Journal of International Commerce, Economics and Policy
(2025) 2550021 (33 pages)

DOI: 10.1142/S1793993325500218

Catalyzing Green Innovation: The Role of Green Finance in Sustainable Development

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Received 14 March 2025
Revised 18 July 2025
Accepted 31 July 2025
Published 8 September 2025

Utilizing China's Green Finance Reform and Innovation Pilot Zone (GFRIP) policy as a quasi-natural experiment, we investigate the impact of green finance on green innovation. Analyzing data from publicly listed companies from 2010 to 2020, our study finds that the number of green patents in GFRIP regions exceeds those in other regions by 33.1%. Additionally, the GFRIP policy demonstrates anticipatory, long-term, and spillover effects on the number of corporate green innovations. The policy's impact is more pronounced in economically developed regions, ecologically resource-rich areas, and among private enterprises. Furthermore, the GFRIP policy enhances corporate environmental behavior, alleviates corporate financing constraints, and boosts corporate R&D investment.

Keywords: Green finance policy; green transformation; financing constraints; staggered DID.

1. Introduction

Climate change has emerged as a paramount global concern. Given China's status as the world's largest energy consumer, with a total energy consumption of 5.41 billion tons of standard coal in 2022 (of which fossil energy constitutes 82.6%), achieving the "3060" target (aiming for peak CO_2 emissions by 2030 and carbon neutrality by 2060) poses a formidable challenge. Green innovation, crucial for enhancing energy efficiency and green productivity, faces challenges due to its high investment requirements, substantial risk, and lengthy payback cycles. These factors often create gaps in R&D funding, necessitating market-based mechanisms to attract social capital into green innovation. Consequently, understanding the impact of green finance (GF)

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on corporate green innovation (CGI) mechanisms is a priority for policymakers and academics.

To investigate this, we employ the Green Finance Reform and Innovation Pilot Zone (GFRIP) policy implemented in 2017 as a quasi-natural experiment. Using a staggered difference-in-differences (DID) approach, we assess whether the GFRIP policy significantly affects CGI. Additionally, we explore the influence of corporate characteristics (such as firm size and ownership attributes) and regional factors (resource endowment and environmental regulation) on CGI. Our analysis considers two pathways: external incentives, where the GFRIP policy encourages firms to acquire government R&D subsidies and financial institution credits, and internal incentives, where the policy stimulates enterprises' environmental protection efforts, eases financing constraints, and boosts R&D investments.

Despite China issuing several policy documents related to GF and CGI, the effective integration of these two remains a challenge. The academic literature on this topic is limited. Notably, only a few studies have explored the relationship between GF and CGI. For instance, Li *et al*. (2018) theoretically confirm that GF promotes cleaner production. Additionally, De Haas and Popov (2023) and Flammer (2021) provide empirical evidence that green bond issuance and stock market sophistication contribute to CGI. Liu *et al*. (2021) find that green credit policies reduce long-term debt for polluting enterprises and encourage green innovation. At the macro level, green innovation serves as a vital driver for sustainable development, enhancing ecological quality and promoting environmental sustainability. On a micro level, green innovation increasingly incentivizes enterprises to enhance their competitive edge, accelerate energy efficiency, reduce emissions, and facilitate the transition toward greener practices.

Studies associated with this paper include two strands of literature: the environmental effects of GF, and the influencing factors of green innovation. Regarding the environmental effects of GF, some studies have used an indicator system to measure the GF index (Lv *et al*., 2021), while others have focused on subsectors of GF, including green credits (Galán and Tan, 2024), green bonds (Cao *et al*., 2021), green funds (Ibikunle and Steffen, 2017), green equities (Pham *et al*., 2023), as well as climate investment and finance (Lee *et al*., 2022). Most studies agree that GF has a positive role in mitigating climate change and achieving sustainable development, for example, it can reduce carbon emissions (Al Mamun *et al*., 2022), promote green innovation, optimize industrial structure, enhance business performance, improve energy efficiency, and reduce pollution emissions, etc. Some scholars have also questioned that GF does not always promote green innovation due to insufficient scale of development, low allocative efficiency, etc., and may have a dampening effect on innovation in the short term (Pang *et al*., 2022).

In the context of CGI determinants, a comprehensive review is presented by Del Río González (2009), Hojnik and Ruzzier (2016), and Triguero *et al*. (2013). This review primarily encompasses command regulation policies, market-oriented regulation policies, and the structure of corporate organizations. Command regulation policies include programs for voluntary emission reduction (Carrión-Flores *et al.*, 2013; Li, 2017), environmental regulations (Xu *et al.*, 2022), and government subsidies (Huang *et al.*, 2019), among others. Market-oriented regulation policies encompass trading of carbon emissions (Salman *et al.*, 2023) and environmental rights and interests (Weber and Neuhoff, 2010; Zhou and Wang, 2022). The structure of corporate organizations includes mechanisms of corporate governance, systems for managing environmental quality, and pressures from stakeholders (Amore and Bennedsen, 2016; Krueger *et al.*, 2020; Shive and Forster, 2020).

This study potentially offers three incremental contributions. First, it scrutinizes the influence of green financial policies, which are region-specific, on CGI, adopting the fresh viewpoint of GFRIP. This extends the associated studies concerning the environmental implications of green financial policies. Although there is already some literature focusing on GFRIP (Cheng *et al.*, 2023), this paper differs in that it proposes a more rational method for identifying enterprises belonging to GFRIP. Currently, three of the 10 approved pilot zones in China are state-level new areas, and most of the existing studies fuzzy-match enterprises with the geographic scope of the pilot zones, i.e., expanding the geographic scope of the state-level new areas to prefectural-level cities (Liu and Xiong, 2022). This paper uses enterprise geographic location information data to accurately identify whether an enterprise belongs to the geographic scope of the pilot zones, so as to obtain more accurate policy effects, and further extends the pilot zones to the prefecture-level cities and provinces where they are located, and identifies the spillover effects of the GFRIP policy.

Second, we identify regional differences in the effects of GFRIP policy. Existing literature focuses on analyzing the average total effect of GFRIP policy (Li *et al.*, 2023; Zhang *et al.*, 2023), while ignoring individual differences. On the one hand, we categorize the pilot zones into economically developed regions, ecologically rich regions, and the core regions of the "Belt and Road" according to their regional characteristics, and measure the green innovation effects of different types of pilot zones. On the other hand, we used the synthetic control method (SCM) to evaluate the green innovation effects of the existing 10 pilot zones, and obtained the evidence of the individual empirical analysis of GFRIP policy.

Lastly, this paper enriches the empirical research on green patents. Most of the existing studies on green innovation are measured using green patents (Bianchini *et al.*, 2023). In this paper, based on the international patent classification (IPC) numbers of patents, green patents are subdivided into seven specific categories, which are further categorized into energy-saving and emission-reduction categories for empirical analysis. Our research confirms the phenomenon that GF favors more emission-reduction patents.

2. Institutional Background, Theoretical Mechanisms and Research Hypotheses

2.1. *Institutional background*

GFRIP is an important element in the construction of China's GF development. On June 14, 2017, Premier Li Keqiang proposed to carry out the construction of GFRIP. After 2017, China decided on the construction of GFRIP in a total of 10 regions in seven provinces (Fig. 1). As the construction experience of the pilot zones disseminates, the expansion of these zones is concurrently progressing. This specifically involves three key aspects.

The first aspect is the enhancement of the supply level of green financial products and services. This primarily targets innovative transformations of green credit, green bonds, green insurance, green funds, and carbon finance. For instance, Huzhou and Quzhou are venturing into the development of credit and pledge financing operations such as sewage rights and carbon trading rights. Guangzhou and Gui'an New Area are offering green credit products to back the construction of green transportation and green building projects. Gui'an New Area is advocating for the securitization of green assets to aid the growth of clean energy. Chongqing has introduced innovative insurance products like environmental pollution liability insurance and green building performance insurance. Lanzhou New Area has established a green industry development fund.

Second, expanding financing avenues for green industries. For example, Gui'an New Area is using the advantages of the big data industry to build a green project library; Chongqing strongly supports the green transformation, the application of green buildings, and the construction of green transportation; the cities of Hami, Changji and Karamay in Xinjiang province have set up financial services channels for green industries, focusing on the environmentally friendly clean industries, eco-agriculture and green mines.

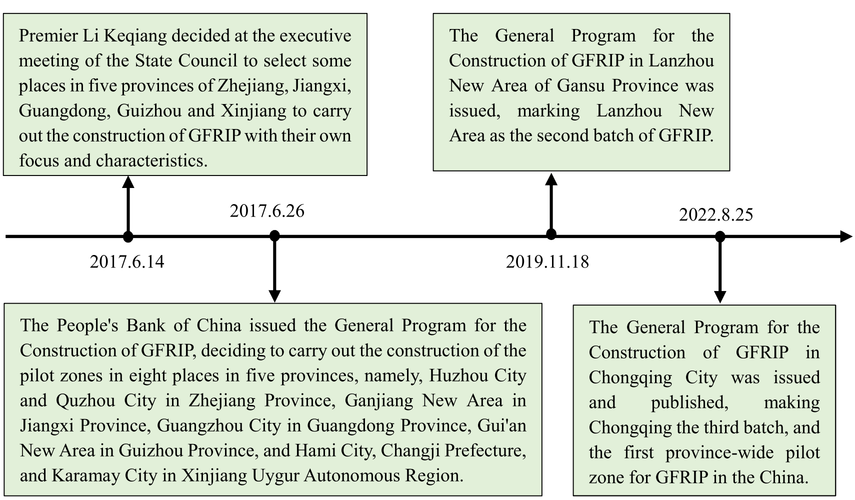

Fig. 1. Progress of GFRIP construction in China.

Third, consolidating the platform for the development of GF. Based on their existing conditions, all pilot zones have utilized digital technology to build green financial service platforms and establish a sound early warning mechanism for green financial risks. In addition, some pilot zones have built green financial industry development carriers. For example, Huzhou has set up the Taihu lake green financial town to create a green financial industry cluster; Huadu District of Guangzhou has created a green financial and green industry development cluster integrating production, financing and research; Ganjiang New Area has built a green innovation and development complex consisting of three panels: a green financial demonstration street, a human resources service industrial park, and an innovation and entrepreneurship market.

The pilot zones have undertaken a series of practical explorations with a focus on enhancing the green financial system. Each exploration has its unique focus and has resulted in a set of valuable experiences that can be replicated and promoted. With the rapid construction of the GFRIP, enterprises can access substantial capital during the green transformation process, which is beneficial for the advancement of green innovation activities.

2.2. *Theoretical mechanisms and research hypotheses*

2.2.1. *GFRIP and green innovation*

Positive environmental externalities of green innovation lead to an "inherent lack" of investment by enterprises in green innovation (Chen *et al.*, 2023; Shi and Wang, 2024). Green innovation is characterized by a long return cycle and high risk, which has led to insufficient support for green innovation from the traditional financial system due to problems such as information asymmetry and the lack of high-quality collateral for R&D-based enterprises. Relying on enterprises' own financing channels, it is difficult to sustain continuous R&D investment during a complete green technology R&D cycle.

