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Responses of Green Innovation to Carbon Emission Policies in China's Construction Industry

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A B S T R A C T

Under the global trend of carbon peak and neutrality, the effectiveness of the carbon emission in construction industry remains unverified. This research investigates the impact of carbon emission policies on green innovation in the construction industry. Utilizing a multi-period Difference-in-Differences (DID) model, this study analyzes data on the quantity and quality of green innovation patents. Findings indicate that carbon peaking policies significantly enhance both the quality and quantity of green innovations, particularly in fossil fuel decarbonization and pollution control. The analysis reveals that the policy's short-term effects are stable and do not exhibit lagging impacts. This study provides a framework for assessing the influence of carbon emission policies on green innovation, aiding in the formulation of effective carbon emission strategies tailored to the industrial context.

1. Introduction

In response to climate change, the traditional economic development model prioritizing environmental sacrifices is increasingly misaligned with societal demands (O'Connell 2024; Shui et al. 2024). Over 100 nations have committed to achieving carbon peak and carbon neutrality, which involves controlling greenhouse gas emissions at their highest point and subsequently reducing or offsetting these emissions (Khanna et al. 2023; Loewen 2022). Green innovation refers to the development of new processes, products, and technologies aimed at minimizing environmental harm and has been shown to mitigate carbon emissions (Guo and Cai 2022; Kunapatarawong and Martínez-Ros 2016; Sun 2022). In response, governments have enacted carbon emission policies to encourage the adoption of green technologies in various industries, aiming to reduce energy consumption and pollutant emissions (Lu and Feng 2024; Zhang et al. 2024). However, the effectiveness of these policies remains unverified, and analyses of their mechanisms for promoting green innovation are limited.

The construction sector, unlike other advanced industries, has been criticized for resisting technological change and wasting energy (Wang et al. 2024; Zhang et al., 2024). The 2018 Global Status Report on Building and Construction reveals that the construction sector is responsible for 40% of global energy consumption and 36% of carbon emissions (Ahmed et al. 2022; IEA 2019). The contradiction between the development of the construction industry and carbon emission reduction has become increasingly prominent (Li et al. 2021). However, its investment in research and development (R&D) and innovation remain significantly lower than that of other industries (Suprun and Stewart 2015). Therefore, promoting green innovation in the construction industry presents a challenge for the countries striving to achieve carbon peaking and carbon neutrality. There are numerous factors impeding innovation in the construction industry, such as additional costs associated with innovation, lack of innovation experience, resistance to change, and a lack of necessary products (Ozorhon 2013; Yu et al. 2021). These obstacles result in relatively lower economic benefits from innovation in the construction industry compared to other sectors. When companies bear a large portion of the innovation costs, they may lack the motivation to drive necessary innovation (Silajdžić et al. 2015). In the face of the aforementioned obstacles, policy may serve as an external factor that promotes innovation in the construction industry and effectively incentivizes the sector to adopt relevant measures. Research has found that the subsidy policy can stimulate the application of renewable

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energy (Li et al. 2018), offsetting the additional costs associated with innovation activities (Chang et al. 2016). For instance, the subsidies for electric vehicles have propelled the development of the electric vehicle industry and energy economy (Lin et al. 2023). Carbon trading policies and green credit policies have also been found to have significant promoting effects on innovation (Hu et al. 2021; Yang et al. 2023). Carbon targets constraints will compel high-carbon product sectors to transition from being energy and labor-intensive to capital and technology-intensive (Wang et al. 2023). However, most of these studies focused on technology-intensive industries or broadly considered all industries without considering the disparities between different sectors and how to facilitate green transition of the traditional industries.

This study aims to analyze the impact of carbon emission policies on green innovation in the construction sector, considering carbon peak and neutrality goals. A multi-period Difference-in-Differences (DID) model will be employed to assess the effects of these policies through a quasi-natural experiment, accounting for dynamic impacts and heterogeneity in green innovation. Data on green innovation patents in China's construction industry, collected before and after the implementation of carbon emission policies, will be analyzed. This research seeks to clarify how green innovation responds to carbon emission policies, using China's construction industry as a case study, thereby supporting the objectives of carbon peaking and neutrality.

2. Literature Review

2.1. Green Policy Effect Studies

Green policies, including government regulations, environmental taxes, and tradable emission permits, are often perceived by economists and managers as imposing additional costs that may hinder green innovation (Yang et al. 2023). However, the strong version of the Porter hypothesis suggests that environmental regulations can actually stimulate innovation, thereby offsetting these additional compliance costs (Porter and Van der Linde 1995). Although numerous studies support this hypothesis (He et al. 2020; Jin et al. 2022), most have focused on developed economies or mature policy frameworks in emerging countries, indicating that the findings may not be universally applicable (Borsatto and Amui 2019).

Research on the strong version of the Porter hypothesis has yielded contradictory results. Evidence from Chinese manufacturing firms indicates that stringent environmental regulations may lead to increased pollution control costs, potentially crowding out R&D investments (Guo et al. 2018; Lai and Wong 2012). Additionally, Shen et al. (2020) found that pollutant charges positively impact green process innovation but negatively affect sustainable product innovation, while emission trading mechanisms show no significant effect on green innovation. These inconsistent findings provide evidence for the evolving versions of the Porter hypothesis, the weak and narrow versions (Jaffe and Palmer 1997). Weak version of Porter hypothesis highlights only carefully crafted environmental regulations can effectively drive innovation. Narrow version of Porter hypothesis considers the diversity of policies to encourage flexible regulations that support corporate innovation.

