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Green Credit Policy and the Sustainability of Green Innovation: Symbolic or Substantive Responses from High-Polluting Firms

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Abstract: Amid global carbon neutrality and sustainable development goals, and China's transition toward high-quality green and sustainable growth, this study investigates how the Green Credit Policy (GCP) influences the sustainable innovation performance of high-polluting firms. Using Chinese A-share listed firms from 2007 to 2019 and a difference-in-differences (DID) design, we exploit the implementation of the GCP as a quasi-natural experiment to assess its long-term sustainability effects on corporate green transformation. The results reveal that while the GCP significantly promotes symbolic green innovation associated with regulatory compliance, it does not substantially enhance substantive green innovation, raising concerns about the effectiveness of green finance in fostering authentic and high-quality sustainability-oriented innovation. Further analysis shows pronounced heterogeneity across firm types. State-owned enterprises (SOEs) and large firms exhibit improvements in substantive green innovation, thereby contributing more effectively to long-term environmental sustainability and green transformation, whereas non-SOEs and small firms experience tightened financial constraints that crowd out R&D investment, ultimately undermining their sustainable innovation capacity. A series of robustness tests confirms the reliability of these findings. Overall, this study advances the literature on green finance and corporate sustainability by revealing firms' strategic compliance behavior under sustainability-oriented financial regulation, highlighting uneven sustainability outcomes across firm types, and offering policy implications for refining green credit mechanisms to better support genuine green innovation and long-term sustainable development.

Keywords: Green Credit Policy; Sustainable Innovation; Symbolic Green Innovation; Green Technological Transformation; Sustainability; Green Economy

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1. Introduction

In the context of China's commitment to high-quality green growth and long-term sustainable development, and global agenda for carbon neutrality and sustainability transiton, green finance has become a critical policy lever for advancing the economy-wide transition toward environmental sustainability [1,2]. Among various green finance instruments, the Green Credit Policy (GCP) represents a cornerstone initiative by embedding environmental sustainability criteria into credit allocation decisions [3]. Introduced in 2012 through the Green Credit Guidelines, the policy links firms' financing accessibility to their environmental performance, thereby increasing borrowing costs for high-polluting firms while incentivizing investment in cleaner production and sustainable technological upgrading [4-6]. By aligning financial resource allocation with ecological priorities, the GCP plays a key role in steering firms toward more sustainable development pathways and long-term environmental outcomes [7].

Existing research suggests that green credit influences firm behavior through financing constraints, capital costs, and signaling effects [8-10]. However, most studies emphasize innovation quantity rather than sustainability quality of innovation, overlooking the heterogeneity between substantive and symbolic innovations [11,12]. In reality, policy-driven innovation may expand in quantity but deteriorate in quality firms may strategically pursue low-cost, short-term patenting to satisfy compliance requirements. Such behavior risks generating symbolic sustainability outcomes without corresponding improvements in genuine environmental performance, resulting in what has been described as "greenwashing innovation" [13,14].

Using the GCP as a quasi-natural experiment, this study examines how green credit affects both the quantity and sustainability quality of green innovation among China's heavily polluting firms. We distinguish between substantive innovation and symbolic innovation to assess the policy's true contribution to sustainable technological progress and green transformation. Empirical evidence reveals a clear pattern: while the GCP stimulates more green patenting activity, most of this increase stems from symbolic rather than substantive innovation, suggesting a divergence between formal compliance and substantive sustainability advancement.

This behavior reflects firms' rational responses to regulatory incentives: when policy monitoring focuses on whether firms innovate rather than whether such innovation contributes to long-term sustainability, high-pollution firms tend to favor low-cost, low-risk patenting strategies. Further heterogeneity analysis shows that state-owned and large firms benefit more from green credit access and are more capable of shifting toward substantive green innovation that supports sustainable transformation, whereas non-state and smaller firms face financing barriers and respond primarily through symbolic innovation, thereby experiencing weaker sustainability outcomes.

This study contributes to the literature by (1) differentiating between symbolic and substantive green innovation from a corporate sustainability perspective, (2) providing causal evidence of the GCP's uneven sustainability effects using a DID framework, and (3) offering policy implications to enhance the quality-oriented and sustainability-driven design of China's green finance system.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and outlines the research questions. Section 3 describes the data, sample selection, and empirical research design. Section 4 presents the main empirical results and robustness tests. Section 5 conducts heterogeneity analyses to explore differential policy effects across firm types. Section 6 concludes the study and discusses the key findings and implications for sustainable development and green finance policy.

2. Theoretical background and research questions

The GCP represents one of the earliest and most influential institutional frameworks within China's green finance system [15]. As a foundational policy instrument supporting China's transition toward high-quality green growth and long-term sustainable development, the GCP signifies a paradigm shift in financial resource allocation from prioritizing high-growth yet high-emission industries toward encouraging environmentally sustainable, low-carbon, and innovation-driven sectors [16]. By internalizing environmental considerations into credit allocation decisions, the GCP promotes the alignment of financial development with ecological protection and long-term sustainability outcomes [17]. Its core objective is to channel financial resources toward low-carbon, energy-efficient, and innovation-driven firms while compelling highly polluting enterprises to transform and upgrade through differentiated credit allocation [5,18]. In this way, the GCP operationalizes environmental policy through the financial system, using credit as a lever to influence firm behavior [8,10]. By embedding environmental constraints into credit evaluation and loan approval procedures, the policy turns "green performance" into a critical criterion for obtaining financial support [19,20], thereby reshaping firms' innovation incentives and investment decisions in ways that support sustainability-oriented technological upgrading [21,22].

From a theoretical perspective, the GCP draws on both the Porter Hypothesis and the principles of financial constraint theory [23,24]. According to the Porter Hypothesis, well-designed environmental regulation can stimulate firms to innovate, offsetting compliance costs through efficiency gains and new technologies [25,26]. The GCP reflects this notion by linking credit access to environmental performance: firms are encouraged to engage in cleaner production, develop green technologies, and upgrade their innovation capabilities to maintain financial competitiveness while advancing the sustainability transition [27]. At the same time, financial constraint theory suggests that limited access to credit can affect firms' investment behavior, particularly in capital-intensive activities like R&D [28]. Under the GCP framework, firms with poor environmental compliance experience restricted credit availability and higher borrowing costs, which exert both pressure and motivation to innovate in order to restore creditworthiness and improve sustainability performance [29]. This dual mechanism of incentive and constraint differentiates green credit from traditional forms of environmental regulation that rely purely on administrative penalties or subsidies [30].

