise function, as shown below:

$$x = \begin{cases} \frac{k}{w_1} & when\ k < \frac{w_2 a}{b} \\ \frac{k}{2w_1} + \frac{aw_2}{2bw_1} & when\ k \geq \frac{w_2 a}{b} \end{cases} \tag{15}$$

Accordingly, when k is smaller than $\frac{w_2 a}{b}$ and y is negative, firms will invest their entire budget in increasing the quantity of green innovation as investing in its quality will yield negative results. On the other hand, when k is greater than $\frac{w_2 a}{b}$ and y is positive, firms will invest with the aim of increasing the green innovation quantity according to Equation (12).

The piecewise functions given in Equation (14) and (15) demonstrate how firms tend to prioritize the quantity of green innovation over its quality when funding is limited ($k \leq \frac{w_2 a}{b}$). Therefore, theoretically, the carbon trading policy should have a greater impact on the quantity than on the quality of green innovation, leading to the following proposition:

Proposition 1: The carbon trading policy increases the quantity of green innovation more strongly that its quality.

5.2 Model with Externalities

To evaluate and compare the effects of carbon trading on green innovation in different industries, the impact of externalities must be considered. Similar to all innovations, green innovations are influenced by the knowledge spillover from other firms, as it reduces the cost of research and development. While such externalities exist in all industries, the magnitude of their impact varies. In particular, the extent of this externality is sensitive to the homogeneity of products in an industry. If firms in an industry provide relatively similar products with similar ownership attributes, the effect of knowledge spillover will be more pronounced, as an innovation developed by one firm could be easily replicated by another firm. Converse is true for firms that operate in an industry that provides relatively diversified products. In comparison to other industries, firms in the electric power industry provide relatively homogenous products, due to which they will be affected to a greater extent by knowledge spillover than those operating in other industries (Borenstein & Bushnell, 2022; Nemoto & Goto, 2004; Thopil & Pouris, 2010).

In addition, as shown in Section 4, carbon trading exerts significant effect on green innovation quantity, while its impact on its quality is marginally significant. Accordingly, when investigating the heterogeneity between different industries, focus will be given on the quality of green innovation.

Assuming the presence of externalities with the potential for knowledge spillover, the total quantity of green innovation can be expressed as:

$$x = x_1 + \sigma\bar{x} \quad (16)$$

where x refers to the final quantity of green innovation of a firm after considering externality effects, x_1 denotes the quantity of green innovation developed independently by a firm, $\bar{x}$ represents the total quantity of green innovation developed by other firms in the industry, and σ refers to the extent of the effect of externalities on the green innovation quantity. We assumed $0 \leq \sigma \leq 1$, where $\sigma = 0$ represents no externalities, indicating that the firm does not utilize innovations produced by others, due to which $x = x_1$. Conversely, $\sigma = 1$ indicates that all innovations in the industry could be utilized with zero cost, leading to $x = x_1 + \bar{x}$. Therefore, σ reflects the difficulty with which a firm can use other firms' innovations.

In practice, externalities and knowledge spillover might also influence the green innovation quality, which was in the prior analyses represented as IPC classification diversity.

However, the effect of knowledge spillover on IPC classification diversity is highly random and ambiguous. Therefore, in the following analyses, it is assumed to exert an overall neutral effect on the quality of green innovation, due to which $y = y_1$.

We further assumed that using others' innovation does not incur any costs because, in comparison with w_1 and w_2, the cost of adopting others' innovation is negligible. If this was not the case, it would be more profitable for the firm to conduct proprietary research. After considering the effect of σ, the profit function of a firm is expressed as:

$$\pi = pq - cq + qmv\left(1 - e^{-a(x_1+\sigma\bar{x})-b(x_1+\sigma\bar{x})(y_1)}\right) - w_1x_1 - w_2y_1 \tag{18}$$

It is important to note that firms only bear the cost of developing proprietary green innovations, as they can freely use others' innovations. Therefore, the cost of developing green innovation changes from $w_1x + w_2y$ to $w_1x_1 + w_2y_1$. Similarly, the Lagrange equation can be expressed as:

$$L = pq - cq + qmv\left(1 - e^{-a(x_1+\sigma\bar{x})-b(x_1+\sigma\bar{x})(y_1)}\right) - w_1x_1 - w_2y_1 + \lambda(k - w_1x_1 - w_2y_1) \tag{19}$$