While existing literature has examined the various versions of the Porter hypothesis, further exploration is needed in developing countries where research evidence is still emerging. Given that the structural framework for China's carbon peaking and neutrality policies is still evolving, it is crucial to investigate how these policies influence green innovation. This is particularly important in the context of developing countries, where low labor costs may pose challenges to technological advancement.

2.2. Problems in Green Policy and Innovation

Government carbon emission policies targeting carbon peaking and neutrality are not uniformly implemented across regions or industries in China. In the construction sector, various government agencies issue green policies, including regulations and standards, at different times and levels. Consequently, the implementation of these policies can vary significantly among construction companies based on their size and geographic location. This variability leads to dynamic effects of carbon emission policies on green innovation.

Green innovation encompasses processes that develop new production methods and technologies aimed at minimizing pollution and the negative impacts of resource extraction (Ponta et al. 2021). One common indicator for measuring green innovation is the quantity of relevant patents (Lindman and Söderholm 2016; Luis Míguez et al. 2018; Zhu et al. 2019). However, there is heterogeneity among these patents, as not all carry equal significance. Relying solely on patent quantity to assess the impact of environmental policies can introduce biases. Some companies may pursue innovation primarily to secure government subsidies or competitive advantages, leading to the pursuit of low-quality patents (Rong et al. 2017). This phenomenon can result in a bubble in green patents, where an increase in quantity does not correlate with quality (Tao et al. 2021). Therefore, this study will evaluate green innovation based on both the quantity and quality of patents, referred to as innovation quantity and innovation quality.

Conventional green innovation includes a range of sustainable technologies, such as renewable energy solutions, clean production technologies, and energy-saving systems. Previous research has highlighted the varying mechanisms and effectiveness of different green innovations in reducing carbon emissions. For instance, Jiao et al. (2020) examined seven green technologies categorized in the International Patent Classification (IPC) green list, revealing significant heterogeneity in their effectiveness across industries. In the refining industry of Mexico, carbon capture technology was identified as the most efficient (Díaz et al. 2016), while biomass energy and carbon capture technologies were deemed most effective in China's power sector (Wang et al. 2018).

This study will focus on China's construction sector to investigate how government policies influence green innovation. It will explore the dynamics of policy effects and the differences among various innovation categories, as well as between the quantity and quality of innovations. The research aims to clarify how the construction industry, historically characterized by an innovation deficit, can enhance green innovation under policy guidance. Additionally, it seeks to reveal pathways for similar industries to respond effectively to carbon emission policies, contributing to broader sustainability goals.

2.3. Policy Analysis Approaches

Public policy analysis requires causal inference to evaluate past policies and inform future priorities. A widely recommended approach is to utilize natural experiments, analyzing outcomes from groups subjected to different policies and environmental conditions over time (Atanasov and Black 2021; Athey and Imbens 2017). This methodology is known as the Difference-in-Differences (DID) design, which has been a key estimation technique for causal inference in various fields, including finance, accounting, and policy research, for the past thirty years (Baker et al. 2022). The DID method typically compares a treatment group affected by new laws or regulations with a control group not impacted, assessing differential outcomes over time to deduce causal effects. Its broader application has increased due to the gradual enforcement of laws across states or countries.

However, many empirical applications of the DID method deviate from the standard framework, incorporating multiple time periods and varying treatment timings. The staggered DID approach is commonly used to evaluate policies implemented gradually across different regions. This method is more suitable for cases where the same policy is rolled out over time, gaining traction in the last decade (Baker et al. 2022). Despite its advantages, the staggered DID has faced criticism for producing estimates that represent a weighted average of various treatment effects (Callaway and Sant'Anna 2021; Goodman-Bacon 2021). The changing treatment and control groups at different time points can lead to varying treatment effects that the staggered DID may not fully capture. Consequently, a new method, the multi-period DID model, has been proposed to evaluate differences across multiple time periods (Callaway and Sant'Anna 2021).

The multi-period DID model involves three steps: identifying causal parameters relevant to the policy, combining these factors to create summary measures of causality, and estimating various target parameters (Callaway and Sant'Anna 2021).. This approach allows for clear causal parameter estimation, addressing dynamics and heterogeneity in treatment effects, thus avoiding the challenges of interpreting standard two-way fixed effects (TWFE) regressions as causal effects in the DID framework(de Chaisemartin and D'Haultfoeuille 2023; Sun and Abraham 2021).

This study adopts the multi-period Difference-in-Differences (DID) model due to the phased implementation and dynamic nature of carbon emission policies. These policies are enacted at different times across regions, and their effects may accumulate over time or exhibit lagged impacts. Compared to the traditional DID model, the multi-period DID framework effectively captures the dynamic treatment effects of policies on green innovation. By analyzing data across multiple time points, it distinguishes between short-term and long-term impacts while controlling fixed effects associated with time and regional factors, thereby enhancing the precision of causal inference. Furthermore, this model addresses heterogeneity in treatment timing, providing a more comprehensive understanding of how policy implementation affects green innovation differently across regions. This feature makes it particularly well-suited for the construction industry, where technological complexities and regional disparities are pronounced. Thus, the multi-period DID approach offers a robust and nuanced framework for examining the dynamic and region-specific effects of carbon emission policies on green innovation.

3. Methodology and Data

3.1. Assumptions of Multi-Period DID

A list of notations is provided in Appendix to explain the formulas in this section, shown in A.1.

To illustrate a natural extension of the parallel trend assumption with different time periods and different regions, formula 1 is given.

$$\mathrm{E}[\mathrm{Y}_t(0) - \mathrm{Y}_{t-1}(0)|\mathrm{G} = \mathrm{g}] = \mathrm{E}[\mathrm{Y}_t(0) - \mathrm{Y}_{t-1}(0)|\mathrm{C} = 1] \tag{1}$$

It indicates that, without intervention, the typical untreated potential results for the group initially treated at that time and the "never treated" group would have exhibited similar trends in all periods following the treatment t≥g. This naturally extends the parallel trend assumption in the context of two periods and two groups. If g is the time point of policy implementation, at the time $t \geq g$, the areas where the policy has not been enacted and those where it has been implemented follow similar trajectories.