GF has some public goods attributes, focusing on ecological environmental protection, mainly serving the development needs of green industries and green projects, and can effectively solve the problem of "market failure" in green innovation (Laurinavicius and Laurinavicius, 2025). The establishment of GFRIP has released positive market signals that capital, product and technology trading markets will promote green development, and that demand for green investment and green products will increase, contributing to the green technology market.

Hypothesis 1: *The GFRIP enhances the level of CGI in the pilot zones.*

2.2.2. *External incentive mechanisms*

The inception of the GFRIP provides an enhanced impetus for pilot zones to devise strategies that bolster the growth of GF. This establishment is poised to alter the decision-making behaviors of governments and financial institutions in favor of green transformation, thereby generating external stimuli for CGI.

From the government's perspective, the evolution of GF should not only leverage the market's decisive role in resource allocation but also proactively undertake the responsibility of guidance and promotion. The core objective of GFRIP's inception is to foster a holistic green transformation of the economy and society via the growth of GF, with green innovation being a pivotal player in this transformation. The government can bolster the R&D activities of enterprises in green and low-carbon technology through fiscal policy tools such as R&D subsidies, thereby sending positive signals to the capital market and facilitating an increase in green R&D investment and financing by enterprises.

For financial institutions, the inception of the GFRIP provides an added incentive to offer green innovative financial products and services. The green investment and financing in the pilot zone are relatively more advantageous. Under conditions of capital mobility, capital inflows into the pilot zones from other regions, further enhancing the green investment capacity of financial institutions (Muganyi *et al.*, 2021). In addition, the pilot zones encourage social capital to participate in green investment through government-social capital partnership. In summary, the establishment of GFRIP not only increases capital inflows, but also broadens the ways of green investment and financing.

Hypothesis 2: *The establishment of the GFRIP will not only encourage governments to increase the level of R&D subsidies to enterprises, but will also encourage financial institutions to increase their green investments.*

2.2.3. *Internal incentive mechanisms*

From an enterprise perspective, the likelihood of securing financial backing for activities related to green innovation, the advancement of the green industry, and the construction of environmental infrastructure within the pilot zones is heightened. The pilot zones, with their focus on green ideologies, emit signals that encourage enterprises to augment their R&D investments in green and low-carbon technologies. This, in turn, hastens the green transformation of their production techniques, culminating in the creation of internal incentive structures.

First, the GFRIP incentivizes enterprises to strengthen environmental behavior. Under the objective of resource and environmental constraints, GF will change the credit ration, making the financial market environment more favorable to the development of green industries. All pilot zones have strengthened the standardization of green financial systems, defining standards for green projects, thus increasing the cost of "regulatory capture" under traditional environmental regulations (Gmeiner, 2019). In the face of GF's swift progression, enterprises have the opportunity to enhance their production apparatus through technological innovation. This enhancement can either augment the efficiency of energy use at the initial stages or curtail pollution emissions at the final stages. To secure green financial backing, enterprises within the pilot zones are persistently fortifying their environmental conduct, thereby fueling their drive for green innovation.

Second, GFRIP alleviates corporate financial constraints. Green innovation mostly relies on external sources of financing, as enterprises do not have enough internal funds of their own. The pilot zones promote the flow of financial resources to the field of green development, which is conducive to the corporate R&D of green technologies. During the construction of the pilot zones, the production or products of enterprises should meet the standards, which is conducive to the establishment of an environment-friendly corporate social image. The gradual emergence of green consumption trend enhances the market share of green products of environment-friendly enterprises, which brings more cash flow for the enterprises; on the other hand, a good social image increases the trust of investors, which helps enterprises to obtain more social financial assistance (He and Liu, 2023). Therefore, with long-term stable financial support, CGI has a stable guarantee.

Third, GF incentivizes corporate R&D investment (Yan *et al.*, 2022). In the presence of external stimuli from governmental bodies and financial institutions, enterprises operating within the pilot zones stand a better chance of securing R&D subsidies and green investments while partaking in green innovation endeavors. These external funds, which are evidently purpose-driven, induce them to recruit more innovative talents and augment the count of R&D equipment. In the context of the "3060" objective and sustainable development, enterprises have proactively escalated their green R&D investment with the aim of securing a position in the future's green, circular, and low-carbon development paradigm through technological breakthroughs in areas like new energy sources, waste management, resource recycling, and so forth.

Hypothesis 3: *The establishment of the GFRIP will incentivize enterprises to strengthen their environmental behavior, alleviate financial constraints, and increase investment in R&D.*

Overall, the influence mechanisms of the GFRIP policy on CGI includes two channels: external and internal incentives (Fig. 2).

3. Empirical Strategy

3.1. *Research methodology*

3.1.1. *Staggered difference-in-differences*

The traditional DID approach requires that the timing of policy shocks to all treatment groups must be consistent (Wang *et al.*, 2021). However, GFRIP has been expanding and upgrading since 2017 with an increasing number of pilot zones. The traditional DID approach is clearly not applicable to the situation of this paper. A commonly used measure is the staggered DID, which is applicable to policy types with multiple intervention points in time. Therefore, in order to measure the green innovation effect of

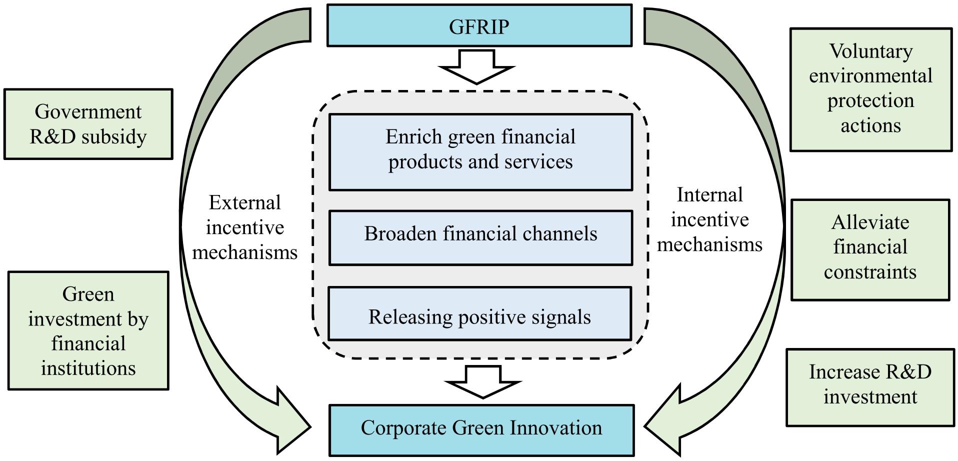

Fig. 2. Mechanisms of the influence of GRFIP policy on CGI.

the GFRIP policy, the staggered DID approach was utilized as the baseline regression model.

$$Y_{i,t} = \alpha + \beta D_{i,t} + \gamma X_{i,t} + \eta_i + \theta_t + \varepsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ denotes the explanatory variable, which is the level of CGI. $D_{i,t}$ denotes the state of individual i in period t, which is the estimator of the GFRIP policy, and is equal to 1 if it is impacted by the policy, and vice versa, 0. $X_{i,t}$, η_i, θ_t and $\varepsilon_{i,t}$ are the control variables, individual fixed effects, time fixed effects, and disturbance terms, respectively.

The staggered DID approach may have some biases in estimation. Its estimation principle is a weighted average effects, and it is possible to have negative weights, which can lead to biased estimation, or even a situation where the estimated value has the opposite sign of the true value (Athey and Imbens, 2022; Goodman-Bacon, 2021). Callaway and Sant'Anna (2021) proposed a multi-period DID estimation method that can solve this problem. First, the treatment individuals need to be categorized into different groups, denoted by g, based on differences in the time of being treated by the policy. Second, the treatment effect $ATT(g,t)$ is estimated for different groups g at time t. The nonparametric point estimate of $ATT(g,t)$ is calculated using an inverse probability weighting method and is shown in the following equation:

$$ATT(g,t) = E\left[\left(\frac{G_g}{E\left[G_g\right]} - \frac{\dfrac{p_g(X)C}{1-p_g(X)}}{E\left[\dfrac{p_g(X)C}{1-p_g(X)}\right]}\right)(Y_t - Y_{g-1})\right]. \tag{2}$$

Finally, we obtain the average total treatment (ATT) effect with equal weights.

$$ATT = \sum_{g \in G} \sum_{t=1}^{\tau} w(g,t) \cdot ATT(g,t). \tag{3}$$

Based on this, we utilize the above methodology to conduct robustness tests on the regression of the staggered DID approach.

3.1.2. *Matching methods*

In China, the pilot policy is not a completely randomized experiment, and the straightforward use of the DID approach may lead to biased estimates. To reduce individual differences, Propensity Score Matching (PSM) is commonly used. The basic idea of the PSM approach is to select a set of exogenous control variables, obtain a propensity score by logistically conducting a regression on the policy variables, and finally match the treatment and control groups based on the propensity score.

The traditional PSM method eliminates the information of unmatched sample data, and the regression results are not convincing enough. Hainmueller (2012) proposed Entropy Balancing Matching (EBM). This method automatically calculates the optimal weights matching the constraints by setting the constraints in advance, so as to match each sample of the treatment group with a control group that is exactly similar to it in the overall samples, thus retaining all the sample information and maximizing the elimination of endogenous bias in the samples, and realizing the accurate matching of both samples.

In order to eliminate the endogeneity problem caused by the differences between individuals in both groups, the data were processed using two matching methods, PSM and EBM, for robustness tests.

3.1.3. *Synthetic control method*

SCM was proposed by Abadie *et al*. (2010) and is considered to be the most innovative estimation method in the policy evaluation studies within the last decade or so (Athey and Imbens, 2017). The basic idea is to estimate the counterfactual outcome using the weighted average of the control group samples (the synthetic treatment group), and then to quantitatively evaluate the policy effect in terms of the difference between the treatment group and the synthetic treatment group.

Suppose there are $J + 1$ individuals in the sample with a total of T periods of data. Treated individual is labeled as $j = 1$, while control group individuals are labeled as $j = 2, \ldots, j + 1$. The policy intervention occurs in period T_0. The pre-intervention (Pre) time set is denoted as $T_0 \subseteq \{1,\ldots,T_0\}$, and the post-intervention (Post) time set is denoted as $T_1 \subseteq \{T_0 + 1,\ldots,T\}$. Assume that Y_{jt}^I and Y_{jt}^N represent the "potential outcomes" in the "with" and "without" policy intervention scenarios, respectively. Then the observed outcome variable is $Y_{jt} = (1 - D_{jt})Y_{jt}^N + D_{jt}Y_{jt}^I$, where $D_{jt} = 1\{t \in T_1, j = 1\}$

. Thus, the treatment effect of the treated individual ($j = 1$) at time point t ($t \in T_1$) after the policy intervention is as follows:

$$Gap_{1t}^{Post} = Y_{1t}^{I} - Y_{1t}^{N}. \tag{4}$$

Clearly, Y_{1t}^{N} is unobservable, and Abadie *et al.* (2010) recommend using a weighted average estimate of individuals in the control group:

$$\hat{Y}_{1t}^{N} = \sum_{j=2}^{J+1} \omega_j^* Y_{jt}. \tag{5}$$

Thus, the treatment effects estimated by the SCM are as follows:

$$\widehat{Gap}_{1t}^{Post} = Y_{1t}^{I} - \hat{Y}_{1t}^{N}. \tag{6}$$

3.2. *Variables and data sources*

3.2.1. *Variable selections*

The dependent variable is *CGI*, which is measured using logarithmized green patent applications of listed companies.