To find the profit maximizing value of x_1 and y_1, we take three derivatives of L with respect to x_1, y_1, and λ:

$$\frac{dL}{dx_1} = qmv\left(1 - e^{-a(x_1+\sigma\bar{x})-b(x_1+\sigma\bar{x})(y_1)}\right)(a + by_1) - (1+\lambda)(w_1) = 0$$

$$\frac{dL}{dy_1} = qmv\left(1 - e^{-a(x_1+\sigma\bar{x})-b(x_1+\sigma\bar{x})(y_1)}\right)(b)(x_1 + \sigma\bar{x}) - (1+\lambda)(w_2) = 0$$

$$\frac{dL}{d\lambda} = k - w_1x_1 - w_2y_1 = 0$$

By solving this system of three equations, the value of x_1 and y_1 can be calculated as follows:

$$x_1 = \frac{k - w_1\sigma\bar{x}}{2w_1} + \frac{aw_2}{2bw_1} \tag{20}$$

$$y_1 = \frac{k + w_1\sigma\bar{x}}{2w_2} - \frac{a}{2b} \tag{21}$$

As we assumed that two identical firms in an industry, the Nash equilibrium, whereby $\bar{x} = x_1$, the equilibrium value of x_1 and y_1 can be expressed as:

$$x_1 = \frac{k}{w_1(2+\sigma)} + \frac{aw_2}{bw_1(2+\sigma)} \tag{22}$$

$$y_1 = \frac{k}{w_2} - \frac{k}{w_2(2+\sigma)} - \frac{a}{b(2+\sigma)} \tag{23}$$

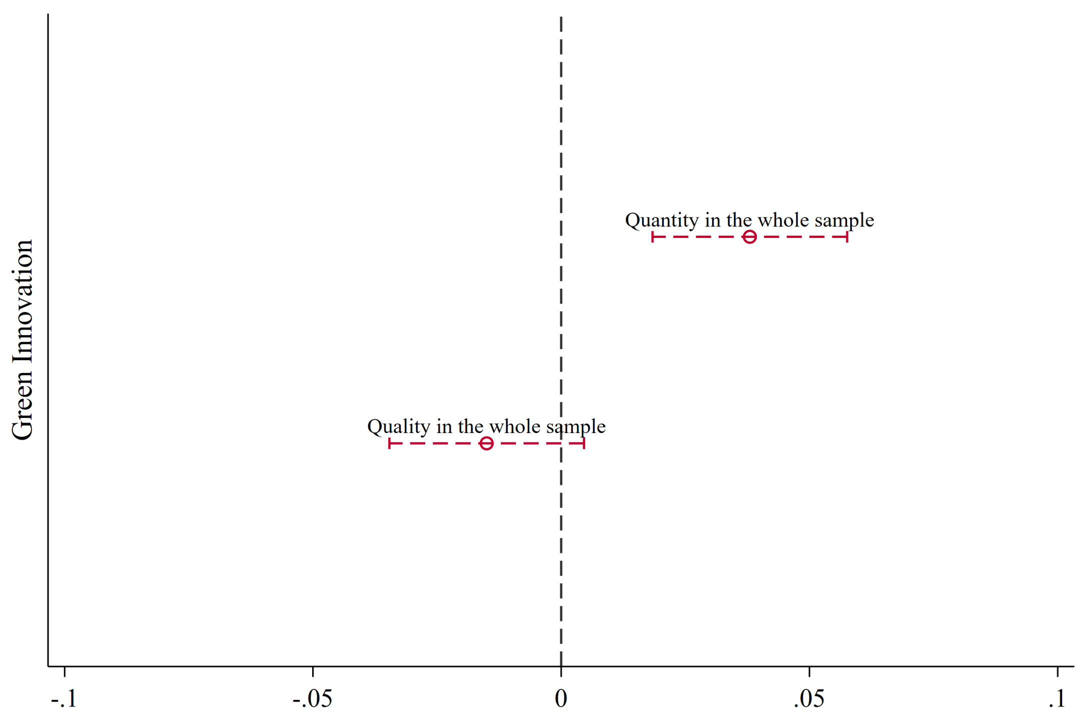
From Equation (23), it is evident that the value of σ is positively correlated with y_1, implying that firms operating in an industry with high externalities and strong potential for knowledge spillover will have greater quality of green innovation. This result can be generalized to multiple firms in the market, as outlined in Appendix. Given that, according to Nemoto and Goto (2004), Thopil and Pouris (2010), and Borenstein and Bushnell (2022), the externalities are higher in the electric power industry, participating firms will have higher quality of green innovation in comparison to firms in other industries, as reflected in our second proposition:

Proposition 2: The carbon trading policy increases the quality of green innovation more strongly for firms in the electric power industry than for those in other industries.