The parallel trend assumption is deemed more reliable if it remains valid even when covariates are included. Formula 2 demonstrates the parallel trend assumption after incorporating covariates.

$$\mathrm{E}[\mathrm{Y}_t(0) - \mathrm{Y}_{t-1}(0)|\mathrm{X}, \mathrm{G} = \mathrm{g}] = \mathrm{E}[\mathrm{Y}_t(0) - \mathrm{Y}_{t-1}(0)|\mathrm{X}, \mathrm{C} = 1] \tag{2}$$

This is an advanced version of the parallel trend assumption, which incorporates covariates into the original assumption.

3.2. Multi-Period DID Model

ATE (Average Treatment Effects) refers to the treatment effect of randomly selecting an individual from the entire sample, reflecting the typical impact of the policy intervention on green innovation. It represents the expected level of green innovation for a randomly selected sample company if the policy is implemented. ATT (Average Treatment Effects on the Treated) considers only the samples from regions where the policy has been implemented, representing the treatment effect within the treated group. It focuses on measuring the effect of the policy on green innovation specifically within the treated regions. Under the condition of random assignment, where D_i is independent of $[Y_{it}(1), Y_{it}(0)]$, ATE = ATT. Since ATE includes both the treatment and control group individuals, some scholars criticize its broad definition. However, for policy makers, ATT may be a more important consideration as it directly measures the benefits of individuals in the treatment group before and after policy impact.

When $= 2$ *and* $t = 2$, $ATT(g=2, t=2)$ represents the promotion effect of green innovation in the policy-implemented regions in the second period of the DID analysis. Additionally, considering the case of multiple periods DID, $ATT(g=2, t=3)$ represents the treatment impact of individuals who underwent treatment in the second period at $t = 3$; $ATT(g=3, t=3)$ represents the treatment effect of individuals who received treatment in the third period at $t = 3$.

The estimation of the Average Treatment Effect (ATE), which is the ATT for each group after receiving policy impact, can be calculated using the following formula:

$$\theta_s(g) = \frac{1}{\tau - g + 1} \sum_{t=2}^{\tau} 1\{g \leq t\} ATT(g, t) \tag{3}$$

The overall treatment effect for all individuals in the treatment group after participating in the treatment is:

$$\theta_s^0(\mathrm{g}) = \sum_{\mathrm{g}=2}^{\tau} \theta_s(\mathrm{g}) \mathrm{P}(\mathrm{G} = \mathrm{g}) \tag{4}$$

The formula for estimating dynamic effects is:

$$\theta_{\mathrm{D}}(\mathrm{e}) = \sum_{t=2}^{\tau} 1|\mathrm{g} + 2 \leq \tau| \mathrm{ATT}(\mathrm{g}, \mathrm{g} + \mathrm{e}) \mathrm{P}(\mathrm{G} = \mathrm{g}) |\mathrm{G} + \mathrm{e} \leq \tau) \tag{5}$$

In the above equation, e represents the duration that the treatment group has been exposed to the policy impact.

3.3. Data and Variable Description

This research examines China's recent carbon emission policies as a case study, focusing on their impact on green innovation within the construction sector. As the largest developing nation, China leads the world in energy consumption and carbon dioxide emissions, accounting for 26.1% and 30.9% of global energy use and emissions, respectively, in 2020 (Sun et al. 2023). Decarbonization in China is critical for global climate change mitigation (Chen et al. 2023). To meet its carbon reduction targets, the Chinese government has committed to advancing relevant policies proactively (Duan et al. 2017). In 2020, China announced its goal to peak carbon emissions before 2030 and achieve carbon neutrality by 2060 (Wang et al. 2023). Local authorities have implemented action plans to pursue these goals.

Choosing China's carbon emission policy as a representative study is justified for two reasons. First, as the largest carbon emitter globally, understanding the effectiveness of policies on green innovation in China's construction sector can provide valuable insights for other countries' green transformations. Second, as an advocate of the Paris Agreement, China's carbon action plan holds significant relevance and can offer lessons for global efforts toward carbon peaking and neutrality.

To assess the impact of carbon emission policies on green innovation, a quasi-natural experiment was designed using data from eight provinces in China. Policy documents for carbon peaking action plans were released on February 17, April 21, June 19, and June 23, 2022, in the provinces of Zhejiang, Chongqing, Hebei, and Guangdong, respectively. As a control group, the study selected four other provinces—Shanxi, Jiangsu, Henan, and Gansu—where carbon peaking action plans were gradually released after 2023. The relevant policy documents explicitly mention goals related to green innovation, stating that by 2030, significant progress should be made in zero-carbon and negative-carbon technology innovation and industrial development. Based on the temporal differences in the release of local policies, the study designed a quasi-natural experiment to compare the experimental group with the control group. A multi-period difference-in-differences (DID) approach was employed to analyze data from 2021 to 2022, exploring the short-term effects of carbon peaking policies on green innovation in the construction industry.