The independent variable is the green finance policy, denoted by *GFRIP*. We regarded listed companies whose registrations are located in the pilot zones as the treatment group, and due to the different time points of policy interventions, if companies in the treatment group are affected by the policy, *GFRIP* = 1; otherwise *GFRIP* = 0. Most of the existing literature obtains the treatment group by matching the location of listed companies with the province where the pilot zones are located or the prefecture-level city where they are located, which expands the geographic scope of the pilot zones and can lead to biased estimation of policy effects. We manually match the specific address data of listed companies' registered places with the address ranges of the 10 pilot zones (Huzhou and Quzhou City in Zhejiang Province, Ganjiang New Area in Jiangxi Province, Guangzhou City in Guangdong Province, Guian New Area in Guizhou Province, Hami City, Changji Prefecture, and Karamay City in Xinjiang Uygur Autonomous Region, Lanzhou New Area in Gansu Province, and Chongqing Municipality), so as to obtain the precise data of the listed companies that are located in the geographic scope of the pilot zones.

Referring to the related literature (Zhu and Tan, 2022), the selected control variables are: company size (*Size*), leverage (*Lev*), rate of return on total assets (*ROA*), ratio of independent directors (*Indep*), number of directors (*Board*), growth rate of operating income (*Growth*), cashflow ratio (*Cashflow*), firm age (*FirmAge*), shareholding proportion of the controlling shareholder (*Top*1), equity restriction ratio (*Balance*), duality of COB and CEO (*Dual*), and Tobin's Q ratio (*TobinQ*).

According to the theoretical mechanisms and research hypotheses, the external incentive mechanisms of green finance policy include the mediating variables of government R&D subsidies (*Subsidy*) and financial institutions' credit scale (*Credit*), and the internal incentive mechanisms include the mediating variables of voluntary environmental protection actions (*VEP*), financial constraints (*SA*), and R&D investment (*R&D*). The variables are defined as shown in Table 1.

3.2.2. *Data processing and descriptive statistics*

The research in this study is based on a sample of companies listed in 2016, spanning the period from 2010 to 2020. The CNRDS database provided the data for measuring corporate green patents and *VEP*; while the CSMAR database was the source for control variables on corporate finance and governance, as well as financial constraints and R&D investment. Credit information was extracted from the China Urban Statistical Yearbook. The authors calculated the GFRIP policy variable and compiled the data on R&D investment using the financial reports of the listed companies. To mitigate the effects of heteroscedasticity and large gaps between variables, some of the data were transformed using logarithms.

The sample was refined through the following process: (a) Companies that had been listed for less than a year, had been delisted, or had been suspended were removed from the sample. (b) All variables were Winsorized at the 1% and 99% quantile levels. It is worth noting that there are some missing variables in the empirical analysis, but

Table 1. Results of descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
CGI	22176	1.591	1.718	0.000	9.290
GFRIP	22176	0.014	0.117	0.000	1.000
Size	21807	22.397	1.511	19.208	27.709
Lev	21807	0.477	0.224	0.052	1.003
ROA	21808	0.032	0.069	−0.299	0.222
Indep	21774	0.373	0.053	0.333	0.571
Board	21774	2.159	0.204	1.609	2.708
Growth	21503	0.198	0.650	−0.683	4.871
Cashflow	21807	0.040	0.076	−0.215	0.247
FirmAge	21808	2.865	0.388	1.386	3.497
*Top*1	21808	0.339	0.151	0.084	0.744
Balance	21808	0.672	0.587	0.024	2.599
Dual	21428	0.215	0.411	0.000	1.000
TobinQ	21219	2.102	1.643	0.843	11.422
Subsidy	10696	13.937	1.989	8.189	18.234
Credit	21795	18.269	1.437	13.585	20.513
VEP	7084	1.211	0.779	0.000	2.000
SA	22012	−3.768	0.329	−4.889	−0.271
R&D	15545	17.756	1.720	12.804	21.909

Note: The table presents descriptive statistics for all the main variables, with missing values in some of the micro firm data, resulting in an inconsistent number of observations.

they do not account for more than 5% of all observations, which does not significantly affect the regression results. Table 1 presents the descriptive statistics for the main variables.

4. Empirical Findings and Discussion

4.1. *Baseline regression*

Before conducting the regression analysis, we calculated the variance inflation factor (VIF) to ensure that multicollinearity was not a concern. The findings revealed that all variables had VIF values less than 3, with an average value of 1.440.

Table 2 presents the outcomes of the baseline regression. We added control variables, city fixed effects, industry fixed effects, and year fixed effects sequentially from Models (1) to (5). The coefficient values of the green finance policy in all models were significantly positive. For instance, in Model (5), with all other conditions held constant, the coefficient value of *GFRIP* is 0.331, which is significantly positive at the 1% level. This indicates that enterprises in the pilot zones will experience a 33.1% surge in the number of green patent applications relative to enterprises in other regions. Therefore, hypothesis 1 is confirmed. The regression outcomes of the control variables align with the existing literature (Benkraiem *et al*., 2023; Wu *et al*., 2024). For instance, firm size, number of board of directors, and Tobin's q value are positively associated with CGI, while the number of years since the company's establishment, the proportion of shares held by the largest shareholder, and Dual have a negative relationship with CGI.

4.2. *Further analysis*

4.2.1. *Types of green patents*

This paper further investigates what types of green patents are "preferred" by GF in the GFRIP.

The limitations of the government in evaluating and monitoring innovation outcomes may lead some enterprises to engage in "strategic innovation", mainly utility model patents, in order to obtain government R&D subsidies, resulting in "subsidy fraud". Therefore, this paper constructs four variables, green invention patent applications (*CGI_inv*), green utility model patent applications (*CGI_uti*), granted green invention patents (*CGI_G_inv*) and granted green utility model patents (*CGI_G _inv*). The study finds that GFRIP promotes both types of green patent applications (Models (1) and (2) in Table 3) and granted green patents (Models (3) and (4) in Table 3). The empirical results show that GFRIP not only promotes enterprises to apply for green patents, but also the number of green patents granted has also been increased, thus the level of green innovation in all aspects of enterprises has been improved. The results show that the pilot zones have established a relatively well developed green financial system, and it is more appropriate for financial institutions to define the investment and financing criteria for enterprises' green innovation projects.

Table 2. The results of the baseline regression.

	(1)	(2)	(3)	(4)	(5)
Variables	*CGI*	*CGI*	*CGI*	*CGI*	*CGI*
GFRIP	1.155***	0.706***	1.106***	0.872***	0.331***
	(13.084)	(7.694)	(10.701)	(10.899)	(4.166)
Size	—	0.606***	0.575***	0.686***	0.545***
		(53.729)	(50.047)	(71.736)	(55.085)
Lev	—	−0.987***	−0.979***	−0.563***	−0.041
		(17.805)	(17.223)	(10.813)	(0.815)
ROA	—	−1.827***	−1.934***	−1.369***	0.113
		(10.267)	(11.152)	(8.981)	(0.765)
Indep	—	−0.394	−0.209	−0.294	−0.148
		(1.605)	(0.844)	(1.500)	(0.800)
Board	—	−0.501***	−0.466***	−0.230***	0.133**
		(7.304)	(6.620)	(3.924)	(2.394)
Growth	—	−0.099***	−0.086***	−0.100***	−0.070***
		(6.400)	(5.694)	(7.621)	(5.710)
Cashflow	—	0.831***	0.875***	0.605***	0.171
		(5.646)	(6.001)	(4.995)	(1.488)
FirmAge	—	0.002	0.182***	0.539***	−0.175***
		(0.085)	(5.904)	(20.141)	(5.964)
*Top*1	—	−1.618***	−1.570***	−0.846***	−0.833***
		(15.666)	(14.773)	(9.176)	(9.615)
Balance	—	−0.215***	−0.212***	−0.145***	−0.228***
		(8.586)	(8.174)	(6.801)	(11.296)
Dual	—	0.079***	0.041	0.001	−0.053**
		(3.062)	(1.617)	(0.059)	(2.575)
TobinQ	—	0.052***	0.060***	0.070***	0.060***
		(7.964)	(8.847)	(11.396)	(9.625)
City fixed	N	N	Y	Y	Y
Industry fixed	N	N	N	Y	Y
Year fixed	N	N	N	N	Y
Observations	22176	20529	20517	20517	20517
R^2	0.006	0.196	0.282	0.528	0.584

Note: ***, **, and * indicate statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

Based on the IPC Green Inventory, this paper extracts and matches the patent classification numbers belonging to green patents, which specifically include seven categories. We further classify green patents into three variables: energy-saving patents (*CGI_energy*), emission-reduction patents (*CGI_emission*), and other patents (*CGI_other*). In particular, energy-saving patents include alternative energy production, transportation, energy conservation, and nuclear power categories, emission-reduction patents include two categories of waste management and agriculture/forestry, while other types of patents are those for administrative regulation and design.

Table 3. Differences in types of green patents.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	*CGI_inv*	*CGI_uti*	*CGI_G_inv*	*CGI_G_uti*	*CGI_energy*	*CGI_emission*	*CGI_other*
GFRIP	0.233***	0.216***	0.118**	0.164**	0.064	0.136**	0.052
	(2.975)	(2.956)	(2.000)	(2.210)	(1.166)	(2.071)	(1.162)
Control variables	Y	Y	Y	Y	Y	Y	Y
City, industry and year fixed	Y	Y	Y	Y	Y	Y	Y
Observations	20517	20517	20517	20517	7766	6169	8414
R^2	0.544	0.545	0.418	0.502	0.705	0.667	0.284

Note: The table presents the impact of GFRIP on different types of green patents in two categorical ways. Since the results of the control variable regressions are already reported in the baseline regressions, they are not presented in subsequent tables. ***, **, and * indicate statistical significance at $p<0.01$, $p<0.05$, and $p<0.1$, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

According to Models (5)–(7) in Table 3, GFRIP favors emission-reduction innovations, and does not significantly contribute to energy-saving innovations and administrative regulation and design innovations. The empirical results suggest that GF is more biased towards innovative projects with emission reduction effects. The reason why energy-saving innovations are not significant is that, on the one hand, during the study sample period (2010–2020), China's ecological environmental protection tasks were more focused on the treatment of various types of pollutants and the construction of ecological environment infrastructure, and the performance assessment objectives of higher-level governments for the leadership of local governments were more focused on the reduction of various types of pollutants; on the other hand, President Xi Jinping first put forward the "3060" goal in 2020, and energy-saving innovations have received more attention only in the last few years. Innovations in the administrative regulation and design category generally do not require large amounts of capital, and are not in strong demand for GF. Furthermore, they are generally not favored because the value and practical effects of their innovations are not obvious.