Existing research indicates that the GCP affects corporate innovation through both positive incentive effects and disciplinary constraint effects [17,31]. On the one hand, green-oriented firms benefit from lower financing costs, improved risk ratings, and increased access to financial markets, enabling them to expand their R&D investment and pursue long-term innovation projects with greater sustainability value [18]. Empirical evidence shows that credit incentives under green finance frameworks can effectively promote R&D spending and enhance firms' capacity for technological upgrading [30]. On the other hand, highly polluting firms face stricter credit supervision and financing pressures, which may initially constrain their operations but also motivate them to improve environmental performance and technological capability to regain credit access [9,21]. Through this process, the GCP creates a self-reinforcing mechanism in which financial constraints encourage green transformation by altering the cost–benefit structure of pollution and innovation. Therefore, it is reasonable to expect that the GCP contributes positively to the green innovation activities of highly polluting enterprises and their sustainability-oriented upgrading. Accordingly, we propose the following research question:

RQ1: Does the Green Credit Policy significantly enhance the green innovation of highly polluting firms?

While the implementation of the GCP is expected to stimulate overall green innovation, an increase in the quantity of innovations does not necessarily translate into an improvement in their quality or their sustainability relevance [8,22]. Quantity-based measures such as patent counts may overestimate the effectiveness of environmental policies if the underlying innovations lack technological substance or market applicability and fail to generate measurable sustainability outcomes [20]. According to the Porter Hypothesis, only well-designed and flexible environmental regulations can induce high-quality innovation through the so-called innovation compensation effect, in which firms compensate for regulatory costs by developing new technologies that enhance efficiency and competitiveness while supporting the sustainability transition [26]. However, in practice, financing constraints, short-term performance assessments, and regulatory compliance pressures may distort firms' innovation behavior, driving them to pursue compliance-oriented innovation rather than genuine technological breakthroughs that deliver long-term environmental and sustainability benefits [32].

For heavily polluting firms, the GCP functions as both a constraint and a signal [33]. On one side, it raises financing costs and limits long-term credit availability, making sustained investment in risky, high-value innovation projects more difficult [34]. On the other side, it signals governmental and societal expectations for firms to demonstrate "green behavior" through visible outputs such as green patents [35]. Under this dual pressure, firms may strategically shift their innovation strategy toward low-cost, low-risk patenting activities that satisfy external evaluation metrics but lack substantive technological value and contribute little to long-term sustainable development. This leads to what recent studies have described as a quantity–quality mismatch in green innovation outcomes, where the number of green patents rises while their novelty and impact decline while limited improvements in sustainability performance [36].

Building on this logic, this study extends the existing literature by investigating the heterogeneous effects of the GCP on different types of green innovation and theil implications for sustainable development [37]. Specifically, we distinguish between substantive green innovation and symbolic green innovation. Substantive green innovation refers to technological activities that lead to genuine environmental and technological progress, typically represented by green invention patents [33]. These patents involve higher R&D input, longer development cycles, and greater uncertainty, but they contribute meaningfully to firms' long-term competitiveness and environmental performance and thereby strengthen sustainability outcomes [30]. Symbolic green innovation, in contrast, refers to innovations that are primarily quantitative and strategic, represented by green utility model patents. These innovations often require less investment and are pursued to demonstrate compliance with environmental regulations or to improve firms' public image without generating substantial sustainability impact or yielding substantial technological breakthroughs [29,38].

This differentiation is important because it captures how firms internalize environmental financial policies in their innovation behavior and whether green finance drives substantive sustainability transformation. If the GCP primarily stimulates symbolic innovation, it may indicate that the policy is effective in promoting visible but superficial compliance; however, if it encourages substantive innovation, it would confirm that green finance has succeeded in driving meaningful technological transformation consistent with the sustainability transiton. The distinction between these two innovation types also aligns with the broader debate in sustainability research regarding greenwashing behaviors—where firms adopt the appearance of environmental responsibility without significant environmental impact improvement or sustained progress toward sustainable development goals. Accordingly, this study proposes the following research questions to guide the empirical analysis:

RQ2: Does the Green Credit Policy promote substantive green innovation among firms?

RQ3: Does the Green Credit Policy promote symbolic green innovation among firms?

3. Sample and research design

3.1 Sample and Data

This study employs a panel dataset of Chinese A-share listed firms spanning the period from 2007 to 2019. Owing to the disruptions introduced by the COVID-19 pandemic, the most recent observations were excluded from the sample [39]. Data on firms' green patents are obtained from the China Research Data Services (CNRDS) platform, while financial and accounting indicators are primarily drawn from the China Stock Market & Accounting Research (CSMAR) database. Following established practices in prior studies, we exclude several types of firms to ensure sample consistency and data reliability [40]. Specifically, we remove: (1) listed companies engaged in monetary and financial services, such as banking and insurance; (2) ST, ST, and PT firms that are subject to special treatment due to abnormal financial conditions; (3) firms with a leverage ratio greater than 1 or less than 0; and (4) firms with severe data deficiencies or missing key variables.

After applying these screening criteria, the final sample consists of 10,489 firm-year observations. To mitigate the influence of outliers and enhance the robustness of the results, all continuous variables are winsorized at the 1st and 99th percentiles [41]. This process minimizes the impact of extreme values and ensures the reliability and stability of subsequent empirical analyses.

3.2 Research Design

3.2.1 Dependent Variable

The dependent variable in this study is firms' green innovation, which is further divided into three dimensions to capture heterogeneity in innovation characteristics: substantive green innovation, symbolic green innovation, and overall green innovation level. (1) Substantive green innovation is measured by the number of green invention patent applications filed by a firm in a given year (G_inva). (2) Symbolic green innovation is measured by the number of green utility model patent applications filed by a firm in the same period (G_uma). (3) Green innovation level represents the total number of green patent applications, including both invention and utility model patents (G_total).

To address potential issues of heteroscedasticity and skewed distribution in patent data, the quantities of all three types of patents are transformed by taking the natural logarithm of (1 + number of patents) [42]. This logarithmic adjustment helps stabilize variance and allows for more consistent statistical estimation across firms and years.