Previous research has typically measured innovation through interviews or surveys with managers. However, due to the sensitivity of internal processes, few companies are willing to answer related questions (Ponta et al. 2021), leading to studies based on small sample sizes (Kitsios et al. 2016). Additionally, survey results may be influenced by respondent subjectivity. To address the uncertainties associated with interview data, recent studies have proposed alternative methods using indirect data, such as patent or publication data to measure innovation (Chen et al., 2023; Zhang et al. 2023). Patents are evaluated based on criteria of utility, novelty, and non-obviousness (Encaoua et al. 2006), providing both qualitative and quantitative insights into technological changes (Lee et al. 2011). The availability of patent databases offers a straightforward source for assessing innovation performance in both academic and industrial contexts (Ponta et al. 2021). This study utilizes green patent data from the IncoPat database, which offers extensive information and analysis on global patents. Focusing on categories such as construction, civil engineering, building installation, and decoration, the research integrates quarterly green patent application data from 2021 to 2022, as published by the National Intellectual Property Administration. This results in a final sample of 9,498 quarterly observations.

The dependent variable consists of the total number of patents and the average quality of patents, representing both the quantity and quality of innovation. The quantity of innovation refers to the number of patent applications submitted by each company on a quarterly basis. While the number of patents indicates a company's level of innovation, it does not fully reflect the quality of innovation due to the potential for patent bubbles. To assess patent quality, this study utilizes the Shared Value Index (SVI) from the IncoPat database. The SVI evaluates patent value based on three criteria: technological stability, advancement, and scope of protection (Wang and Liu, 2023; Xiao et al., 2023; She et al., 2019). The scoring for technological stability includes several factors, such as the validity of utility model patents, any history of litigation, instances of pledge preservation, whether the applicant has requested a reexamination, and whether the patent has been declared invalid. The criteria for assessing technological advancement include whether the patent and its family patents have been cited globally at least once, the breadth of application fields, investment in R&D personnel, occurrences of licensing, and instances of transfer. The scoring for the scope of protection considers the breadth of claims, whether the remaining validity period exceeds three years, and whether a patent portfolio has been applied for. The SVI integrates the scores from these three dimensions to generate a parameter based on patent value. Unlike citation counts, which may fluctuate over time, the SVI provides a stable measure of innovation quality, making it suitable for evaluating the short-term impacts of policy changes.

The primary explanatory variable is a binary indicator of whether a company is affected by the carbon emission policy. A value of 1 indicates regions where the policy is in effect (treatment group), while a value of 0 denotes regions without the policy (control group).

Control variables include GDP, GDP growth rate (Bilbao-Osorio and Rodríguez-Pose 2004), GDP in the construction sector, the number of employees in the construction industry, and the cumulative number of construction enterprises. Data for these socio-economic variables were sourced from China's National Bureau of Statistics.

This study matches patent data with economic data based on the year of patent application and the corresponding region. Typically, patent data includes information on the applicant's address or region, while economic data is organized by region and year. Utilizing these details, each patent can be linked to its respective regional economic data, enabling the calculation of innovation-related parameters, such as the annual number of patent applications and average patent quality for each region. Descriptive statistics tables, providing a comprehensive overview of the datasets used in this study, are included in Appendix A.2. For a detailed classification of green patents and their trends, refer to Appendix A.3. This research aims to explore the relationship between carbon emission policies and green innovation, contributing to a better understanding of how policy frameworks can effectively promote sustainable practices within the construction industry.

4. Results and Analysis

4.1. Baseline regression result

Based on the model specifications mentioned earlier, Table 1 presents the main regression results. Columns (1) and (2) present the regression findings for innovation quality, whereas columns (3) and (4) illustrate the regression results for innovation quantity. Columns (1) and (3) represent the cases that control the time & region-fixed effects but do not control the covariates, while columns (2) and (4) represent the cases that control both the time & region-fixed effects and the covariates. The treatment × post is an interaction term used to investigate if there are variations in the effect of the policy (treatment) on the post-implementation outcomes. It provides a deeper understanding of the treatment effects. The covariates are used to control additional factors that could affect the results, ensuring more accurate and reliable estimation of the treatment effects.

Based on the results in columns (1) and (2) of Table 1, the coefficient of the core explanatory variable, treatment × post, is significantly positive regardless of whether the covariates are considered. This suggests that the carbon emission action plans have a notably positive effect on the quality of innovation. Likewise, the findings in columns (3) and (4) show that the treatment post coefficient remains significantly positive, regardless of covariate adjustments. This further indicates a substantial positive impact of the policy on the quantity of innovation.

Columns (2) and (4) represent the results controlling for covariates. The controlled covariates include GDP (Hu et al. 2023), GDP growth rate (Bilbao-Osorio and Rodríguez-Pose 2004), GDP in the construction industry (Nie et al. 2022), the number of employees in the construction industry and the cumulative number of the construction enterprises (Miao et al. 2021). The introduction of covariates eliminates the influence of unobservable factors specific to individuals or regions on the results. Meanwhile, the multi-period DID model itself controls causal trends before and after policy implementation. The regression coefficients of the core explanatory variable, treat × post, are statistically

Table 1
Baseline Result. Effect of Action Plans on Carbon Emission on Green Innovation.

	Dependent variable: PTQL		**Dependent variable: PTQT**	
	(1) No control of covariates	**(2)** Control of covariates	**(3)** No control of covariates	**(4)** Control of covariates
treat × post	0.1241* (0.0209, 0.2274)	0.3324* (0.0312,0.6337)	0.3204* (0.0857, 0.5551)	0.5652* (0.0697,1.0606)
Controls		✓		✓
City fixed effect (FE)	✓	✓	✓	✓
Year fixed effect (FE)	✓	✓	✓	✓
Observations	9498	9498	9498	9498
Std. Error	0.0527	0.1537	0.1198	0.2528

significant at the 10% level, indicating a significant improvement in both the quality and quantity of green innovation in the respective regions. The regression values after controlling for space and time are 0.3324 and 0.5652 which implies that the announcement of the Action Plans to Carbon Peaking will lead to the pilot group of 33.2% increase in innovation quality and 56.2% increase in innovation quantity. These findings are based on the assumption that there is no effect difference between the treatment group receiving the treatment and the control group without receiving the treatment before the policy implementation, which has been verified through the previously mentioned parallel trend. These results demonstrate a significant impact of the policy on green innovation in the construction industry with regards to the case of China. The results from the strict specification model provide further support for these findings.

