The Impact of Green Credit Policy on The Firms' Green Strategy Choices: Green Innovation or Green-Washing?

ling he (1120821982@qq.com)
Sichuan University
shengdao gan
Sichuan University Liberal Arts and Sciences Library: Sichuan University
tingyong zhong
Chongqing Technology and Business University

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Abstract

Taking the green credit policy in 2012 as a quasi-natural experiment, this paper has investigated the impact of green credit policy on firms' green strategy choices in China by using the panel data of the A-share firms listed from 2008 to 2019. The results reveal that green credit improves firms' green innovation overall. In terms of time, listed firms' green-washing can be significantly increased at the early stage of the implementation of green credit policy, but as time goes by, such green behavior of firms will be detected, which in turn will motivate firms to improve green innovation. Furthermore, the green credit policy has a more significant effect on the green innovation in firms in localities under high environmental regulation, economically developed regions, and without other alternative financing channels. Firms located in economically underdeveloped and low environmental regulation regions prefer to adopt the behavior of green-washing environmental information. Besides, green innovation by firms after the implementation of green credit can promote corporate financial, environmental, and social performance, while green-washing behavior will damage corporate financial, environmental, and social performance. Our findings contribute to the literature on green credit policy, corporate green innovation, environmental disclosure, and also provide some policy implications to improve the quality of green credit policy in the future.

Introduction

China ranks 120th out of 180 countries with an environmental performance score of 37.3, far below the world average, according to the 2020 Global Environmental Performance Index report. China has ranked first in power generation and energy consumption in the world for several years, and its high energy consumption has brought lots of pollution problems. Although high-polluting enterprises are the largest energy consumption and pollution emission subjects in China, they are also the main force to promote the green transformation of industrial structure and achieve the goal of dual carbon (Wen et al., 2021). However, firms, whose priority is profit maximization, have always lacked the motivation to actively carry out environmental protection, so it is essential to regulate the behaviors of firms through government policy intervention.

High-polluting enterprises are capital-intensive industries and mainly rely on external bank credit financing to obtain business development funds (Liu et al., 2019; Yao et al., 2021; Wang et al., 2020). Therefore, to urge high-polluting enterprises to implement green transformation at source, the Chinese government promulgated the "Green Credit Guidelines" in 2012. The policy requires commercial banks to incorporate corporate environmental performance into credit access criteria, directing capital to green environmental projects and enterprises and limiting loans to polluting projects and enterprises, which is a "carrots and sticks" financial and environmental policy. It aims to internalize external environmental problems by allocating financial resources through credit. As for China, by the end of 2021, the green credit balance of 21 major banking financial institutions had reached CNY 11 trillion, showing the rapid development of green credit in China and its growing importance for enterprises to access credit financing. In the context of low-carbon development driven by green finance, the main organizational

level directly affected by the green credit policy is the micro-enterprise, so whether the policy can produce green effects depends largely on high-polluting enterprises' response strategy.

A series of studies have been conducted by many scholars on the impact of green credit policy on high-polluting enterprises. For instance, Li et al. (2021), Liu et al. (2019), Peng et al. (2021), and Xu and Li (2020) both believed that green credit policy has a financing penalty effect, which significantly increases the difficulty of debt financing for high-polluting enterprises. Liu et al. (2017) and Wang et al. (2020) found that the policy inhibits the level of investment in polluting enterprises. Wen et al. (2021) pointed out that the green credit policy under the Green Credit Guidelines in 2012 has a significantly negative effect on the allocation efficiency of credit and the upgrade of energy-intensive enterprises. Yao et al. (2021) demonstrated the green credit policy has a "penalty effect", which would significantly reduce firm performance in heavily polluting industries. The ultimate goal of green credit is to promote polluting enterprises to achieve transformation and upgrading or to exit projects that may cause major polluting problems rather than directly close these enterprises. In practice, the promulgation of green credit policies leads to many capital constraints and greening problems for high-polluting enterprises, which will undoubtedly have a great negative impact on the production and operation activities of these enterprises. Therefore, an interesting topic worthy of further study is what kind of green strategic behaviors will high-polluting enterprises choose to respond to the great development pressure brought by the green credit policy? This remains to be corroborated by more empirical studies.

Some scholars have explored the strategic choice of enterprises suffering negative impacts. Mohamed et al. (1999) clearly indicated that direct (apology and correction) and indirect (other actions to divert public attention) can be adopted when a company's reputation was damaged. Lindblom (1994) pointed out that when an enterprise is threatened by legitimacy, it may adopt the following four strategies: the first is to change public perception; the second is to manipulate public perception by diverting public attention; the third is to falsely inform the public of changes in corporate behavior through certain signaling mechanisms; the fourth is to take action that meets the expectations of the public and society. It can be seen that the current scholars on the way companies respond to negative impacts can be summarized into two points: first, changing the public perception of the company through information disclosure, and second, companies adopting actual improvement behaviors.