3.2.2 Independent Variable

The core independent variable of this study is the interaction term between the policy shock and the treatment group—denoted as ($Treat_i \times Post_t$)—which captures the net impact of the GCP on the green innovation of high-polluting firms.

The treatment group dummy variable ($Treat_i$) is defined according to the Guidelines for the Classification of Listed

Companies' Industries. Firms operating in 19 high-polluting industries—including thermal power, iron and steel, and chemical engineering—are assigned a value of 1, while firms in non-polluting industries are assigned 0.

The policy timing dummy variable ($Post_t$) equals 1 for the years 2012 and beyond, representing the period after the introduction of the Green Credit Guidelines, and 0 for years prior to 2012.

The interaction term ($Treat_i \times Post_t$) takes the value of 1 when a firm belongs to a high-polluting industry ($Treat_i = 1$) during or after 2012 ($Post_t = 1$), and 0 otherwise. The coefficient of this interaction term reflects the causal effect of the GCP on the green innovation activities of high-polluting firms, isolating the policy's impact from temporal and sectoral heterogeneity.

3.2.3 Control Variables

To mitigate potential endogeneity and omitted-variable bias, this study includes a comprehensive set of firm-level control variables that may influence green innovation performance [43].

We control for Tobin's Q (Tobin Q) to capture firm market valuation and Return on Assets (ROA) to measure profitability. Leverage ratio (Lev) reflects the firm's capital structure, while the book-to-market ratio (BM) represents valuation relative to underlying fundamentals. Furthermore, firm size (Size) and firm age (Age) are included to account for heterogeneity in firm scale and maturity, both of which may affect firms' innovation capacity and risk tolerance. Property, Plant, and Equipment ratio (PPE) captures asset intensity, R&D intensity (R&D) measures the proportion of resources devoted to innovation activities, and cash ratio (Cash) reflects liquidity conditions.

All control variables are defined consistently with prior empirical studies on green finance and corporate innovation. Detailed definitions and measurement descriptions of all variables are presented in Table 1.

Table 1. Variable definitions.

Variable	Definition
G_inva	green invention patents
G_uma	green utility model patents
G_total	total green patents
treat	1 for high-polluting firms, 0 for non- high-polluting firms
post	1 if years from 2012 onward, otherwise 0
Treat*Post	Interaction term of the DID treatment dummy variable
Tobin Q	Market value of equity plus total liabilities divided by total assets
Roa	Net profit divided by total assets
Lev	Total liabilities divided by total assets
BM	Book-to-market ratio
Size	Natural logarithm of total assets
Age	Natural logarithm of years since firm establishment
PPE	Net value of fixed assets divided by total assets
R&D	R&D expenditure divided by operating revenue
Cash	Cash holdings divided by total assets

3.2.4 Descriptive statistics

Table 2 reports the descriptive statistics for 10,489 observations. The mean values of green invention patents (G_inva), green utility model patents (G_uma), and total green patents (G_total) are 0.790, 0.765, and 1.108, respectively, with large dispersions, suggesting low but heterogeneous green innovation performance. Among policy variables, 37.9% of firms are in the treatment group, 61.6% fall within the post-policy period, and the interaction term has a mean of 0.233, ensuring adequate variation for policy identification. Regarding firm characteristics, the mean Tobin's Q is 1.933, ROA is 0.043, and leverage is 0.484, indicating moderate profitability and leverage. Average firm size is 22.48, while R&D intensity (0.013) remains low, implying limited innovation investment among high-polluting firms. Overall, the results indicate that green innovation levels are modest but heterogeneous, and the GCP provides a suitable setting to examine differential innovation responses.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
G_inva	10489	0.790	1.239	0	5.056
G_uma	10489	0.765	1.219	0	4.736
G_total	10489	1.108	1.477	0	5.587
Treat	10489	0.379	0.485	0	1
Post	10489	0.616	0.486	0	1
Treat*Post	10489	0.233	0.423	0	1
Tobin Q	10489	1.933	1.196	0.855	7.722
Roa	10489	0.043	0.047	-0.102	0.204
Lev	10489	0.484	0.188	0.075	0.860
BM	10489	0.313	0.143	0.071	0.758
Size	10489	22.48	1.349	19.90	26.39
Age	10489	2.775	0.351	1.792	3.401
PPE	10489	0.255	0.182	0.002	0.752
R&D	10489	0.013	0.023	0	0.119
Cash	10489	0.589	0.831	0.029	5.565

3.3 Research Design

In line with the research purpose of this paper and the aforementioned theoretical analysis, we construct the following baseline model using the difference-in-differences method:

$$greenpatent_{it} = \beta_0 + \beta_1 treat_i + \beta_2 post_t + \beta_3 treat_i * post_t + \gamma Control_{it} + Firm_i + Year_t + \varepsilon_{it} \tag{1}$$

4. Empirical results

4.1 Baseline results

Table 3 reports the benchmark regression results examining the impact of the GCP on the green innovation activities of high-polluting firms. The policy effect is captured by the did interaction term, with both firm and year fixed effects included to control for unobserved heterogeneity and time-specific influences. Columns (1) – (3) present results without control variables, while Columns (4) – (6) include firm-level controls. The dependent variables are G_inva, G_uma, and G_total, respectively.

In the baseline model without controls, the coefficient of did is G_inva (–0.0352, $p > 0.1$), for G_uma (0.1065, $p < 0.05$), and G_total (0.0830, $p > 0.1$). The positive and significant coefficient for G_uma at the 5% level indicates that the GCP significantly promotes the application of green utility model patents. In contrast, the coefficients for G_inva and G_total are statistically insignificant, suggesting that the policy has little influence on either substantive innovation or total green innovation output.

After including control variables, the results remain consistent. The coefficient for G_uma (0.1184, $p < 0.05$) increases slightly, confirming the policy's positive impact on incremental green innovation. The coefficient for G_inva (–0.0163, $p > 0.1$) remains negative and statistically insignificant, implying that the GCP does not significantly enhance high-quality innovation. The coefficient for G_total (0.1035, $p < 0.1$), this improvement is mainly driven by the expansion of G_uma, indicating that the increase in total green patents stems primarily from low-cost, short-cycle innovations.