4.2. Dynamic Effect on Green Innovation

The foundation of the multi-period DID method is that prior to the policy's effect, there is no notable difference in innovation levels between the pilot and non-pilot regions, suggesting that the parallel trends assumption is valid. To test the parallel trends and assess the effects of the treatment by addressing dynamic policy effect, the study replaced the treatment indicator with a set of eight dummy variables representing the four quarters before treatment, the treatment period, and the first, second, and third quarters after treatment.

For Figs 1 and 2, the horizontal axis represents the timeline of policy impact, with quarters representing different time periods. Quarter 0 represents the implementation time point of the policy, while -4 to -1 indicates the periods before policy implementation, and 0 to 3 indicates the periods after policy implementation. As shown in the Figs 1 and 2, for both innovation measures, the coefficients of all pre-treatment dummies are small and statistically insignificant. This finding is reassuring as it indicates the absence of pre-existing trends in the data, meeting the parallel trends assumption. Conversely, following the policy's effect, the construction sector of the experimental group has seen a notable rise in green innovation levels, confirming the earlier trend. Furthermore, the dynamic effects indicate that the level of sustainable innovation in the construction sector remains significant in the current period (i.e., implementation time) and several quarters thereafter. This validates the stability of the policy's short-term effects.

4.3. Heterogenous Effect on Green Innovation

According to the "Classification System for Green Technology Patents" issued by the National Intellectual Property Administration (2023), green patents related to the construction industry include clean energy, decarbonization of fossil fuels, energy and water conservation, green building, green transportation, greenhouse gas capture and utilization, pollution control and management, recycling, green management, green material, and energy storage. Different types of green patents have varying mechanisms and effectiveness in reducing carbon emissions (Díaz et al. 2016; Jiao et al. 2020). These differences may result in different impacts on green innovation across various categories of the carbon peaking policy. Therefore, regressions on different categories of green patents are conducted on the basis of "Classification System for Green Technology Patents". The corresponding results and analyses are presented as follows.

Table 2 shows the heterogeneity analysis of green innovation. Columns (1) to (8) represent clean energy, decarbonization of fossil fuels, energy and water conservation, green building, green transportation, greenhouse gas capture and utilization, pollution control and management, and recycling respectively. Due to the small sample size, green management, green material, and energy storage are combined into one, as shown in column (9).

Table 2. (a) represents the regression results for innovation quality. From Table 2. (a), it can be observed that the treat $\times$ post coefficients for the categories of Decarbonization of fossil fuels and Pollution control and management are notably positive at the 10% significance level. This suggests that the carbon emission policy has enhanced the quality of innovation in these two areas. Table 2. (b) presents the regression results for innovation quantity. Column (7) of Table 2.(b) clearly shows that the treat post coefficient for Pollution Control and Management is significantly positive at the 10% level. It is suggested that the carbon emission policy has increased the quantity of patents in the pollution control and management category.

The findings from the heterogeneity analysis suggest that due to the impact of the carbon emission policy, higher effectiveness on green innovation in pollution control and management are demonstrated, with

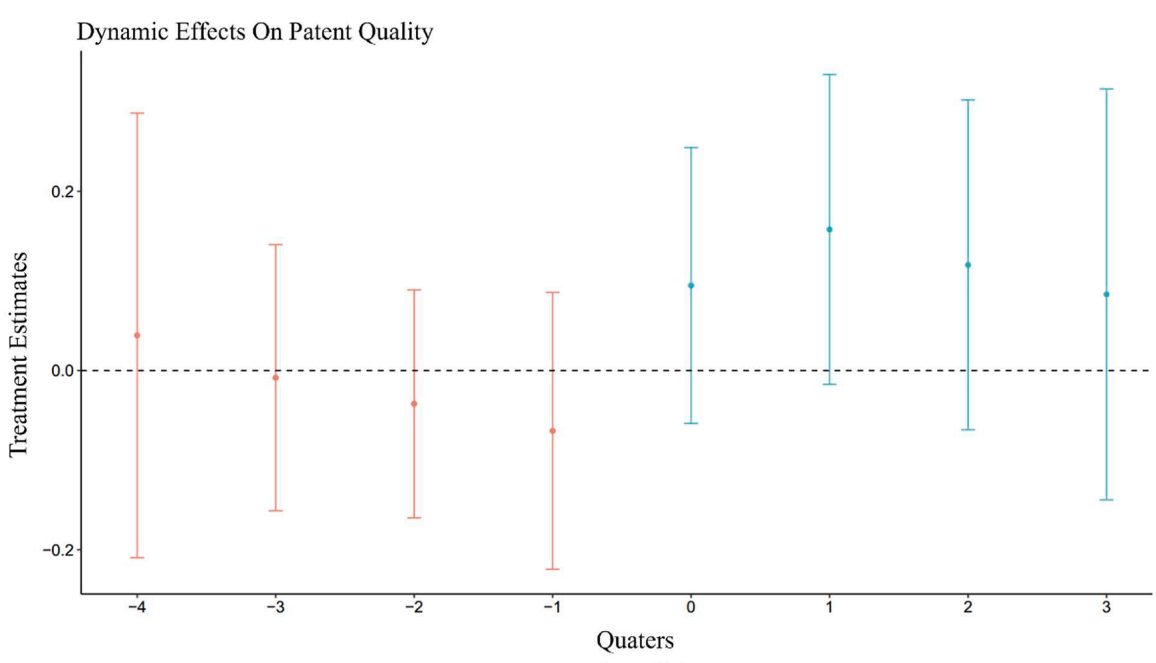

Fig 1. Dynamic Effects on Patent Quality.