According to this logic, then there are two ways for high-polluting enterprises to lessen the negative impact of green credit policy, on the one hand by conveying more environmental information to external information users, and on the other hand by adopting more environmental protection behaviors. These two approaches satisfy the research framework of Brammer et al. (2007), Tilt (2006), and Passetti et al. (2018) that divides enterprise green activities into external green activities and internal green activities. External green activities refer to the company's communication with external stakeholders through information disclosure, while internal green activities are expressed as actual technical and management changes within the company.

Therefore, this paper focuses on external green-washing environmental disclosure and internal green innovation. We try to assess the effectiveness of China's green credit policy via a key question, that is, which green behavior will companies choose under the green credit policy? To answer the question, we undertake an empirical analysis using panel data of 3272 listed enterprises from 2008 to 2019 and test the effects of the green credit policy on green innovation and green-washing. Further, we explore the variability of this issue across time, space, external environments, and firm resources. And we also consider the economic consequences of adopting different green behaviors by firms to provide empirical guidance for choosing appropriate behaviors. Solving these problems has important practical implications for accelerating green credit and sustainable development in many developing countries.

Our study makes several contributions to previous research. First, we add to the emerging literature on the economic consequences of green credit policy. To the best of our knowledge, this is the first paper to illustrate the relationship between green credit policy and two different green behaviors of enterprises. Our methodology allows us to open the black box and explain the motivations of the policy that affect firms' choice of green behavior, and also provides guidance for developing countries to improve the green financial system and ultimately achieve sustainable development. Second, the research results of green innovation and environmental disclosure are supplemented. Although previous literature has investigated the impact of green credit policy on enterprises' green innovation and environmental information disclosure (Liu et al., 2021; Wang et al., 2019), they have not incorporated these two green behaviors into a unified analytical framework and have not discussed enterprises' choice of two different green behaviors in different environments. This paper discusses the enterprises' choice strategies for these two green behaviors from the four dimensions of time, space, external environment, and enterprise resources, thus supplementing the relevant literature on enterprise environment behavior. Third, it enriches the scope of research on the motives of corporate green strategy choices. Relevant documents have begun to notice the instrumental motivation behind corporate environmental responsibility behavior (Jiang et al., 2021). By collecting the motives of enterprises' green strategy choices under green credit policies, this paper finds that high-polluting enterprises will use green-washing to build an environmentally friendly image. From the perspective of policy, this paper provides a new research perspective to reveal the instrumental motivation of corporate environmental information disclosure, and also finds that corporate green-washing behavior hinders the effectiveness of China's green credit policy implementation. This has important theoretical and practical value.

The content of the rest of this paper is structured as follows. The "Background and hypotheses development" section clarifies the existing literature, summarizes the research direction of this article, and proposes hypotheses. The "Sample and empirical methodology" section explains the research design and data sources. The "Results and analysis" section analyzes the empirical process. The "Robustness test" section provides robustness tests. The "Conclusions and recommendations" section gives conclusions and policy suggestions.

Background and hypotheses development

Green credit policy

Under the realistic background of global climate change and serious environmental pollution in the 1980s, the concept of green finance was derived from the lack of green investment channels and motivation to boost economic growth. As an important part of green finance, green credit has both green and credit attributes. In 2007, China officially proposed the concept of “green credit” and initiated a small-scale pilot. In February 2012, the CBRC (China Banking Regulatory Commission) issued the “Green Credit Guidelines”, which is considered as the core of China’s green credit policy system and the first normative document for green credit. The core content of “Green Credit Guidelines” can be summarized into two aspects. First, under the guidance of credit policy, commercial institutions by the tools of loan products, loan maturity, loan interest rate, and credit quota to allocate more financial resources to environment-friendly enterprises or projects. Second, commercial institutions set more strict conditions for access to financing, enterprises or projects that violate energy conservation, emission reduction, and environmental protection will be punished by suspending loans and delaying loans, or even recovering loans. The essence of green credit policy is to allocate resources through financial leverage, actively provide credit support to environmental-friendly enterprises and green projects, simultaneously restrict credit support to high-polluting and energy-intensive enterprises and projects, and ultimately guide the green development of the economy.