4.2.2. *Quality of green innovation*

The following two methods are used to measure quality of green innovation (QGI). First, we used knowledge width method (Aghion *et al.*, 2019; Akcigit *et al.*, 2016). Generally, patents contain one or more IPC numbers. The basic idea of the breadth of a patent is that the more IPC numbers the patent contains, the more complex the knowledge used in the patent, then the higher the quality of the patent.

The specific calculations are as follows:

$$patent\_knowledge_{it,type} = 1 - \sum \alpha^2, \tag{7}$$

where α represents the proportion of each major group classification in all IPC numbers contained in a patent.

The breadth of all green patents owned by an enterprise is averaged according to the "enterprise-year" dimension, and the QGIs is obtained as shown in the following equation:

$$Quality_{it} = \underset{type}{\text{mean}}(patent\_knowledge_{it,type}). \tag{8}$$

QGI measured using the knowledge width method is denoted by CGI_Q_1.

Second, this paper adopted the number of citations of listed companies' green patents, excluding self-citations, to measure QGI, which is denoted by CGI_Q_2.

The findings indicate that the GFRIP does not significantly influence QGI, as measured by both methods (Models (1) and (2) in Table 4). Under the pressure of the GFRIP policy, enterprise managers may develop a short-sighted mentality and produce green innovation behaviors that "emphasize quantity over quality" in order to obtain green financing.

4.2.3. *Spillover effects of GFRIP policy*

In the process of GFRIP implementation, certain pilot zones have established leading bodies at the city or provincial level to manage the distribution of financial resources, thereby fostering a conducive environment for GF development within the city or province. For instance, the establishment of pilot zones in Ganjiang New Area led to the formation of a provincial-level leading organization in Jiangxi Province. Similarly, the creation of pilot zones in Gui'an New Area resulted in the development of assessment

Table 4. Green innovation quality and policy spillovers.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	CGI_Q_1	CGI_Q_2	*CGI*	*CGI*	*CGI*	*CGI*
GFRIP	−0.042	0.021	—	—		
	(0.877)	(0.191)				
GFRIP_city	—	—	0.234***	—	0.085	
			(3.190)		(0.600)	
GFRIP_province	—	—	—	0.092**		0.062*
				(2.555)		(1.745)
Control variables	Y	Y	Y	Y	Y	Y
City, industry and year fixed	Y	Y	Y	Y	Y	Y
Observations	3520	9963	20517	20517	19732	19732
R^2	0.212	0.452	0.584	0.584	0.578	0.578

Note: Models (1) and (2) in the table present the effect of GFRIP on the quality of green patents measured by two different methods. Models (3) and (4) present the spillover effects of GFRIP at different spatial scales. Models (5) and (6) are the results generated after removing the samples within the pilot zones in order to measure the net spillover effect. ***, **, and * indicate statistical significance at p<0.01, p<0.05, and p<0.1, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

standards and procedures for green projects in Guizhou Province. Furthermore, major banks in Zhejiang Province have introduced a range of innovative green financial products, including the “Eco-loan” and the Green Industry Park Loan. As demonstrated by these practices, the GFRIP policy has spillover effects. Consequently, this study expands the treatment group to include the prefecture-level city and province where the pilot zones are situated, resulting in two types of policy variables, namely, *GFRIP_city* and *GFRIP_province*. As per Models (3) and (4) in Table 4, the policy effects observed at the prefecture and provincial levels are significantly positive, with coefficient values of 0.234 and 0.092, respectively. These values are lower than the baseline regression of 0.331, indicating that the GFRIP policy does exhibit a spillover effect, albeit with a decreasing impact on green innovation as the geographical scope expands.

To better capture the spillover effects on firms located outside the pilot zones, and these firms are in the provinces or prefecture-level cities of the pilot zones, this paper further excludes all the firms in the pilot zones, totaling 77 firms. Then, this paper re-regresses Models (3) and (4) in Table 4, and the regression results are shown in Models (5) and (6) in Table 4. The regression results show that the GFRIP only has a significant positive effect on the enterprises within the provinces of the pilot zones but not within the pilot zones, with a coefficient value of 0.062. The reason why there is no significant impact on firms within the prefecture-level cities of the pilot areas is that among the 10 pilot zones, 3 belong to industrial parks, 6 belong to prefecture-level administrative regions, and 1 belongs to a provincial-level administrative region. If the firms in the pilot zones are excluded, there will only be data from the prefecture-level cities where the three industrial parks belong, and the data sample is insufficient, which may lead to insignificant regression results.

4.3. *Robustness tests*

This paper takes the following series of approaches to conduct robustness tests. Some of the robustness test results are presented in Appendix A.

4.3.1. *Match treatment and control groups*

In order to mitigate estimation bias due to individual differences, two methods, PSM and EBM, were used to match both groups. In this case, PSM used 1:3 nearest neighbor matching and EBM was constrained by moments of third order. We used all the control variables as matching information and selected the control group that matched all aspects of the endowment conditions of the enterprises in the pilot zones. According to Figs. A.1, A.2, and Table A.2 in Appendix A, the results of the tests for PSM and EBM indicate that all control variables are well balanced in both the treatment and matched control groups. Models (1) and (2) in Table A.3 show the regression results for PSM-DID and EBM-DID, respectively, and it can be found that the regression results are significantly positive after matching, with coefficient values of 0.569 and 0.299, respectively.

4.3.2. *Parallel trend test*

To mitigate the issue of endogeneity, we employed the parallel trend test to validate that the treatment and control groups exhibited a shared trend prior to the enforcement of the GFRIP policy.

Initially, we utilized data pertaining to the number of green patent applications to compute the average observations for the treatment and control groups during each period. The comparative analysis results are depicted in Fig. 3. The left image represents the actual observed results, while the right image normalizes the starting points of the treatment and control groups to a common location, based on the fitted values from the baseline regression model. The findings reveal that the treatment and control groups maintained parallel trends before the pilot policy was put into effect.

The reason why the parallel trend test can be passed is that the treatment and control groups are similar in terms of development characteristics. GFRIP zones were selected with full consideration of regional differences. In terms of location, the pilot zones cover the east, center and west, which helps to explore the path of green

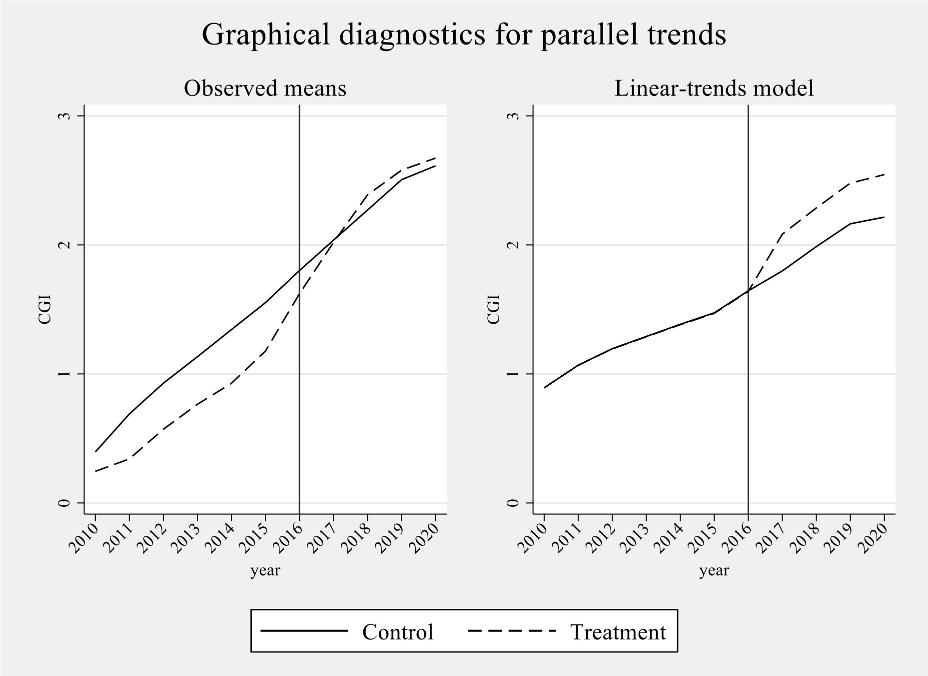

Fig. 3. Parallel trend test results-A.

financial development in different regions, such as Xinjiang in the westernmost part of China, which is lagging behind in terms of economic development, but Guangdong and Zhejiang in the coastal areas, which have developed their economies. In terms of resource endowment, Guangdong and Zhejiang have well-developed financial industries, while Jiangxi, Guizhou and Xinjiang are rich in natural resources, and can introduce targeted financial policies, respectively. In industrial development, the eastern provinces need to cultivate new green growth momentum, and the central and western provinces need to be based on resource endowment, to promote the transformation and upgrading of high-pollution and high-energy-consumption industries. The selection criteria for the pilot zones are basically random, covering the different characteristics of China's three major geographic regions of east, central and west, and are similar to the characteristics of non-test zones in the same geographic region.

Subsequently, drawing inspiration from Baker *et al*. (2022), we embraced the concept of the event study to create dummy variables for all years. We also generated interaction terms with the dummy variable indicating whether it belongs to the pilot zone (treat), and incorporated all the interaction terms into the baseline regression model. The updated model is illustrated in the following equation:

$$CGI = \alpha + \sum_{j=-1}^{-7} \beta_{j+8} GFRIP_j + \beta_8 GFRIP + \sum_{\varphi=1}^{3} \beta_{\varphi+8} GFRIP_\varphi + \gamma X. \tag{9}$$

The regression outcomes of Eq. (9) are displayed in Model (3) of Table A.3, and the parallel trend plot is shown in Fig. 4. The findings indicate that the coefficient values of the interaction terms were predominantly insignificant before the policy was enacted

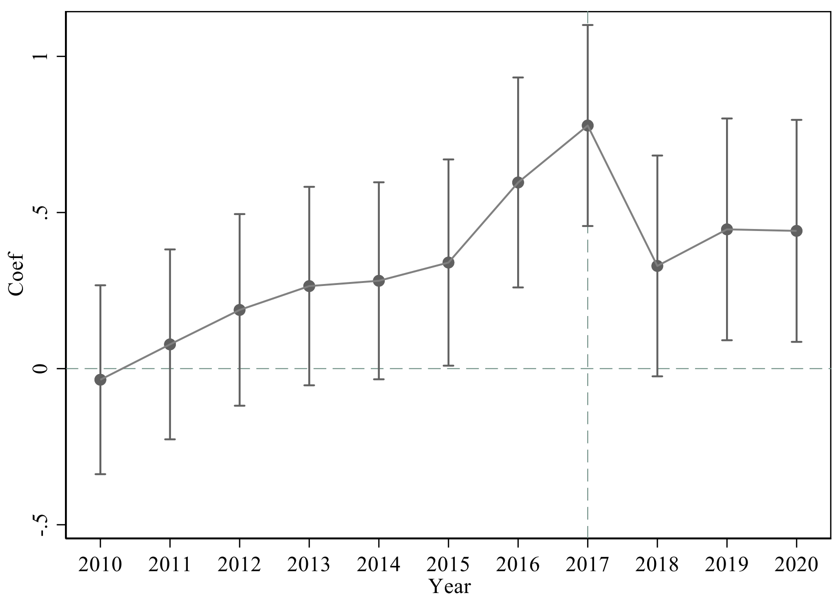

Fig. 4. Parallel trend test results-B.

in 2017, except for the first three years of the policy, when they were significantly positive. However, post the policy's implementation, the coefficient values of the interaction terms were all significantly positive.