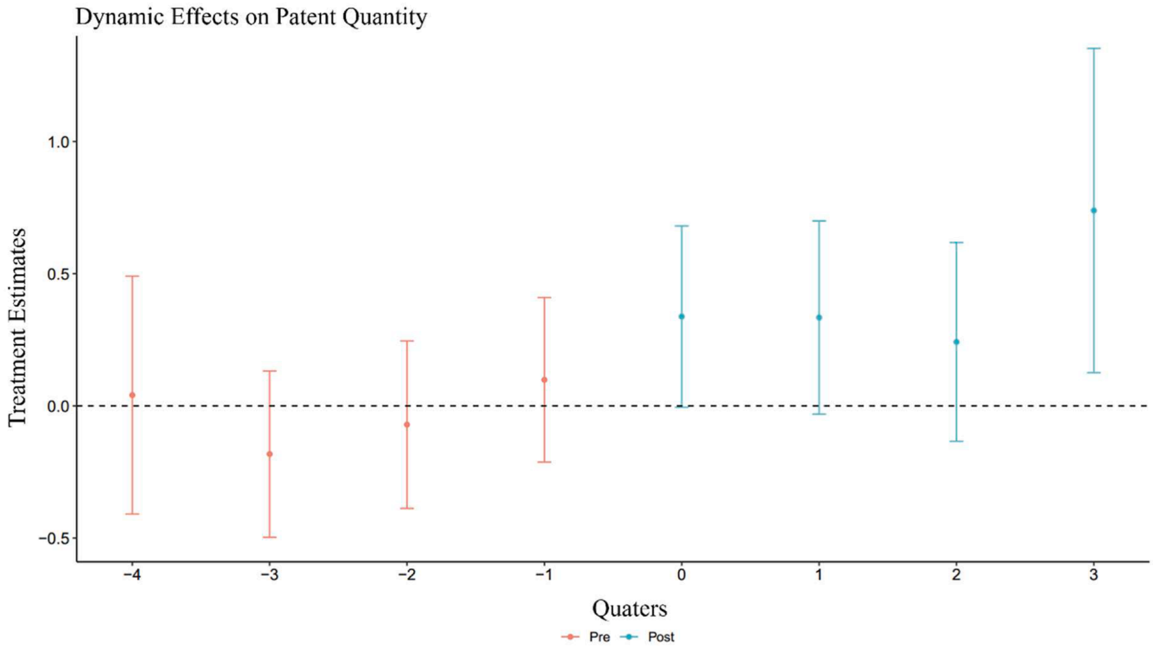

Fig 2. Dynamic Effects on Patent Quantity.

Table 2
Heterogeneity in Green Innovation.

(a) Dependent variable: GI quantity	1	2	3	4	5	6	7	8	9
treat × post	0.1019	0.242*	0.127	0.0319	0.4059	0.2061	0.5523*	0.2128	-0.1027
City fixed effect (FE)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effect (FE)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3797	2068	1045	1179	678	990	1096	1765	703
Std. Error	0.1015	0.1126	0.1963	0.1533	0.2736	0.1878	0.1668	0.1585	0.2288
(b) Dependent variable: GI quality	1	2	3	4	5	6	7	8	9
treat × post	0.1918	0.0915	-0.0567	0.0729	0.0867	0.0999	0.1619*	0.0297	0.1019
City fixed effect (FE)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effect (FE)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3797	2068	1045	1179	678	990	1096	1765	703
Std. Error	0.1676	0.1507	0.1205	0.1379	0.1038	0.1051	0.0774	0.0866	0.0872

significant improvements in terms of both the amount and the quality of green innovation. However, for other directions of green innovation, besides the enhanced quality of Decarbonization of fossil fuels innovation, no significant impact of the carbon emission policy was found in the remaining categories.

4.4. Robustness check

After obtaining the results as above, a series of robustness checks are carried out. A Placebo simulation is conducted to ensure that the green innovation increase in the construction industry is not caused by other policies. In addition, the propensity score matching (PSM) method is applied to exclude the selection bias.

4.4.1. Placebo test

The model assumes that the ecological civilization pilot policy is exogenous and not influenced by unobservable factors. However, in reality, these policies are often shaped by various observable and unobservable influences (Wu et al. 2023). As a result, the control variables in this study may not fully account for these factors, potentially leading to biased estimation outcomes. To address this concern, a placebo test is conducted to verify the findings.

The placebo test assesses whether the observed effects stem from the treatment itself rather than other influencing factors. In this test, a placebo group is introduced as a control group that receives a false treatment or no treatment at all, while the treatment group receives the actual intervention. If a significant difference is observed between the treatment and placebo groups, it can be inferred that this difference is attributable to the treatment, specifically the policy itself. The placebo test effectively controls confounding variables and biases, enhancing the reliability of the research findings.

Fig 3 illustrates the distribution of coefficient estimates derived from 500 randomly sampled pseudo-policy variables in the regression of the core explanatory variable. The x-axis represents the size of the estimated coefficients for the pseudo-policy variables, while the y-axis shows the corresponding kernel density. The figure indicates that the estimated coefficients for these 500 pseudo-policy variables follow a normal distribution, peaking at an estimated coefficient of 0. The estimated true regression coefficients—0.33 for patent quality and 0.56 for innovation quantity—are identified as outliers in the placebo test, further validating the robustness of the previous research findings.