These results demonstrate that the GCP primarily stimulates symbolic or incremental green innovation, rather than substantive technological innovation. The findings support the view that high-polluting firms, under financial constraints and regulatory pressure, prefer low-cost, compliance-oriented innovation instead of engaging in high-risk, technology-intensive R&D.

Table 3. Benchmark regression results.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	G_inva	**G_uma**	**G_total**	**G_inva**	**G_uma**	**G_total**
treat*post	-0.0352	0.1065**	0.0830	-0.0163	0.1184**	0.1035*
	(0.0544)	(0.0521)	(0.0613)	(0.0528)	(0.0510)	(0.0591)
Tobin Q				0.0062	-0.0137	-0.0153
				(0.0175)	(0.0166)	(0.0191)
Roa				-0.2963	-0.1412	-0.3002
				(0.3116)	(0.3135)	(0.3705)
Lev				-0.1979	-0.1284	-0.2307
				(0.1831)	(0.1786)	(0.2066)
BM				0.0581	-0.0715	-0.1125
				(0.1857)	(0.1879)	(0.2104)
Size				0.3642***	0.2884***	0.4107***
				(0.0468)	(0.0451)	(0.0526)
Age				0.3710	0.1494	0.3868
				(0.2274)	(0.2247)	(0.2471)
PPE				0.1201	0.4369***	0.2670
				(0.1559)	(0.1595)	(0.1871)
R&D				5.5574***	3.0497***	5.4147***
				(1.0434)	(1.0230)	(1.0879)
Cash				-0.0540***	-0.0148	-0.0456**
				(0.0175)	(0.0178)	(0.0203)
Constant	0.2360***	0.2079***	0.3411***	-8.4758***	-6.4055***	-9.3541***
	(0.0260)	(0.0257)	(0.0304)	(1.0426)	(0.9986)	(1.1335)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	10,489	10,489	10,489	10,489	10,489	10,489
R-squared	0.2125	0.2029	0.2662	0.2507	0.2250	0.3000

Note: ***, **, and * indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

4.2 Robustness checks

To further verify the reliability of the benchmark regression results and the validity of causal inference, this section systematically rules out potential confounding factors through multiple robustness tests, including parallel trend test, Placebo test, counterfactual tests, Propensity Score Matching-Difference-in-Differences (PSM-DID), replacement of dependent variables, and lagged independent variables.

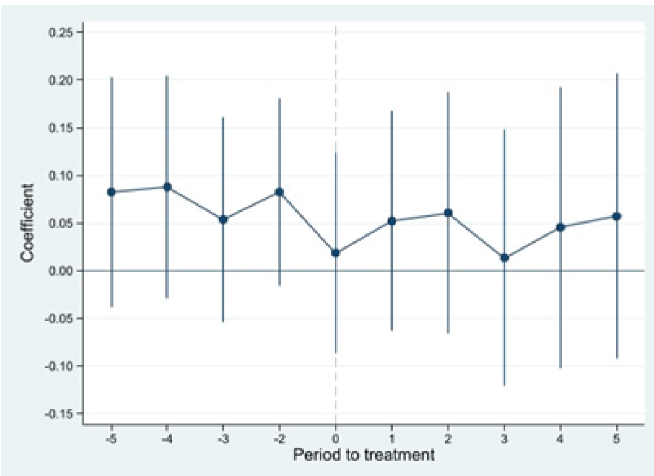
4.2.1 Parallel trend test

Passing the parallel trend test is one of the important conditions for satisfying the $Treat_i \times Post_t$ premise. According to the methods of Liu and Qiu [44], this paper introduces the continuous $Treat_i \times Post_t$ model for parallel trend test. The specific model settings are as follows:

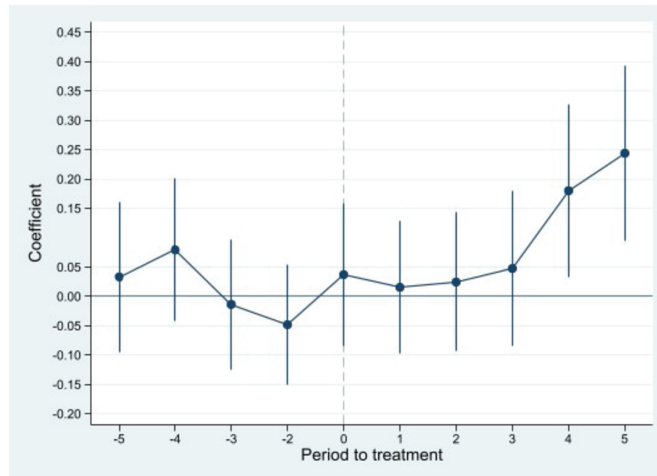
$$greenpatent_{it} = \alpha_0 + \sum_{t=2019,\ t\neq 2011}^{2007} \alpha_t treat_i * post_t + \gamma Control_{it} + Firm_i + Year_t + \varepsilon_{it} \tag{2}$$

Fig. 1 presents the parallel trend test results for the three types of green innovation indicators: G_inva, G_uma, and G_total. Before the implementation of the GCP, the estimated coefficients for all three indicators fluctuate narrowly around zero without a significant upward or downward trend, indicating that the treatment and control groups followed a similar trajectory prior to the policy. This finding satisfies the parallel trend assumption required for the DID framework, supporting the credibility of subsequent causal inference. After the policy implementation, the coefficients of G_uma and G_total show a mild but steady increase, whereas G_inva remains largely unchanged, suggesting that the observed post-policy rise in total green patents is primarily driven by growth in green utility model patents rather than substantive invention patents. This pattern preliminarily implies that the GCP may have encouraged symbolic rather than substantive green innovation among heavily polluting firms.

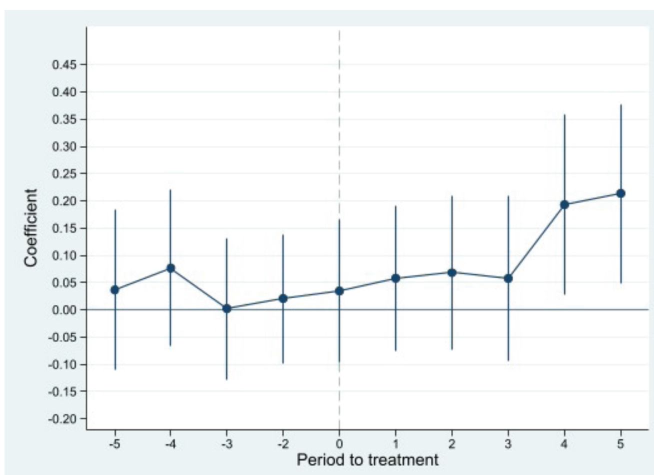
Figure 1. Parallel trend test.