Based on the test outcomes, it can be inferred that both groups followed a common trend before the policy was implemented, and the GFRIP policy has both an anticipated effect and a long-term effect on CGI. This implies that the establishment of the pilot zones requires advanced planning of several years and a solid foundation, thereby enhancing the likelihood of successful approval. Once approved as a pilot, the GFRIP policy exerts a long-term positive impact on the CGI.

4.3.3. *Placebo tests*

We demonstrate the effectiveness of the GFRIP policy using two counterfactual placebo tests that front-load the time of policy occurrence and fictionalize the treatment group.

We made an assumption that the pilot zone policy was enacted three or four years earlier, specifically in 2014 or 2013. The outcomes of this assumption are displayed in Models (4) and (5) of Table A.3, where all the hypothetical policy variables are found to be insignificant. In another approach, we maintained the count of treatment groups and the timing of policy enforcement constant, and randomly partitioned the treatment and control groups from the complete sample. This process was repeated 500 and 1000 times. The estimated results are illustrated in Fig. A.3, which reveals that the coefficient values for the placebo tests (500 and 1000 times repeated regression) have mean values approximating 0 and the majority of p-values exceed 0.1, indicating insignificance at the 10% level.

4.3.4. *Replacement of estimation methodology*

To mitigate the problem of staggered DID estimation bias, we re-estimated the baseline regression model using the multi-period DID estimation method with stata's "csdid" command (Callaway and Sant'Anna, 2021). The results show that the ATT effect is 0.210, which is significant at the 5% level (as shown in Model (6) of Table A.3).

4.3.5. *Difference-in-differences-in-differences*

To further ascertain the causal impact of the GFRIP policy on CGI, this study constructs a triple differences estimator (*DDD*) by multiplying the policy variable with a dummy variable that indicates whether the enterprise is part of a heavily polluting industry. The fundamental role of the pilot zone policy is to facilitate the green transformation of the economy via the reallocation of financial resources. Hence, the incentive constraints of the pilot policy are more pronounced for enterprises in heavily polluting industries. As shown in Model (1) in Table A.4, the *DDD* is significantly positive at the 1% level, with a coefficient value of 0.570, which exceeds the baseline regression result of 0.331. The regression outcomes indicate that the GFRIP policy has a green innovation effect, and the incentive constraints are more stringent for heavily polluting industries.

4.3.6. *Impact on non-green patents*

By deducting the number of green patent applications from the total number of patent applications, we derive data on the number of non-green patent applications for listed companies, and take the natural logarithm as the explanatory variable (*Non_CGI*). As per Model (2) in Table A.4, the regression outcomes reveal that the GFRIP policy does not significantly influence non-green patents. Thus, it can be further established that the pilot policy only exerts a significantly positive impact on green patents.

4.3.7. *Substitution of dependent variables*

Given the variety of indicators for gauging the level of CGI, we employ another commonly used academic indicator, green granted patents, to replace the dependent variables. Further, considering the lag between patent application and grant, we regress the policy variables on the number of green granted patents in the current period (CGI_1) and the number of green granted patents in the previous period (F.CGI_1), respectively. The outcomes demonstrate that the policy effect of GFRIP remains significantly positive after substituting applications with grants (as depicted in Models (3) and (4) of Table A.4).

4.3.8. *Exclusion of abnormal samples*

Among the 10 pilot zones, there are three special areas: Lanzhou New Area, Gui'an New Area, and Ganjiang New Area. These three New Areas are tasked with China's major strategic objectives of development, reform, and opening-up, and the policy effects of GFRIP in the New Areas may differ from those in other zones. Additionally, Chongqing Municipality was authorized for the GFRIP in 2022, and the baseline regression includes Chongqing Municipality as a control group due to data constraints. Generally, preparatory work needs to be undertaken before the authorization of the pilot zone, and it necessitates planning several years in advance, thus the level of green financial development of Chongqing could be relatively higher than that of other regions. Therefore, this study excludes the data samples of the three New Areas and Chongqing Municipality, and the regression outcomes are presented in Model (5) of Table A.4, which indicates that the policy effect remains significantly positive at the 1% level. Furthermore, the study also excludes the samples of listed companies in the financial and real estate industries, and the regression outcomes remain consistent (Model (6) in Table A.4).

4.3.9. *Competing hypothesis tests*

According to related literature (Li *et al*., 2022; Wang *et al*., 2022), other policy factors also affect CGI. Although this paper has controlled year fixed effects, the omission of the effects of other relevant policy variables still creates an endogeneity problem. This paper utilizes the DID approach to construct estimators for the following three types of policies: carbon emissions trading pilot policy (*CET*), low-carbon pilot policy (*LC*), and national innovative city pilot policy (*NIC*). In the baseline regression framework, the GFRIP policy effect remains significantly positive with the inclusion of the three DID estimators (as shown in Model (7) of Table A.4).

4.4. *Heterogeneity analysis*

4.4.1. *Regional heterogeneity*

(a) Heterogeneity analysis of pilot zone types. It can be reflected in the differences in resource endowment (Zhang *et al*., 2022): first, economically developed zones, including Huzhou, Quzhou, and Guangzhou, which share the common characteristics of a high economic level and adequate development of the financial industry; second, ecologically rich zones, including Ganjiang New Area and Gui'an New Area, which belong to the national ecological civilization advance demonstration zones; third, the core zones of the "Belt and Road", including Karamay City, Changji State, Hami City, and Lanzhou City, which are the important pivots for China's opening to the west and the bridgeheads for building the Green Silk Road.

According to the type of pilot zones, this paper constructs three dummy variables (*ED* for economically developed zones, *ER* for ecologically rich zones, and *BR* for core zones of the "Belt and Road"), which are interacted with the policy variables of *GFRIP* to form three triple-difference estimators. According to Models (1)–(3) in Table 5, the policy effect is significantly positive in the economically developed and ecologically rich pilot zones, and not significant in the core zones of the "Belt and Road".

(b) Heterogeneity analysis of the intensity of environmental regulation. Governmental environmental regulations amplify the external constraints faced by enterprises. As per the Porter Hypothesis, these regulations stimulate innovation. The advancement of GF aids in alleviating compliance cost pressures on enterprises under environmental regulations, circumventing "regulatory capture", and facilitating the realization of the Porter Hypothesis (Li *et al*., 2023). Consequently, we segment the sample and perform group regressions based on the median environmental regulation intensity of the prefecture-level city where the listed company is located. The intensity of environmental regulation is gauged by the frequency of terms[1] related to "environmental protection"

[1]Specific terms include "PM2.5", "PM10", "sulfur dioxide", "carbon dioxide", "low carbon", "emissions reduction", "chemical oxygen demand", "emissions" and "pollution". "low carbon", "emission reduction", "chemical oxygen demand", "emissions", "pollution". "environmental protection" "environmental protection" "ecology" "air" "green" "energy consumption".

Table 5. Analysis of regional heterogeneity.

	(1)	(2)	(3)	(4)	(5)
Variables	CGI	CGI	CGI	High intensity of environmental regulation	Low intensity of environmental regulation
ED*GFRIP	0.290***	—	—	—	—
	(3.006)				
ER*GFRIP	—	0.569***	—	—	—
		(3.692)			
BR*GFRIP	—	—	−0.495	—	—
			(1.449)		
GFRIP	—	—	—	0.615***	0.157
				(4.737)	(1.578)
Control variables	Y	Y	Y	Y	Y
City, industry and year fixed	Y	Y	Y	Y	Y
Observations	20517	20517	20517	12408	8109
R^2	0.584	0.584	0.584	0.594	0.597

Note: The table presents the results of the heterogeneity of GFRIP policy effects across different levels of economic development, resource and environmental levels, Belt and Road regions, and environmental regulatory intensities. ***, **, and * indicate statistical significance at $p<0.01$, $p<0.05$, and $p<0.1$, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

in the government work reports of prefecture-level cities. Empirical findings indicate that the GFRIP policy is more effective in spurring CGI in regions with a higher intensity of environmental regulation (Models (4) and (5) in Table 5).

(c) Analysis of individual differences in the pilot zones. The GFRIP policy belongs to the regional policy and has been implemented in 10 zones since 2017. Each government of the zones has introduced a corresponding program for the construction of the pilot zone according to its own characteristics, which will cause differences. Hence, we utilize data on the number of green patent applications in prefecture-level cities to analyze individual differences in the policy effects of the pilot zones using an SCM. Specifically, Huzhou, Quzhou, Nanchang, Jiujiang, Guangzhou, Guiyang, Anshun, Karamay, and Lanzhou were chosen as the treatment group, with other prefecture-level cities forming the control group.[2] The predictor variables of the SCM encompass GDP per capita, the proportion of secondary industries, the number of employees in the science and technology service industry, FDI, fiscal science and technology expenditures, the balance of loans from financial institutions, and the number of green patent applications in prefecture-level cities in 2010, 2013, and 2016. The outcomes of the synthetic control analysis are depicted in Fig. 5, which shows that the number of green patent applications in most of the pilot zones (except Jiujiang, Lanzhou and Karamay)

[2]Among the ten pilot zones, Chongqing Municipality is not in the sample period, and data are missing for Hami Municipality and Changji Prefecture, so none of them will be analyzed. Regarding the three national New Areas, we use the prefecture-level cities in which they are located as the treatment group. The Ganjiang New Area is at the junction of Nanchang and Jiujiang, and the Gui'an New Area is at the junction of Guiyang and Anshun, thus both correspond to the four prefecture-level cities of Nanchang, Jiujiang, Guiyang and Anshun.