6. Discussion

The theoretical framework presented in this work shows that the carbon trading policy is expected to exert a stronger effect on the quantity of green innovations than its quality due to budget constraints. This hypothesis explained the empirical conclusion of carbon trading increasing the quantity of green innovation while having marginal effect on the quality of green innovation. Because firms will prioritize the development of the quantity of green innovation when their financial budget is limited, the increase in the quantity of green innovation is consequently more significant than the quality of green innovation (Figure 2).

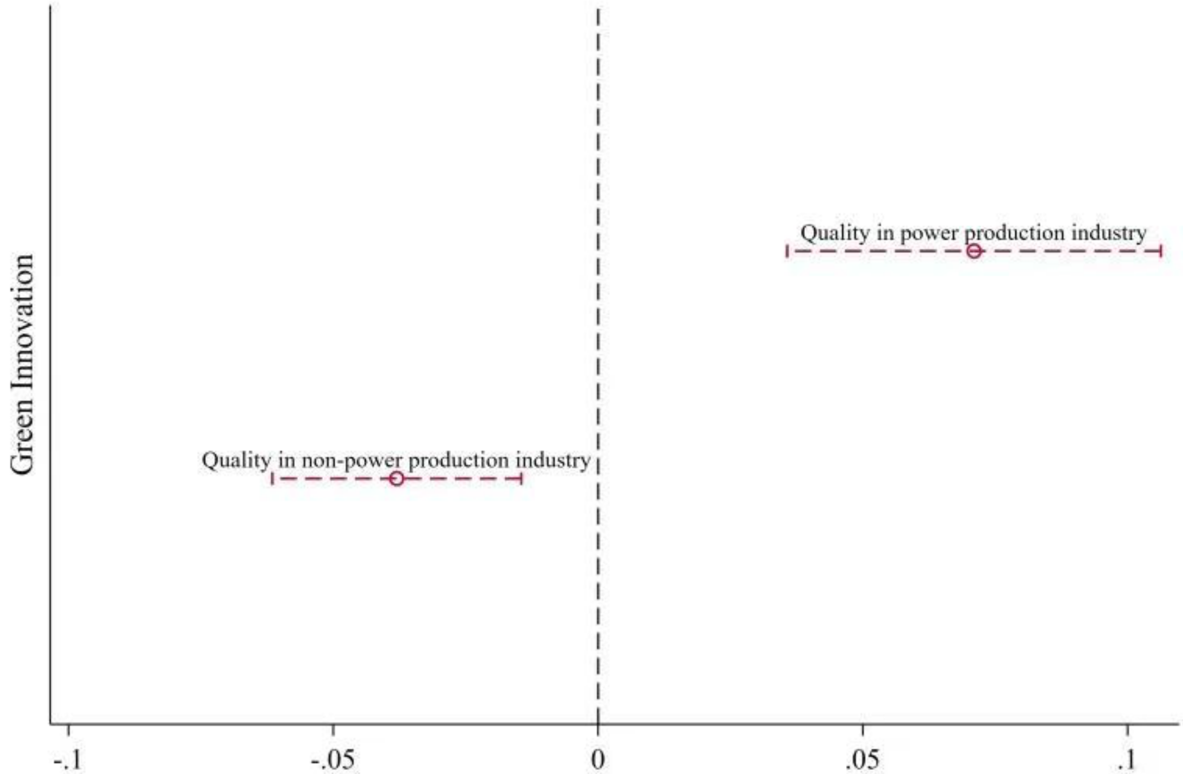
Figure 2: Quantity and Quality of Green Innovation



In addition, the above theoretical expectation shows that the externality of the power production industry is greater than the non-power production industry. Externality is the influence of an enterprise's economic activities on other enterprises and society. This paper focuses on the externalities of knowledge sharing, patent opening and collaborative research and development. Because most power enterprises have similar ownership attributes, it is easier to carry out knowledge sharing, patent opening and collaborative research and development, and more convenient to form an innovation sharing mechanism. We distinguish the firms in the power production industry and the non-power production industry according to the industry in which the enterprise is located, to test the externalities in industries with subsamples.