(a) Green invention patents (G_inva)



(b) Green utility model patents(G_uma)



(c) Total green patents (G_total)

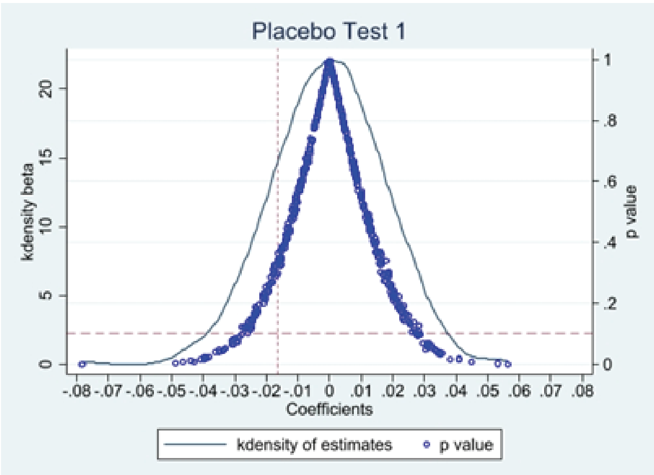
4.2.2 Placebo test

To verify that the impact of the GCP on corporate green innovation is not driven by random factors, we conduct a placebo test to mitigate potential bias from omitted variables. Specifically, 500 random samples are drawn from the full dataset to generate pseudo-policy dummy variables (Treat_c × Post_t), and the baseline model (1) is re-estimated accordingly. Since the placebo treatment is randomly assigned, its estimated coefficients should not systematically deviate from zero.

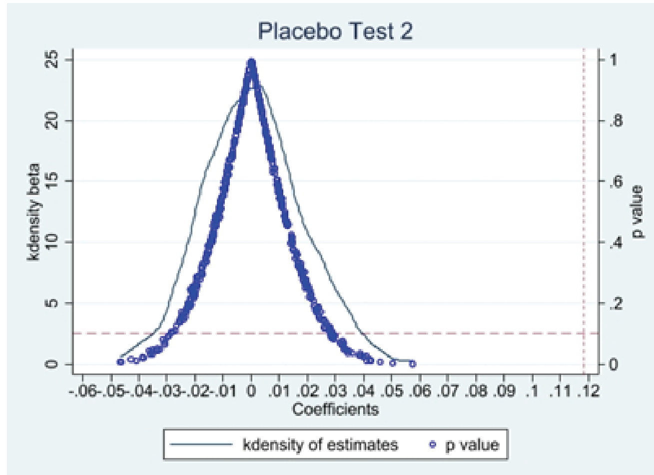
As shown in Fig. 2, the results support this expectation. For G_uma and G_total, the average estimated coefficients of the placebo variables are close to zero and far smaller than the corresponding baseline estimates. The distributions are approximately normal, with most p-values exceeding 0.10, indicating a lack of statistical significance. In contrast, the benchmark coefficient of G_inva lies within the high-density region of the placebo estimates, suggesting that the observed effect of the GCP on substantive innovation may be partly influenced by random variation.

These results reinforce the robustness of the baseline findings. The GCP has a statistically reliable effect on green utility model patents and total green patents, whereas its impact on green invention patents is less stable, consistent with the interpretation that the policy primarily stimulates symbolic rather than substantive green innovation among heavily polluting firms.

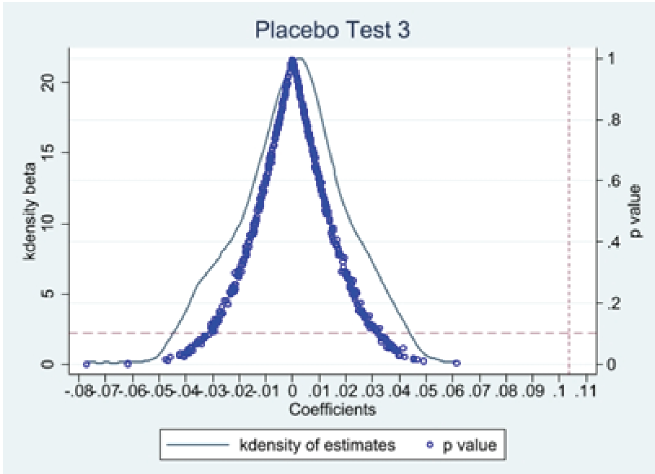
Figure 2. Placebo test.



(a) Green invention patents (G_inva)



(b) Green utility model patents(G_uma)



(c) Total green patents (G_total)

4.2.3 Counterfactual test

To eliminate concerns about spurious time shocks, we construct a counterfactual interaction term (P.treat*post) and regress it on the green innovation indicators. As reported in Table 4 (columns 1–3), the coefficients of P.treat*post for G_inva (-0.0293), G_uma (0.0633), and G_total (0.0673) are all statistically insignificant ($p > 0.1$). These results indicate no differential pre-policy trends in green innovation between treatment and control groups when the actual 2012 policy is excluded, confirming that the baseline effects are indeed driven by the implementation of the GCP rather than by random or time-specific factors.

4.2.4 PSM-DID

To address potential selection bias, we employ nearest-neighbor matching to construct a balanced treatment and control sample. As reported in Table 4 (columns 4–6), the DID coefficient remains significant for G_uma (0.1144, $p < 0.05$) and G_total (0.1055 $p < 0.1$), but insignificant for G_inva (-0.0135, $p > 0.1$). The matched samples also yield higher R^2 values (0.680–0.729), indicating improved model fit. These results confirm that the finding the GCP promote symbolic rather than substantive green innovation is robust after accounting for differences in firm characteristics between groups.