4.4.2. PSM-DID

PSM-DID is a commonly used econometric method for estimating

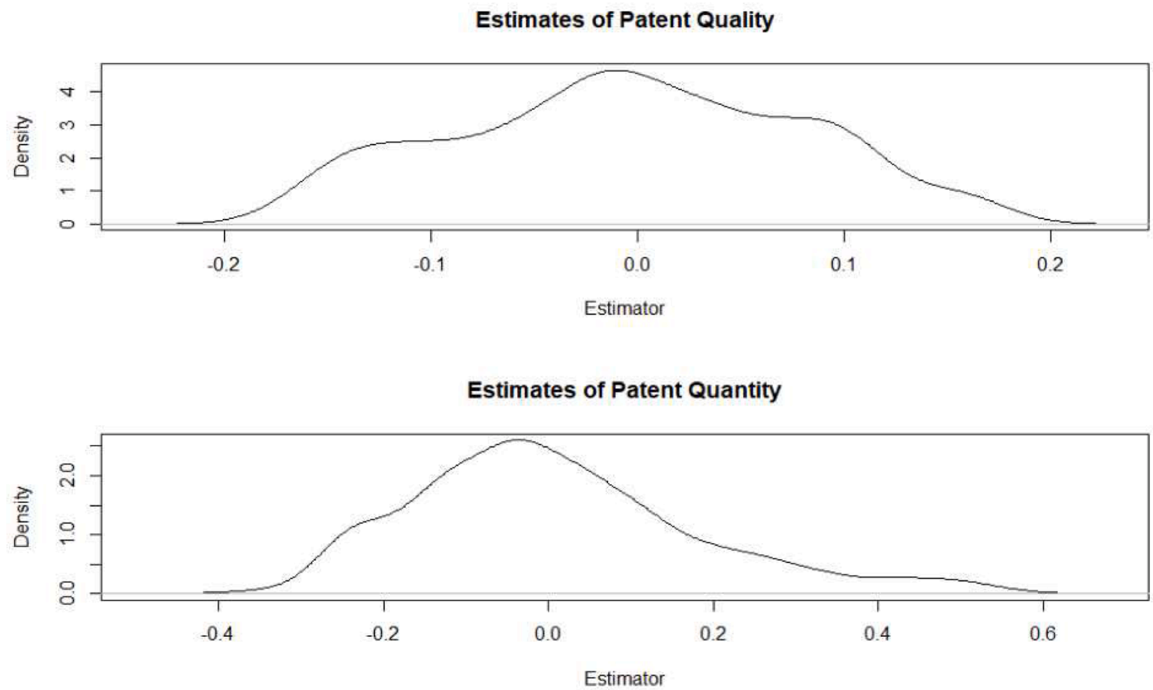

Fig 3. Probability Density Distribution of Placebo Simulation.

treatment effects. The results of PSM-DID are herein utilized to support the policy effects on green innovation. This method first uses a logistic regression model to assess the likelihood of each individual being placed in the treatment group, resulting in a propensity score. Then, using the propensity score matching method, each person in the treatment group is paired with individuals in the control group that have comparable propensity scores. Based on the matched results, a difference-in-differences analysis is conducted. This approach removes possible selection biases by using propensity score matching, allowing for a valid comparison between the treatment and control groups.

Firstly, the treatment and control groups are paired through the nearest-neighbor matching based on the covariates, resulting in a matched sample of 8,880 observations. Table 3 presents the estimation results of the PSM-DID analysis. From Table 3, it can be observed that during the procedure of incorporating control variables into the model, the coefficient of the main explanatory variable, treat post, consistently remains significant. This indicates that even after the propensity score matching, the baseline result still yields consistent conclusions with the main regression, namely that the action plans to carbon emission effectively promote green innovation in the construction industry. This further validates the reliability of the baseline regression findings discussed in this study.

5. Discussion

Based on the empirical results from the multi-period Difference-in-Differences (DID) model, it is evident that local carbon emission policies can effectively enhance both the quantity and quality of green innovation within China's construction sector. The implementation of the carbon emission plan has led to significant increases in green innovation quality and quantity in the experimental group. These substantial impacts can be attributed to China's proactive stance on carbon peak and carbon neutrality targets. The nationwide adoption of these dual carbon goals has fostered collaboration among various stakeholders, including government bodies, industry groups, research organizations, and businesses. This collaboration has facilitated the sharing of knowledge, expertise, and best practices, thereby stimulating innovation in green technologies within the construction industry.

Table 3
Estimation Results of PSM-DID.

	Dependent variable: PTQL		Dependent variable: PTQT	
	(1)	(2)	(3)	(4)
treat × post	0.1318*	0.3424*	0.2893*	0.5385*
Controls		✓		✓
City fixed effect (FE)	✓	✓	✓	✓
Year fixed effect (FE)	✓	✓	✓	✓
Observations	8880	8880	8880	8880
Std. Error	0.0595	0.1587	0.1177	0.2652

Figs 1 and 2 illustrate a declining trend in innovation quality alongside a significant increase in innovation quantity. This trend is particularly noticeable in the fourth quarter following the policy announcement, raising concerns about a potential patent bubble. Additionally, there is a slight upward trend in innovation quantity prior to policy implementation, suggesting a pre-treatment effect likely due to information dissemination before the policy's release. This indicates that innovation quantity is sensitive to government-driven incentives, contrasting with innovation quality, which experiences a temporary increase only in the initial stages of the policy announcement. Unlike previous studies that primarily focused on either quality or quantity, this research evaluates the policy's effects in both dimensions. The findings suggest that policy-driven innovation may lead some companies to engage in activities that falsely claim to be green innovation to obtain policy incentives, despite lacking genuine environmental benefits. To mitigate this, relevant authorities should strengthen the patent application review process, reduce ambiguous applications, and prevent the emergence of a patent bubble.