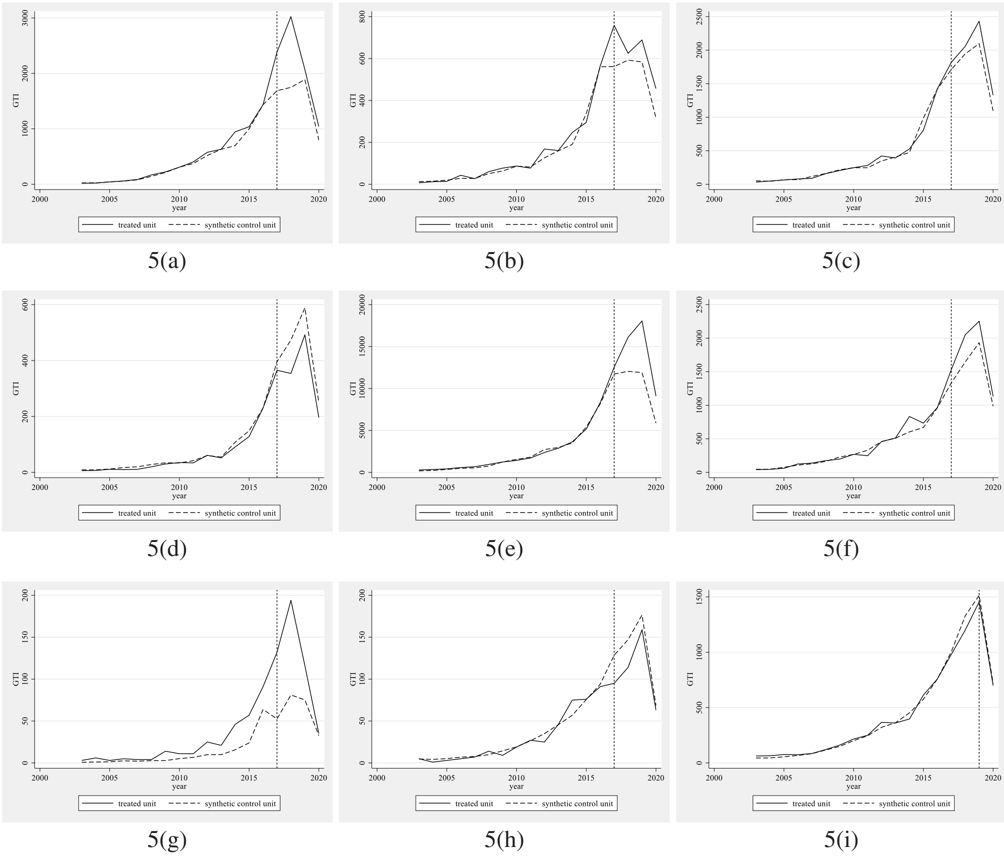

Fig. 5. Results of the SCM.
(*Note*: Figures 5(a)–5(i) denote Huzhou, Quzhou, Nanchang, Jiujiang, Guangzhou, Guiyang, Anshun, Karamay and Lanzhou, respectively. The solid line is the real data, and the dashed line is the data of the synthetic control group).

witnessed a significant increase following the implementation of the GFRIP policy, compared to the virtual synthetic control group.

4.4.2. *Corporate heterogeneity*

(a) Heterogeneity analysis of firm size. The sample is divided into large and small firms, based on median firm assets. The regression results of Models (1) and (2) in Table 6 show that the policy effect is significantly positive for both types of samples. Since the grouped regression coefficients are not directly comparable, we transformed the regression coefficients into Average Marginal Effect (AME) and then compared them. The results show that the difference between the values of the coefficients of the regression results of the two samples 0.144 is not significant. Therefore, we can conclude that the value of the coefficient of policy effect is no difference for the sample of small enterprises (0.401) and large enterprises (0.257). GFRIP produces a positive and significant effect for both large and small-scale enterprises and there is no significant difference in the effect magnitude.

Table 6. Analysis of corporate heterogeneity.

	(1)	(2)	(3)	(4)
Variables	Large	Small	State-owned	Non-state-owned
GFRIP	0.257**	0.401***	0.231**	0.473***
	(2.331)	(3.631)	(2.267)	(4.240)
Control variables	Y	Y	Y	Y
City, industry and year fixed	Y	Y	Y	Y
Observations	10387	10130	9889	10621
R^2	0.652	0.542	0.659	0.583

Note: The table presents the results of the heterogeneity analysis of the grouped regressions in terms of both firm size and firm nature. ***, **, and * indicate statistical significance at $p<0.01$, $p<0.05$, and $p<0.1$, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

(b) Analysis of enterprise nature heterogeneity. The sample was categorized into two groups based on the nature of the enterprises: state-owned enterprises and non-state-owned enterprises. The regression outcomes of Models (3) and (4) in Table 6 indicate that the GFRIP policy engenders green innovation effects on enterprises of varying natures. Similarly, based on the above, we transformed the regression coefficients into AME and found that the difference in coefficient values of the regression results of the two samples, 0.242, is significant at 10% level of significance. Therefore, we can prove that the coefficient value of non-state-owned enterprises (0.473) is significantly higher than the coefficient value of state-owned enterprises (0.231). Owing to the differences in the debt maturity structure under different ownerships, state-owned enterprises find it easier to secure long-term financing. Conversely, private enterprises face challenges in credit financing due to factors such as the business environment, political affiliation, and corporate endowment (Firth *et al*., 2009). The GFRIP policy aids the green transformation of private enterprises by expanding financing channels and reducing financing costs, thereby helping to mitigate the path dependence of "ownership preference" in the credit market.

4.5. *Mechanism analysis*

We examined the external and internal incentives of the GFRIP policy separately, and the results are shown in Table 7. First, the pilot zone policy can significantly increase the size of government R&D subsidies and financial institutions' credit received by enterprises. In the context of the construction of the pilot zones, enterprises oriented towards green transformation and development will have better access to government subsidies and bank credits, and these external funds will flow to the green innovation field. Therefore, hypothesis two holds. Second, the pilot zone policy can significantly promote the adoption of technological means by enterprises to reduce pollution emissions and conserve energy utilization, alleviate financing constraints and promote the strengthening of investment in R&D on new technologies and products. The VEP behavior of enterprises involves the application of energy-saving and emission reduction technologies, which belong to the field of green innovation. In the context of

Table 7. Mechanism analysis.

	(1)	(2)	(3)	(4)	(5)
Variables	*Subsidy*	*Credit*	*VEP*	*SA*	*R&D*
GFRIP	0.317*	0.083***	0.152*	0.030***	0.157***
	(1.697)	(12.266)	(1.778)	(3.843)	(2.815)
Control variables	Y	Y	Y	Y	Y
City, industry and year fixed	Y	Y	Y	Y	Y
Observations	10012	20189	6779	20528	14513
R^2	0.285	0.994	0.318	0.953	0.844

Note: According to the calculation method in this paper, the smaller the SA, the stronger the financial constraint. ***, **, and * indicate statistical significance at $p<0.01$, $p<0.05$, and $p<0.1$, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

the "3060" goal, easing financial constraints is conducive to facilitating enterprises to increase the intensity of their investment in green and low-carbon technology research and development. Thus, hypothesis 3 holds.

5. Conclusions

The GFRIP policy provides a brand-new way of approaching the problem of climate change. Starting from the perspective of CGI, this paper studies China's 2017 GFRIP policy and engages in research utilizing data from 2016 listed companies over the period from 2010 to 2020, leading to the following findings:

(a) The GFRIP policy has a significant positive effect on CGI, with the number of green patent applications of enterprises in the pilot zones being 33.1% higher than that of other regions, and this impact of the policy has both expected and long-term effects. GF resources in the pilot zone are more inclined to emissions reduction innovations than energy saving innovations. The GFRIP has a spillover effect, and the effect on promoting CGI also applies to the prefectures and provinces where the pilot zone is located, and the spillover effect tends to diminish with the expansion of the geographic scope.

(b) GFRIP policy effects have regional and corporate heterogeneity. The green innovation effect is more significant in economically developed and ecologically rich pilot zones than in the core zones of the "Belt and Road". The effect of GFRIP is significantly positive in areas of high environmental regulatory intensity, but not in areas of low environmental regulatory intensity. The pilot zone policy has positively promoted green innovation in enterprises of different sizes and natures, but private enterprises benefit more.

(c) The GFRIP policy influences CGI through two channels: external and internal incentives. The pilot zone policy can increase government R&D subsidies and the scale of credit from financial institutions, with external funds from the government and financial institutions more likely to flow into the green innovation field. Additionally, the pilot zone policy encourages enterprises to speed up the implementation of environmental protection measures or technological methods, alleviates financial constraints, and urges enterprises to increase their R&D investment in green and low-carbon technologies.

In light of the findings, we propose several strategies to optimize the green innovation impacts of the GFRIP policy. First, the government should expedite the development of the GFRIP, establish a regional green financial framework, and proactively offer replicable and scalable models of experience in the reform and innovative progression of Green Finance (GF). It should leverage the spillover effect of the GFRIP policy, stimulate adjacent regions to actively cultivate GF, and foster the research, development, and application of green and low-carbon technologies. Other regions with the necessary prerequisites and conditions can, in line with the principle of simultaneous declaration and creation, learn from the practical experience of the existing pilot zones, and conduct thorough exploration focusing on the support of GF for regional green transformation.

Second, the pilot policy should be adapted to local circumstances. The green innovation impact of the GFRIP policy is more pronounced for private enterprises, thus it is crucial to expand these enterprises' financing avenues and to devise credit products tailored to their needs. The policy effect of the pilot zones with "Belt and Road" attributes (Karamay City, Changji Prefecture, Hami City, Lanzhou New Area) is not substantial. These zones should broaden international collaboration and dialogue on GF, reinforce cooperation with international financial institutions such as the Asian Infrastructure Investment Bank, and concentrate on technical domains such as desertification control, intensive utilization of water resources, and low-carbon carbon sequestration. The pilot zones in the central and western regions should be more proactive in pursuing international cooperation in financial and technological research and development.

The limitation of this study is that it does not open the black box of the GFRIP, a regional policy role in firm innovation. The GFRIP belongs to the macro or meso type of policy and how it acts on the behavior of micro enterprises has not been studied in depth in this paper. We only found that enterprises in the pilot zones had better access to government subsidies and bank credit, and were more proactive in adopting environmentally friendly measures or technological means and increasing their R&D investment. However, to better comprehend the green innovation effects of GFRIP, we still need to answer two questions. First, the direct and indirect effects of the GFRIP policy. The direct effect pertains to the fact that the pilot zones directly influence the behavior of enterprises through financial instruments such as green credit and green bonds, while the indirect effect refers to the fact that the pilot zones collaborate with the promotion of green financial policies through the implementation of fiscal policies, industrial policies, and other policy toolkits. Our study measured only the total effect and lacked measurement of these two effects. Second, it is not precisely known how the external and internal incentives analyzed in this study increase the number of corporate green patents. Due to endogeneity, we only measured the role of the pilot policy on the mediating variables, and as to how the mediating variables promote CGI, we used theoretical analysis and a summary of relevant literature findings to support them.