Table 4. Counterfactual Test and PSM-DID.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	G_inva	G_uma	G_total	G_inva	G_uma	G_total
P. treat*post	-0.0293	0.0633	0.0673			
	(0.0528)	(0.0530)	(0.0613)			
treat*post				-0.0135	0.1144**	0.1055*
				(0.0529)	(0.0513)	(0.0593)
Tobin Q	0.0060	-0.0143	-0.0156	0.0034	-0.0121	-0.0164
	(0.0175)	(0.0166)	(0.0190)	(0.0176)	(0.0171)	(0.0193)
Roa	-0.2972	-0.1201	-0.2829	-0.3180	-0.2156	-0.3625
	(0.3120)	(0.3139)	(0.3707)	(0.3210)	(0.3247)	(0.3830)
Lev	-0.1999	-0.1207	-0.2234	-0.1915	-0.1062	-0.2000
	(0.1829)	(0.1788)	(0.2063)	(0.1841)	(0.1838)	(0.2092)
BM	0.0568	-0.0560	-0.0994	0.0239	-0.1079	-0.1476
	(0.1856)	(0.1871)	(0.2094)	(0.1859)	(0.1910)	(0.2106)
Size	0.3641***	0.2853***	0.4084***	0.3667***	0.2903***	0.4111***
	(0.0468)	(0.0450)	(0.0525)	(0.0475)	(0.0457)	(0.0533)
Age	0.3732	0.1628	0.3962	0.2411	0.0921	0.2466
	(0.2274)	(0.2248)	(0.2471)	(0.2261)	(0.2272)	(0.2463)
PPE	0.1200	0.4476***	0.2756	0.1268	0.4382***	0.2676
	(0.1564)	(0.1603)	(0.1880)	(0.1568)	(0.1627)	(0.1887)
R&D	5.5564***	3.0368***	5.4051***	5.8030***	3.4988***	5.7603***
	(1.0430)	(1.0216)	(1.0854)	(1.0639)	(1.0360)	(1.1092)
Cash	-0.0539***	-0.0145	-0.0455**	-0.0554***	-0.0129	-0.0443**
	(0.0175)	(0.0179)	(0.0204)	(0.0181)	(0.0180)	(0.0210)
Constant	-8.4767***	-6.3819***	-9.3349***	-8.0941***	-6.0653***	-8.7573***
	(1.0425)	(0.9966)	(1.1308)	(1.1164)	(1.0670)	(1.2086)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	10,489	10,489	10,489	10,178	10,178	10,178
R-squared	0.2507	0.2241	0.2995	0.7055	0.6807	0.7291

Note: ***, **, and * indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

4.2.5 Dependent variable replacement

The baseline analysis employs green patent applications, which may overstate actual innovation activity. To address potential measurement bias, we replace the dependent variables with green patent grants (G_inva_grant, G_uma_grant, G_total_grant) to capture realized innovation output. As shown in Table 5 (columns 1–3), the DID coefficient remains significant for G_uma_grant (0.0918, $p < 0.1$) and G_total_grant (0.1166, $p < 0.05$), but insignificant for G_inva_grant (-0.0265, $p > 0.1$). These results eliminate concerns of inflated patent applications and confirm the robustness of the baseline findings demonstrating that the GCP primarily enhances symbolic rather than substantive green innovation.

Enterprise innovation is influenced by multiple factors, and if relevant variables are omitted from the model, potential endogeneity bias may arise. This study examines the extent of omitted variable bias by calculating the ratio of coefficient differences between models with and without observable controls. This ratio serves as an indicator of the magnitude of unobservable bias relative to observable factors.

Table 5. Dependent Variable Replacement.

VARIABLES	(1)	(2)	(3)
	G_inva_grant	G_uma_grant	G_total_grant
treat*post	-0.0265	0.0918*	0.1166**
	(0.0413)	(0.0488)	(0.0546)
Tobin Q	0.0041	-0.0068	-0.0059
	(0.0132)	(0.0161)	(0.0182)
Roa	-0.5944**	-0.3667	-0.6845**
	(0.2377)	(0.2963)	(0.3162)
Lev	-0.1010	-0.0837	-0.2033
	(0.1348)	(0.1689)	(0.1889)
BM	0.1118	-0.0267	-0.0568
	(0.1469)	(0.1781)	(0.1915)
Size	0.1834***	0.2695***	0.3173***
	(0.0324)	(0.0430)	(0.0461)
Age	0.3472*	0.2503	0.3881*
	(0.1959)	(0.2165)	(0.2344)
PPE	0.2693**	0.4628***	0.4436***
	(0.1157)	(0.1495)	(0.1659)
R&D	4.3834***	3.4581***	5.5630***
	(0.7954)	(0.9897)	(0.9945)
Cash	-0.0312**	-0.0075	-0.0318
	(0.0148)	(0.0167)	(0.0193)
Constant	-4.7534***	-6.2954***	-7.5259***
	(0.7839)	(0.9574)	(1.0215)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	10,489	10,489	10,489
R-squared	0.1594	0.2016	0.2542

Note: ***, **, and * indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

5. Heterogeneity analysis

5.1 Firm ownership

Table 6 presents the heterogeneity analysis by ownership structure, dividing the sample into SOEs and non-SOEs. Columns (1)–(3) report the results for SOEs, while columns (4)–(6) correspond to non-SOEs. For SOEs, the DID coefficients are significantly positive across all three innovation indicators: G_inva (0.1117, $p < 0.1$), G_uma (0.2304, $p < 0.01$), and G_total (0.2588, $p < 0.01$). These findings indicate that the GCP has a clear and positive influence on both substantive and symbolic green innovation among SOEs [45]. The stronger responses of SOEs likely reflect their closer alignment with government environmental objectives, higher compliance incentives, and preferential access to bank financing [46]. In addition, SOEs generally possess more abundant R&D resources and stronger technological capabilities, which enable them to transform financial incentives into tangible innovation outcomes [30]. Therefore, the GCP strengthens both policy compliance motivation and innovation-driven competitiveness among SOEs.