The heterogeneity analysis reveals that the carbon emission action plans primarily promote specific types of green innovation, such as fossil fuel decarbonization and pollution control. This indicates that the construction industry has not fully embraced comprehensive green innovation but has instead increased investment in technologies related to decarbonization and pollution control. Notably, energy-saving and green building patents appear unaffected by the policy. This outcome may stem from the construction sector's unique characteristics. Unlike previous studies that treat green innovation as a homogeneous concept (Chen et al. 2021; Hu et al. 2023), this study subdivides green innovation to explore the policy's response pathways within the specific industry context. As an energy-intensive sector, the construction industry relies heavily on fossil fuels, with statistics indicating that 76% of its emissions arise from burning fossil fuels in construction equipment (Lu et al. 2012). Consequently, under carbon reduction policies, the industry focuses more on innovations in decarbonization and pollution control to address its specific environmental challenges, aligning with prior research interests in the sector (Abbasian-Hosseini et al. 2016; Eissa and El-adaway 2024).

The construction sector's focus on pollution control as a key area of green innovation is closely linked to its long-standing innovative environment. Innovation in the construction industry has historically lagged behind other sectors, constrained by high costs, limited R&D investment, and resistance to technological change. These challenges have likely driven the industry to prioritize pollution control, as it offers relatively straightforward and immediate solutions for regulatory compliance without requiring comprehensive systemic transformation. Additionally, the fragmented nature of the construction industry and its reliance on traditional practices further hinder the adoption of advanced energy-saving or renewable energy technologies, which often demand significant coordination and investment. Therefore, the observed emphasis on pollution control may be more a reflection of practical constraints and industry inertia than a deliberate choice rooted in technological maturity.

Stakeholder interests also significantly influence the focus on decarbonization and pollution control, as these areas are directly tied to economic benefits and environmental responsibilities, such as carbon trading. In contrast, energy efficiency and green building innovations often require broader collaboration and coordination among stakeholders, complicating their development. The findings suggest that even with policy guidance, industry transformation remains closely tied to corporate interests. Whether innovations focused on decarbonization and pollution control can drive sustainable transformation in the construction sector remains an open question. To comprehensively promote green innovation, additional policy measures are essential. Future policymakers should consider corporate interests in designing policies to achieve more effective outcomes.

The results also highlight differences between models that include regional control variables and those that do not, as shown in Table 1. While both models validate the efficacy of the carbon reduction strategy in the construction sector, the observed differences are noteworthy. Regional variations in economic structure, energy resources, and industrial layout directly influence the implementation effects of carbon emission policies. China's vast territory and uneven economic development present unique challenges and development needs across different regions. Some areas may rely heavily on fossil fuels, while others may be more suited for renewable energy utilization. Additionally, variations in industrial layout and development stages across regions should be considered. These insights can help policymakers design appropriate carbon emission policies that promote green innovative technologies in the construction industry, tailored to regional characteristics.

6. Conclusion

This study applied a multi-period DID model to analyze the impact of carbon peak-related policies on green innovation in the China's construction industry. A multi-period DID model was constructed, and the quarterly data of green patent from 9,498 firm-level observations between 2020 and 2022 were collected. Based on the regression analysis on the collected using the multi-period DID model, the following findings have been obtained. Firstly, green policy is crucial in promoting green innovation in the construction industry in the pilot areas based on a series of robustness tests such as the dynamic effect test, placebo test, and PSM-DID test. Secondly, the policy impact on green innovation from both quality and quantity perspectives were measured, ruling out the possibility of patent bubbles. Thirdly, the heterogeneity of green innovation has been analyzed to show different degrees of policy impact on different types of green innovation. The policy impact on innovations in the categories of decarbonization of fossil fuels and pollution control and management is more significant. In addition, this study analyzes the dynamic effect of the policy and reveals that the impact of the new policy on green innovation in the construction industry shows a stable trend in the short term without lagging. The research confirmed that the relevant policies can enhance the quantity and quality of innovation in the construction industry, validating Porter's hypothesis and demonstrating the direction of sustainable development in the construction sector.

This research makes both theoretical and practical contributions to understanding the promotion of green innovation in the construction industry. Theoretically, it advances the methodology for evaluating government policies by integrating a multi-period DID model, capturing the heterogeneity of green innovation across regions and industries. Practically, it offers actionable policy insights. Timely policy implementation maximizes impact, while stakeholder collaboration fosters resource alignment and innovation adoption. Strengthening patent review processes prevents patent bubbles and ensures innovation quality. Tailored incentives considering regional and industry-specific differences can address unique challenges. Long-term strategies for policy evaluation and adaptation support sustained progress toward carbon neutrality.

Given the specific context of high emissions and low innovation in the construction industry, it is important to acknowledge the limitations of the research framework. It remains uncertain whether the impact of green innovation on carbon emissions in the construction industry differs from that in other industries. Therefore, future research directions can be expanded in two aspects: First, from an empirical perspective, analyze the actual impact of green innovation on carbon emissions in the construction industry and explore the decarbonization intensity differences of different types of green innovation. Second, consider the heterogeneity in the implementation of carbon peak policies in different regions and discuss how to achieve the maximization of policy benefits by tailoring strategies to local conditions. Although there is currently a lack of data on regional disparities due to the early stage of carbon peak policy implementation, exploring future policy changes is valuable.

CRediT authorship contribution statement

Wenyu Zhang: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shu-Chien Hsu:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Chia-Jung Lee:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Hsi-Hsien Wei:** Writing – review & editing, Writing – original draft, Supervision, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2025.108326.

Data availability

Data will be made available on request.

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