Our theoretical model demonstrated that, since the electric power production industry is subjected to greater externalities, the quality of green innovation in firms that take part in carbon trading is higher than in firms operating in other industries. Accordingly, we conducted the Hausman test to verify Proposition 2, whereby the null hypothesis was that there is no systematic difference in the coefficients related to carbon trading pilots between the electric power generation industry and the non-electric power generation industry in terms of innovation quality (Figure 3). As the p-value was less than 1%, this result confirms a significant difference in the quality of green innovation between these two industry categories.

Figure 3: Quality of Green Innovation in Electric Power Generation and Non-Electric Power Generation Industries



7. Conclusions

Firms' green innovation is pivotal for their sustainable development. Determinants of such innovation (including carbon trading) have been extensively discussed by social scientists. However, empirical data on this subject are presently inconsistent, possibly due to the endogeneity challenges that cast doubt on causality. This discrepancy undermines the efficiency of policy recommendations based on existing research. Utilizing China's 2011 and 2016 carbon trading pilots as quasi-experiments, we constructed a dataset spanning the 2000–2021 period and consisting of 9,998 observed value of A-share listed industrial companies to empirically test the impact of carbon trading pilots on firms' green innovation. We employed the staggered DID method and obtained results indicating that carbon trading pilots increased the quantity of green innovation without affecting its quality, and these findings remained robust after rigorous tests. We also discussed the mechanism underlying these impacts from an externality perspective.

Our work thus highlights the necessity of piloting carbon trading and enhancing externalities in fostering firms' green innovation. First, it is pivotal for the government to broaden the scope of carbon trading trials, as this has proven efficacious in increasing the number of green patents secured by enterprises. Second, amplifying activity in the secondary market is crucial, given that the fundamental economic value of carbon trading is anchored in the tradability of permits, as articulated by Spash (2010). Third, there is a call to augment the adoption of the historical allocation method, which has demonstrated a stronger propensity to stimulate green innovation. Fourth, it is advisable for the government to extend carbon trading trials in sectors analogous to the electricity generation and distribution industry.

However, there are various ways in which the current study can be improved. First, the indicator of green innovation quality adopted in this work is based on the market concentration equation. Accordingly, it is inaccurate as it is possible for a company to specialize in one field and attain multiple high-quality innovations. Therefore, authors of future studies could utilize more accurate indicators and should analyze datasets that include non-industrial companies in China and elsewhere.

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Appendix

To test the generality of the model, we assumed that there are *n* firms in the market, where:

$$\bar{x} = (n-1)x_1$$

Accordingly, x_1 and y_1 can be expressed as:

$$x_1 = \frac{k}{2w_1 + w_1\sigma(n-1)} + \frac{aw_2}{b(w_1)[2+\sigma(n-1)]}$$

$$y_1 = \frac{k}{w_2} - \frac{k}{2w_2 + w_2\sigma(n-1)} - \frac{a}{b[2+\sigma(n-1)]}$$

After including the number of firms (n), as a variable, σ remains positively correlated with y_1. This indicates that our theoretical finding can be generalized.

Acknowledgements

Witnessing environmental degradation, especially air pollution, increasing at a visible rate in my community, I have long pondered about the potential solutions in mitigating climate change. With this in mind, I visited the Shenzhen Emission Exchange Center last summer, where I was first introduced to the policy of carbon trading. Fascinated by its flexible market mechanism, I was immediately intrigued by this policy, particularly how it simultaneously enable emission abatement and economic development at a micro-level. After doing some research, I became aware of Porter's hypothesis, which states how environmental regulations benefit firms by encouraging green innovation. This prompted my research in the relationship between carbon trading and firms' green innovation.

Empirical analysis is essential to explore this issue in-depth. I sought for guidance from professionals who are expert in empirical analysis. That is when I met Professor Shuo Chen. After learning about my research proposal, Professor Chen is willing to guide me with no charge.

Professor Chen has enhanced my understanding of empirical model and also provided me with extensive relevant literature, which together formed the foundation of this paper. After reaching several empirical conclusions, Professor Chen then encouraged me to explore the underlying mechanism behind it, leading to the creation of the theoretical model. Though the field we were exploring has little theoretical foundation, Professor Chen greatly assisted me by proposing a unique angle: the effect of externality and knowledge spillover, which served as the theoretical foundation of the paper.

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