Both of the above questions remain to be studied in the future. Meanwhile, the future research could adopt the sample data of unlisted companies and obtain first-hand data through field research for more detailed and micro-analysis. The operational characteristics of firms could be incorporated into the analytical framework. Relevant future research could collect more detailed data on firm location (proximity to high-tech zones or not), industry-specific innovation indicators, and conduct in-depth case studies to better understand how these factors interact with the GFRIP and influence corporate green innovation behavior. This will provide a more comprehensive and nuanced perspective for understanding the determinants of green innovation and more targeted policy recommendations for promoting sustainable development.

Acknowledgments

This research was financed by the Shanghai Office of Philosophy and Social Science Fund (2024EJB020).

Appendix A

Table A.1. Definition of variables.

Type	Variables	Definition
Dependent variable	*CGI*	*CGI* = ln (green patent applications of listed companies + 1).
Independent variable	*GFRIP*	If companies in the treatment group are affected by the policy, *GFRIP* = 1; otherwise *GFRIP* = 0.
Control variables	*Size*	*Size* = ln (total assets + 1).
	Lev	*Lev* = (total liabilities)/(total assets).
	ROA	*ROA* = (net profit)/(average balance of total assets).
	Indep	*Indep* = (number of independent directors)/(number of directors).
	Board	*Board* = ln (number of board members + 1).
	Growth	*Growth* = (current year's operating income)/(previous year's operating income) − 1.
	Cashflow	*Cashflow* = (net cash flows)/(total assets).
	FirmAge	*FirmAge* = ln (current year − year of establishment of the company + 1).
	*Top*1	*Top*1 = (number of shares held by the largest shareholder)/(total shares)
	Balance	*Balance* = (number of shares held by the second to fifth largest shareholder)/(number of shares held by the first largest shareholder).
	Dual	If the COB and the CEO are the same person, then Dual = 1; otherwise, Dual = 0.
	TobinQ	*TobinQ* = (market value of outstanding shares + number of non-outstanding shares × net assets per share + book value of liabilities)/(total assets).

(*Continued*)

Table A.1. (*Continued*)

Type	Variables	Definition
Mediating variables	*Subsidy*	*Subsidy* = ln (amount of government R&D subsidies received by listed companies + 1).
	Credit	*Credit* = ln (balance of loans from financial institutions at the end of the year in prefecture-level cities + 1).
	VEP	*VEP* = 2 if the listed company has adopted both energy saving and emission reduction measures, *VEP* = 1 if it has adopted only energy saving or emission reduction measures, and *VEP* = 0 if it has adopted neither.
	SA	$SA = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age$, Age = current year − year of establishment of the company.
	R&D	*R&D* = ln (amount of enterprise R&D investment + 1).

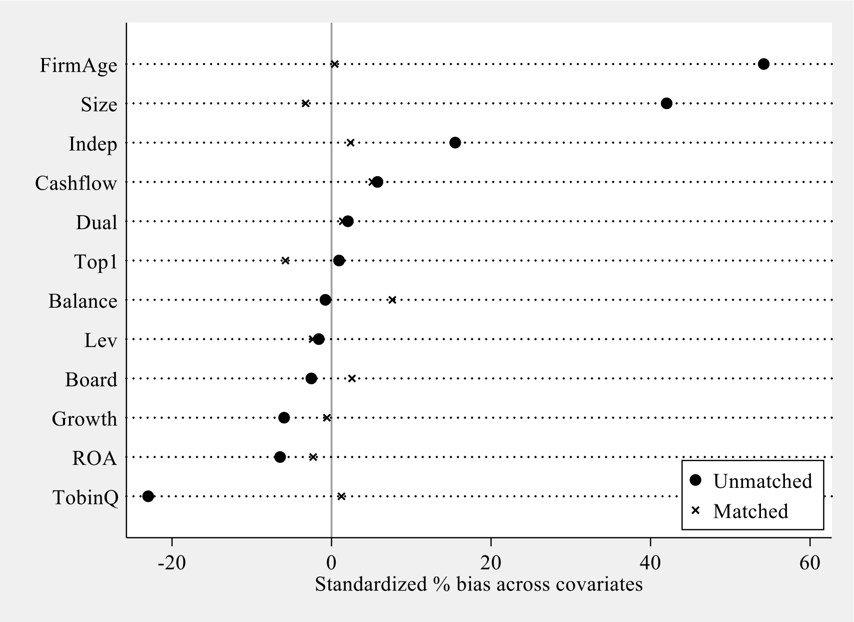

Fig. A.1. Equilibrium test for PSM.

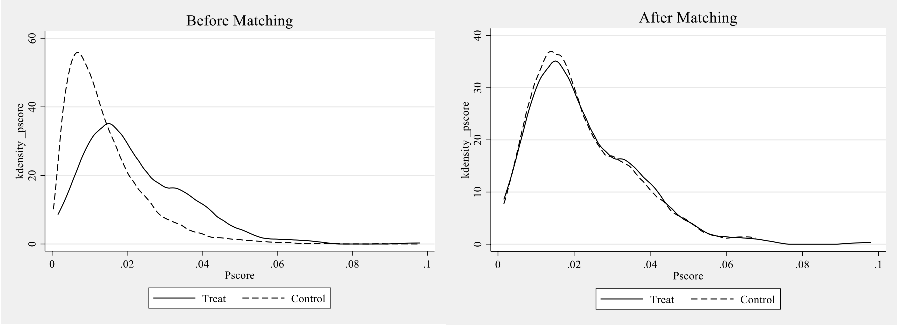

Fig. A.2. Kernel density distribution of propensity scores before and after matching.

Table A.2. Entropy balance matching test results.

	Before matching				After matching			
	Treatment group		Control group		Treatment group		Control group	
Variables	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Size	23.060	2.246	22.430	2.245	23.060	2.246	23.060	2.247
Lev	0.476	0.048	0.479	0.049	0.476	0.048	0.476	0.048
ROA	0.027	0.007	0.032	0.005	0.027	0.007	0.027	0.007
Indep	0.381	0.004	0.373	0.003	0.381	0.004	0.381	0.004
Board	2.156	0.052	2.162	0.041	2.156	0.052	2.156	0.052
Growth	0.157	0.441	0.195	0.402	0.157	0.441	0.157	0.441
Cashflow	0.045	0.005	0.041	0.006	0.045	0.005	0.045	0.005
FirmAge	3.045	0.067	2.871	0.141	3.045	0.067	3.045	0.067
*Top*1	0.341	0.022	0.340	0.023	0.341	0.022	0.341	0.022
Balance	0.661	0.292	0.665	0.341	0.661	0.292	0.661	0.292
Dual	0.220	0.172	0.212	0.167	0.220	0.172	0.221	0.172
TobinQ	1.754	2.096	2.109	2.687	1.754	2.096	1.754	2.095

Note: The table presents the statistic results of the EBM test for both treatment group and control group.

Table A.3. Robustness test results-A.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	PSM-DID	EBM-DID	Parallel trend test	Placebo test-1	Placebo test-2	Csdid
GFRIP	0.569*	0.299***	0.779***	—	—	—
	(1.839)	(4.002)	(4.741)			
treat2014	—	—	—	−0.003	—	—
				(0.032)		
treat2013	—	—	—	—	−0.072	—
					(0.889)	
ATT	—	—	—	—	—	0.210**
						(2.337)
$GFRIP_{-7}$	—	—	−0.036	—	—	—
			(0.230)			
$GFRIP_{-6}$	—	—	0.078	—	—	—
			(0.500)			
$GFRIP_{-5}$	—	—	0.188	—	—	—
			(1.201)			
$GFRIP_{-4}$	—	—	0.264	—	—	—
			(1.631)			
$GFRIP_{-3}$	—	—	0.281*	—	—	—
			(1.748)			
$GFRIP_{-2}$	—	—	0.340**	—	—	—
			(2.016)			
$GFRIP_{-1}$	—	—	0.596***	—	—	—
			(3.476)			
$GFRIP_{1}$	—	—	0.329*	—	—	—
			(1.823)			

(*Continued*)

Table A.3. (*Continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	PSM-DID	EBM-DID	Parallel trend test	Placebo test-1	Placebo test-2	Csdid
$GFRIP_2$	—	—	0.446**	—	—	—
			(2.462)			
$GFRIP_3$	—	—	0.441**	—	—	—
			(2.432)			
Control variables	Y	Y	Y	Y	Y	Y
City, industry and year fixed	Y	Y	Y	Y	Y	Y
Observations	601	20517	20517	20517	20517	20009
R^2	0.958	0.660	0.631	0.584	0.584	—

Note: The table presents the regression results of match treatment and control groups, parallel trend test, placebo tests, and replacement of estimation methodology in Sec. 4.3. ***, **, and * indicate statistical significance at $p<0.01$, $p<0.05$, and $p<0.1$, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

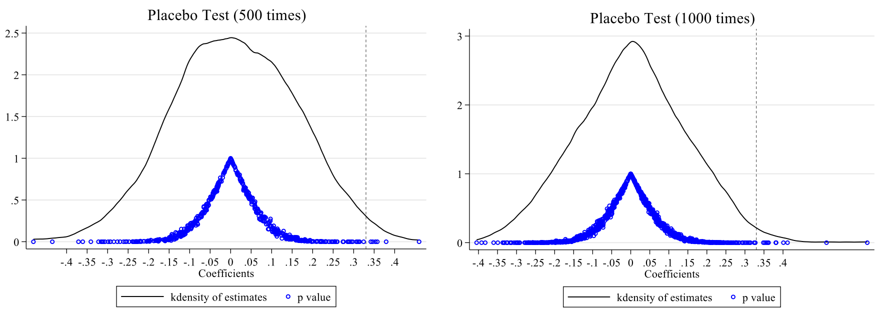

Fig. A.3. Placebo test results.

Table A.4. Robustness test results-B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	*CGI*	*Non_CGI*	CGI_1	F.CGI_1	*CGI*	*CGI*	*CGI*
GFRIP	—	0.027	0.213***	0.209**	0.254***	0.391***	0.337***
		(0.295)	(2.759)	(2.390)	(2.761)	(5.020)	(4.240)
DDD	0.570***	—	—	—	—	—	—
	(5.301)						
CET	—	—	—	—	—	—	0.015
							(0.381)
LC	—	—	—	—	—	—	0.029
							(0.846)
NIC	—	—	—	—	—	—	0.089*
							(1.735)
Control variables	Y	Y	Y	Y	Y	Y	Y
City, industry and year fixed	Y	Y	Y	Y	Y	Y	Y
Observations	20412	20517	20517	18602	20018	17923	20517
R^2	0.884	0.664	0.552	0.553	0.585	0.609	0.584

Note: The table presents the regression results of DDD, impact on non-green patents, substitution of dependent variables, exclusion of abnormal samples, and competing hypothesis tests in Sec. 4.3. ***, **, and * indicate statistical significance at $p<0.01$, $p<0.05$, and $p<0.1$, respectively, and the t statistics calculated from cluster robust standard errors are in parentheses.