In contrast, the results for non-SOEs show an opposite pattern. The DID coefficient for G_inva (-0.2290, $p < 0.01$) is significantly negative, and the coefficient for G_total (-0.1598, $p < 0.05$) is also negative, while that for G_uma (-0.0753) is statistically insignificant. These results suggest that non-SOEs experience a decline in substantive green innovation and obtain little benefit from the GCP. Because non-SOEs rely more on market-based financing and lack the implicit guarantees enjoyed by SOEs, they face tighter credit constraints under the GCP framework [9]. Consequently, these firms tend to reduce investment in costly long-term R&D projects, particularly in green invention patents, and instead prioritize short-term compliance and operational stability. Overall, these findings highlight the asymmetric impact of the GCP across ownership types, revealing that SOEs leverage policy support to enhance innovation, whereas non-SOEs are more vulnerable to financial crowding-out effects.

Table 6. SOEs and non-SOEs.

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	G_inva	**G_uma**	**G_total**	**G_inva**	**G_uma**	**G_total**
treat*post	0.1117*	0.2304***	0.2588***	-0.2290***	-0.0753	-0.1598*
	(0.0665)	(0.0642)	(0.0723)	(0.0831)	(0.0791)	(0.0966)
Tobin Q	0.0388*	-0.0094	0.0106	-0.0360	-0.0262	-0.0516*
	(0.0235)	(0.0211)	(0.0249)	(0.0257)	(0.0257)	(0.0291)
Roa	-0.3894	-0.4488	-0.4037	-0.3511	0.0723	-0.3521
	(0.4073)	(0.3854)	(0.4474)	(0.4723)	(0.4912)	(0.5942)
Lev	-0.0212	-0.2571	-0.1001	-0.6276**	-0.2191	-0.6526**
	(0.2428)	(0.2371)	(0.2639)	(0.2786)	(0.2752)	(0.3303)
BM	0.3367	-0.0666	0.1073	-0.4859*	-0.2772	-0.6086*
	(0.2401)	(0.2433)	(0.2645)	(0.2869)	(0.2849)	(0.3464)
Size	0.3566***	0.3038***	0.4076***	0.4193***	0.3164***	0.4667***
	(0.0609)	(0.0581)	(0.0671)	(0.0734)	(0.0704)	(0.0834)
Age	0.4706	0.4802	0.6030*	0.2480	-0.2200	0.1312
	(0.3097)	(0.3012)	(0.3249)	(0.3406)	(0.3331)	(0.3818)
PPE	-0.0347	0.3702*	0.1318	0.2887	0.4358*	0.3728
	(0.2048)	(0.2024)	(0.2370)	(0.2292)	(0.2548)	(0.3023)
R&D	6.4377***	2.8666**	5.9429***	5.3924***	3.7605***	5.6374***
	(1.5816)	(1.4547)	(1.5956)	(1.3760)	(1.4041)	(1.4750)
Cash	-0.0493**	-0.0220	-0.0410	-0.0672***	-0.0235	-0.0637**
	(0.0250)	(0.0229)	(0.0263)	(0.0229)	(0.0256)	(0.0290)
Constant	-8.8059***	-7.5002***	-10.0202***	-8.8161***	-5.9174***	-9.4056***
	(1.4244)	(1.3409)	(1.4738)	(1.5217)	(1.4302)	(1.7133)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	6,589	6,589	6,589	3,900	3,900	3,900
R-squared	0.2637	0.2434	0.3208	0.2475	0.2099	0.2836

Note: ***, **, and * indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

5.2 Firm size

Table 7 reports the heterogeneity analysis based on firm size, dividing the sample in-to large firms and small firms. Columns (1)–(3) show the results for large firms, while columns (4)–(6) correspond to small firms. For large firms, the DID coefficients are signif-icantly positive for G_uma (0.2595, $p < 0.01$) and G_total (0.2152, $p < 0.05$), but insignifi-cant for G_inva (0.0114, $p > 0.1$). These results indicate that the GCP stimulates the overall green innovation of large firms mainly through symbolic rather than substantive innova-tion.

Large enterprises generally possess stronger R&D capacity, more stable financial structures, and greater adaptability to policy changes [30]. With easier access to external financing and closer relationships with financial institutions, they are better able to re-spond to regulatory requirements [21]. To demonstrate environmental commitment and maintain policy compliance, large firms tend to increase low-cost utility model patents rather than engage in high-risk invention projects [29]. Their green innovation activities therefore expand in scale but not in technological depth, suggesting that the GCP pro-motes compliance-oriented behavior rather than genuine technological advancement among large firms.

In contrast, small firms exhibit negative and weaker effects. The DID coefficients for G_inva (-0.1219, $p < 0.05$), G_uma (-0.1015, $p < 0.1$), and G_total (-0.0923, $p > 0.1$) suggest that the GCP constrains rather than encourages their innovation. Due to resource limita-tions and tighter financing conditions [47], small firms often cut R&D spending to pre-serve liquidity. These findings imply that the GCP imposes heavier financial and adjust-ment pressures on smaller enterprises, reducing their incentives to pursue both substan-tive and symbolic green innovation [9].

Table 7. Firm size.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	G_inva	**G_uma**	**G_total**	**G_inva**	**G_uma**	**G_total**
treat*post	0.0114	0.2595***	0.2152**	-0.1219**	-0.1015*	-0.0923
	(0.0801)	(0.0796)	(0.0876)	(0.0617)	(0.0540)	(0.0707)
Tobin Q	0.0631	0.0373	0.0373	-0.0335*	-0.0539***	-0.0590***
	(0.0383)	(0.0346)	(0.0406)	(0.0186)	(0.0175)	(0.0204)
Roa	-0.9296*	-0.6742	-0.8480	-0.0733	0.1035	-0.1125
	(0.5273)	(0.5256)	(0.6000)	(0.3580)	(0.3546)	(0.4389)
Lev	-0.6762**	-0.4235	-0.6106*	-0.2490	-0.2784	-0.3865
	(0.3414)	(0.3205)	(0.3598)	(0.2058)	(0.2039)	(0.2429)
BM	0.2183	0.1334	0.1382	-0.5342***	-0.6459***	-0.8230***
	(0.3236)	(0.3046)	(0.3398)	(0.1936)	(0.1966)	(0.2294)
Size	0.3740***	0.2896***	0.4084***	0.3252***	0.2604***	0.3824***
	(0.0727)	(0.0734)	(0.0826)	(0.0554)	(0.0498)	(0.0610)
Age	0.4149	0.1435	0.3514	0.6277**	0.4169*	0.7162**
	(0.3494)	(0.3507)	(0.3716)	(0.2611)	(0.2500)	(0.3013)
PPE	0.0756	0.2997	0.1795	-0.0962	0.3088*	0.0643
	(0.2526)	(0.2521)	(0.2957)	(0.1603)	(0.1687)	(0.2020)
R&D	6.5302***	3.5593*	5.4901**	5.7258***	3.3159***	6.0229***
	(2.1119)	(2.0764)	(2.1905)	(1.1053)	(1.1078)	(1.1607)
Cash	-0.0713*	-0.0363	-0.0501	-0.0466***	-0.0071	-0.0406*
	(0.0397)	(0.0430)	(0.0469)	(0.0173)	(0.0177)	(0.0207)
Constant	-8.8684***	-6.5142***	-9.3623***	-7.7265***	-5.9432***	-8.8973***
	(1.7567)	(1.7747)	(1.9453)	(1.1070)	(1.0309)	(1.2043)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	5,172	5,172	5,172	5,317	5,317	5,317
R-squared	0.3214	0.3009	0.3751	0.1986	0.1616	0.2394