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References

Abadie, A, A Diamond and J Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105(490), 493–505, doi:10.1198/jasa.2009.ap08746.

Aghion, P, U Akcigit, A Bergeaud, R Blundell and D Hemous (2019). Innovation and top income inequality. *The Review of Economic Studies*, 86(1), 1–45, doi:10.1093/restud/rdy027.

Akcigit, U, S Baslandze and S Stantcheva (2016). Taxation and the international mobility of inventors. *American Economic Review*, 106(10), 2930–2981, doi:10.1257/aer.20150237.

Al Mamun, M, S Boubaker and DK Nguyen (2022). Green finance and decarbonization: Evidence from around the world. *Finance Research Letters*, 46, 102807, doi:10.1016/j.frl.2022.102807.

Amore, MD and M Bennedsen (2016). Corporate governance and green innovation. *Journal of Environmental Economics and Management*, 75, 54–72, doi:10.1016/j.jeem.2015.11.003.

Athey, S and GW Imbens (2017). The state of applied econometrics: Causality and policy evaluation. *Journal of Economic Perspectives*, 31(2), 3–32, doi:10.1257/jep.31.2.3.

Athey, S and GW Imbens (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, 226(1), 62–79, doi:10.1016/j.jeconom.2020.10.012.

Baker, AC, DF Larcker and CCY Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2), 370–395, doi:10.1016/j.jfineco.2022.01.004.

Benkraiem, R, E Dubocage, Y Lelong and F Shuwaikh (2023). The effects of environmental performance and green innovation on corporate venture capital. *Ecological Economics*, 210, 107860, doi:10.1016/j.ecolecon.2023.107860.

Bianchini, S, G Damioli and C Ghisetti (2023). The environmental effects of the "twin" green and digital transition in European regions. *Environmental and Resource Economics*, 84(4), 877–918, doi:10.1007/s10640-022-00741-7.

Callaway, B and PHC Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230, doi:10.1016/j.jeconom.2020.12.001.

Cao, X, C Jin and W Ma (2021). Motivation of Chinese commercial banks to issue green bonds: Financing costs or regulatory arbitrage? *China Economic Review*, 66, 101582, doi:10.1016/j.chieco.2020.101582.

Carrión-Flores, CE, R Innes and AG Sam (2013). Do voluntary pollution reduction programs (VPRs) spur or deter environmental innovation? Evidence from 33/50. *Journal of Environmental Economics and Management*, 66(3), 444–459, doi:10.1016/j.jeem.2013.05.002.

Chen, L, M Yuan, H Lin, Y Han, Y Yu and C Sun (2023). Organizational improvisation and corporate green innovation: A dynamic capability perspective. *Business Strategy and the Environment*, 32(8), 5686–5701, doi:10.1002/bse.3443.

Cheng, Z, Z Kai and S Zhu (2023). Does green finance regulation improve renewable energy utilization? Evidence from energy consumption efficiency. *Renewable Energy*, 208, 63–75, doi:10.1016/j.renene.2023.03.083.

De Haas, R and A Popov (2023). Finance and green growth. *The Economic Journal*, 133(650), 637–668, doi:10.1093/ej/ueac081.

Del Río González, P (2009). The empirical analysis of the determinants for environmental technological change: A research agenda. *Ecological Economics*, 68(3), 861–878, doi:10.1016/j.ecolecon.2008.07.004.

Firth, M, C Lin, P Liu and SML Wong (2009). Inside the black box: Bank credit allocation in China's private sector. *Journal of Banking & Finance*, 33(6), 1144–1155, doi:10.1016/j.jbankfin.2008.12.008.

Flammer, C (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499–516, doi:10.1016/j.jfineco.2021.01.010.

Galán, JE and Y Tan (2024). Green light for green credit? Evidence from its impact on bank efficiency. *International Journal of Finance & Economics*, 29(1), 531–550, doi:10.1002/ijfe.2697.

Gmeiner, R (2019). Regulatory capture in the US petroleum refining industry. *Journal of Industrial and Business Economics*, 46(4), 459–498, doi:10.1007/s40812-019-00134-w.

Goodman-Bacon, A (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277, doi:10.1016/j.jeconom.2021.03.014.

Hainmueller, J (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20(1), 25–46, doi:10.1093/pan/mpr025.

He, Y and R Liu (2023). The impact of the level of green finance development on corporate debt financing capacity. *Finance Research Letters*, 52, 103552, doi:10.1016/j.frl.2022.103552.

Hojnik, J and M Ruzzier (2016). What drives eco-innovation? A review of an emerging literature. *Environmental Innovation and Societal Transitions*, 19, 31–41, doi:10.1016/j.eist.2015.09.006.

Huang, Z, G Liao and Z Li (2019). Loaning scale and government subsidy for promoting green innovation. *Technological Forecasting and Social Change*, 144, 148–156, doi:10.1016/j.techfore.2019.04.023.

Ibikunle, G and T Steffen (2017). European green mutual fund performance: A comparative analysis with their conventional and black peers. *Journal of Business Ethics*, 145(2), 337–355, doi:10.1007/s10551-015-2850-7.

Krueger, P, Z Sautner and LT Starks (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3), 1067–1111, doi:10.1093/rfs/hhz137.

Laurinavicius, A and A Laurinavicius (2025). Green finance as a catalyst for sustainable development: Evidence from G7 countries. *Journal of International Commerce, Economics and Policy*, 2550009, doi:10.1142/S1793993325500097.

Lee, C-C, X Li, C-H Yu and J Zhao (2022). The contribution of climate finance toward environmental sustainability: New global evidence. *Energy Economics*, 111, 106072, doi:10.1016/j.eneco.2022.106072.

Li, Y (2017). Voluntary disclosure and investment in environmental technology. *Journal of Economic Behavior & Organization*, 133, 331–341, doi:10.1016/j.jebo.2016.11.002.

Li, L, M Li, S Ma, Y Zheng and C Pan (2022). Does the construction of innovative cities promote urban green innovation? *Journal of Environmental Management*, 318, 115605, doi:10.1016/j.jenvman.2022.115605.

Li, Z, G Liao, Z Wang and Z Huang (2018). Green loan and subsidy for promoting clean production innovation. *Journal of Cleaner Production*, 187, 421–431, doi:10.1016/j.jclepro.2018.03.066.

Li, G, L Wang, Z Li and Z Guo (2023). Has pilot zones policy for green finance reform and innovations improved the level of green financial development and environmental quality? *Environmental Science and Pollution Research*, 30(26), 68667–68676, doi:10.1007/s11356-023-27243-3.

Liu, C and M Xiong (2022). Green finance reform and corporate innovation: Evidence from China. *Finance Research Letters*, 48, 102993, doi:10.1016/j.frl.2022.102993.

Liu, S, R Xu and X Chen (2021). Does green credit affect the green innovation performance of high-polluting and energy-intensive enterprises? Evidence from a quasi-natural experiment. *Environmental Science and Pollution Research*, 28(46), 65265–65277, doi:10.1007/s11356-021-15217-2.

Lv, C, B Bian, C-C Lee and Z He (2021). Regional gap and the trend of green finance development in China. *Energy Economics*, 102, 105476, doi:10.1016/j.eneco.2021.105476.

Muganyi, T, L Yan and H-p Sun (2021). Green finance, fintech and environmental protection: Evidence from China. *Environmental Science and Ecotechnology*, 7, 100107, doi:10.1016/j.ese.2021.100107.

Pang, L, MN Zhu and H Yu (2022). Is green finance really a blessing for green technology and carbon efficiency? *Energy Economics*, 114, 106272, doi:10.1016/j.eneco.2022.106272.

Pham, L, W Hao, H Truong and HH Trinh (2023). The impact of climate policy on U.S. environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness. *Energy Economics*, 119, 106564, doi:10.1016/j.eneco.2023.106564.

Salman, A, MGA Razzaq, BH Chang, W-K Wong and MA Uddin (2023). Carbon emissions and its relationship with foreign trade openness and foreign direct investment. *Journal of International Commerce, Economics and Policy*, 14(03), 2350023, doi:10.1142/S1793993323500230.

Shi, P and H Wang (2024). Information acquisition or just going through the motions? Institutional investors' site visits and green innovation. *Corporate Social Responsibility and Environmental Management*, 31(6), 5189–5207, doi:10.1002/csr.2859.

Shive, SA and MM Forster (2020). Corporate governance and pollution externalities of public and private firms. *The Review of Financial Studies*, 33(3), 1296–1330, doi:10.1093/rfs/hhz079.

Triguero, A, L Moreno-Mondéjar and MA Davia (2013). Drivers of different types of eco-innovation in European SMEs. *Ecological Economics*, 92, 25–33, doi:10.1016/j.ecolecon.2013.04.009.

Wang, T, Z Song, J Zhou, H Sun and F Liu (2022). Low-carbon transition and green innovation: Evidence from pilot cities in China. *Sustainability*, 14(12), 7264, doi:10.3390/su14127264.

Wang, L, Z Wang and Y Ma (2021). Environmental effects of trade liberalization–evidence from China's pilot free trade zone. *Journal of International Commerce, Economics and Policy*, 12(03), 2150013, doi:10.1142/S1793993321500137.

Weber, TA and K Neuhoff (2010). Carbon markets and technological innovation. *Journal of Environmental Economics and Management*, 60(2), 115–132, doi:10.1016/j.jeem.2010.04.004.

Wu, Y, L Deng and W Huang (2024). Major government-background customers and corporate green innovation. *Applied Economics*, 56(34), 4049–4063, doi:10.1080/00036846.2023.2209310.

Xu, X, P Hou and Y Liu (2022). The impact of heterogeneous environmental regulations on the technology innovation of urban green energy: A study based on the panel threshold model. *Green Finance*, 4(1), 115–136, doi:10.3934/GF.2022006.

Yan, C, Z Mao and K-C Ho (2022). Effect of green financial reform and innovation pilot zones on corporate investment efficiency. *Energy Economics*, 113, 106185, doi:10.1016/j.eneco.2022.106185.

Zhang, C, X Cheng and Y Ma (2022). Research on the impact of green finance policy on regional green innovation-based on evidence from the pilot zones for green finance reform and innovation. *Frontiers in Environmental Science*, 10, 896661, doi:10.3389/fenvs.2022.896661.

Zhang, H, Y Wang, R Li, H Si and W Liu (2023). Can green finance promote urban green development? Evidence from green finance reform and innovation pilot zone in China. *Environmental Science and Pollution Research*, 30(5), 12041–12058, doi:10.1007/s11356-022-22886-0.

Zhou, F and X Wang (2022). The carbon emissions trading scheme and green technology innovation in China: A new structural economics perspective. *Economic Analysis and Policy*, 74, 365–381, doi:10.1016/j.eap.2022.03.007.

Zhu, Z and Y Tan (2022). Can green industrial policy promote green innovation in heavily polluting enterprises? Evidence from China. *Economic Analysis and Policy*, 74, 59–75, doi:10.1016/j.eap.2022.01.012.