Note: ***, **, and * indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

6. Conclusion and Recommendation

6.1 Conclusions

This study examines the impact of China's GCP on the green innovation behavior of heavily polluting firms and its implications for the sustainability transition under carbon neutrality goals. By distinguishing between substantive and symbolic green innovation, the analysis offers a more nuanced understanding of how sustainability-oriented finan-cial regulation shapes not only the scale but also the quality of corporate innovation that underpins the sustainability transition. Employing a difference-in-differences approach and conducting heterogeneity analyses across firm ownership and firm size, this study identifies the causal effects of the GCP and reveals significant variation in firms' innovation responses and sustainability-relevant outcomes.

The empirical results indicate that the GCP significantly increases total green patent output and primarily promotes symbolic green innovation, while its effect on substantive green innovation remains statistically insignificant. This suggests that, although the poli-cy is effective in expanding the scale of green innovation activities, it falls short in foster-ing deeper, technology-intensive innovation that contributes to genuine and long-term sustainability outcomes, including meaningful emissions reduction and cleaner produc-tion improvements. Further heterogeneity analyses show that SOEs respond most strongly to the GCP by improving both substantive and symbolic green innovation, likely due to their preferential access to credit resources and stronger incentives to comply with policy objectives and demonstrate sustainability performance. Large firms also exhibit a positive response, but this response is mainly symbolic, reflecting a tendency to engage in low-cost patenting strategies to meet regulatory expectations without proportional improvements in sustainability impact. In contrast, non-SOEs and small firms experience tighter financ-ing constraints and limited innovation capacity, which discourages substantive green in-novation and may even crowd out high-quality technological investment, thereby weak-ening their sustainable development capacity.

These findings highlight a potential unintended consequence of green credit policies: heavily polluting firms may prioritize short-term, low-cost compliance-oriented innova-tion rather than pursue meaningful technological upgrading that advances the sustaina-bility transition. To better align green credit instruments with the objectives of high-quality, innovation-driven sustainable development, policymakers should further improve credit accessibility for non-SOEs and small firms, strengthen monitoring mechanisms that link financial incentives to patent quality rather than quantity and to verifiable sustainability outcomes, and refine institutional arrangements that encourage long-term technological breakthroughs and sustained environmental performance improvements. Such policy adjustments are essential for enhancing the effectiveness of green finance in supporting environmentally sustainable and innovation-led economic transformation and for ensur-ing that green credit contributes to carbon-neutral and sustainable development trajecto-ries.

6.2 Recommendations

Based on the empirical findings, this study offers several policy and managerial recommendations to enhance the effectiveness of green credit in promoting high-quality and sustainability-oriented innovation.

First, policymakers should refine the design of green credit evaluation systems by shifting the focus from innovation quantity to innovation quality and verifiable sustaina-bility outcomes. Rather than relying predominantly on patent counts, financial institu-tions should incorporate indicators related to patent novelty, technological impact, and actual environmental performance improvements, such as emissions reduction and en-ergy efficiency gains. This adjustment would help mitigate firms' incentives to engage in symbolic green innovation and reduce the risk of greenwashing behavior under sustaina-bility-oriented financial regulation.

Second, differentiated green credit support mechanisms should be strengthened to address firm heterogeneity. The results indicate that non-SOEs and small firms face tight-er financing constraints that hinder their ability to pursue substantive green innovation. Policymakers should therefore improve inclusive access to green finance, for example through credit guarantees, interest subsidies, or risk-sharing arrangements, to support these firms' participation in long-term sustainable technological upgrading. Such measures would enhance the equity and effectiveness of green finance in fostering econ-omy-wide sustainability transitions.

Third, financial regulators and banks should enhance post-credit monitoring and information disclosure mechanisms to ensure that green credit contributes to sustained environmental and sustainability performance, rather than short-term compliance. Link-ing loan conditions and renewal decisions to firms' long-term innovation trajectories and environmental outcomes can strengthen the credibility of green finance and better align financial incentives with carbon neutrality and sustainable development goals.

6.3 Limitations and future research

Despite its contributions, this study has several limitations that point to promising avenues for future research. First, this study focuses on green patents as proxies for green innovation and sustainability-oriented technological activity. Although patent-based measures are widely used, they may not fully capture firms' actual environmental per-formance or broader sustainability impacts. Future research could integrate firm-level emissions data, energy consumption indicators, or ESG performance metrics to provide a more comprehensive assessment of sustainability outcomes.

Second, while the analysis identifies significant heterogeneity across firm ownership and size, other sources of heterogeneity remain unexplored. Future studies could examine how regional institutional environments, industry-specific characteristics, or differences in local financial development shape the sustainability effects of green credit policies.

Third, this study examines the Green Credit Policy within the Chinese institutional context. Although China provides a valuable setting for studying green finance and sus-tainability-oriented regulation, the findings may not be fully generalizable to other econ-omies with different financial systems or regulatory frameworks. Comparative studies across countries or regions would help assess the external validity of green credit as a tool for promoting sustainable development.

Finally, future research could explore the dynamic and long-term effects of green credit policies on firms' innovation trajectories and environmental performance. Under-standing whether symbolic innovation evolves into substantive innovation over time would offer deeper insights into the long-run sustainability implications of green finance.

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