The practical effects of green credit on enterprises have been explored by academic circles from different perspectives, mainly around environmental and economic dividends. Peng et al. (2021) and Li et al. (2021) adopted a quasi-natural experiment with the implementation of green credit and found that the debt financing capacity of enterprises has decreased significantly. A study by Xu and Li (2020) also came up with similar results, Xu and Li (2020) confirmed that green credit could limit the bank’s credit support to heavily polluting enterprises, which reduces the scale of debt financing and increase costs of enterprises. Liu et al. (2017) and Wang et al. (2020) concluded that the green credit policy is effective in suppressing the investments of high-pollution and energy-intensive enterprises. Also, the policy would reduce the corporate performance of heavily polluting enterprises (Yao et al., 2021) and improve new energy enterprises’ value (Lai et al., 2021). In addition, some scholars choose to focus on the impact of green credit on the green behavior of enterprises. Research by Hong et al. (2021), Hu et al. (2020), and Liu et al. (2021) prove that green credit policy can help to increase investment in green innovation by polluting enterprises. However, some scholars such as Zhang et al. (2022) concluded that the implementation of the green credit policy inhibited the green innovation of all heavy-polluting enterprises, and this inhibition is heterogeneous. Wang et al. (2019) found there is no significant positive correlation between environmental information disclosure and green credit from the perspective of information disclosure.

In summary, the research results, theoretical foundations, and methods of previous scholars are meaningful and provide a research basis for our paper. However, current research on the relationship between green credit policy and corporate environmental activities is insufficient. Firstly, most studies focus on the direct impact of the policy on enterprise financing behavior. The ultimate goal of green credit

policy is to promote the green development of society. Limited research examined the influence of green credit on firm environmental activities, only from a green innovation perspective. We wanted to know whether, throughout the implementation of green credit policy (in the short and long term), firms would choose other green behaviors in addition to choosing green innovation to address policy impacts. Secondly, these studies lack attention to the correlation between green credit policy and firms' internal and external green activities. Passetti et al. (2018), Brammer et al. (2007), and Tilt (2006) divide enterprise green activities into external green activities and internal green activities. Some studies examine the impact of green credit policy on enterprises' environmental behavior in terms of external information disclosure and internal green innovation, respectively, but rarely combine the two behaviors into the same analytical framework to make an overall evaluation. The process of enterprises choosing green strategies is not constant, enterprises will respond to the policy with different behaviors depending on the environment they are in. Therefore, this paper takes environmental disclosure quality and green innovation performance as research objects to explore the impact of green credit policy on firms' strategic choice in both the short-term and long-term and the heterogeneity of firms' green behavior in different environments.

Green credit and corporate green-washing

China's current green credit policy requires commercial banks to take full account of the company's environmental situation and environmental information disclosed when making loan decisions (Wang et al., 2020). Commercial banks usually use environmental information to assess corporate environmental risk and credit risk and then make loans. As a result, we can infer that commercial banks need to make loan decisions based on annual environmental information increments. However, at present, China's environmental information disclosure has the characteristics of incompleteness and concealment. It is usually difficult for information users to fully and accurately grasp the real environmental conditions of enterprises, which is easy to cause the capital mismatch phenomenon in the process of credit allocation by banks (Zhang and Yang, 2011).

Andersen and Høvring (2020) and Marquis et al. (2016) pointed out that a large number of organizations adopt symbolic strategies as their first choice to address complex institutional pressures, and impression management of environmental information provides a channel for enterprises to maintain legitimacy without changing the original business model. This type of impression management is common in corporate environmental governance and is generally referred to as green-washing. Green-washing is a kind of green strategy to meet the requirements of green regulations and the public's environmental needs, with limited green performance or future commitments to cover up their poor environmental performance (Kim and Lyon, 2015; Laufer, 2003; Walker and Wan, 2012). Then for high-polluting firms that are discriminated against by green credit, they may use environmental information to convey to commercial banks and other external information users the environmental content they expect to see, and green-washing environmental information may become a strategy for high-polluting firms to gain organizational legitimacy.

In addition, China's environmental regulatory and supervisory system is not mature enough, commercial banks can not fully identify corporate green motives. Huang et al. (2019) pointed out that green-washing can help alleviate bank credit discrimination of high-polluting enterprises and make it easier for them to obtain debt financing support. Therefore, due to the demand for credit resources and to obtain more bank loans, high-polluting enterprises have a strong initiative to green-wash environmental information. From the perspective of cost and benefit, in the short term, in the case of loopholes in the regulatory system, the cost of the green-washing strategy adopted by enterprises with oral commitment and the symbolic solution is often very low, and the private cost of green-washing enterprises is lower than the social cost, which can bring benefits to enterprises (Lyon and Maxwell, 2011).

Based on the above analysis, the following hypothesis is proposed:

H1: With the green credit, high-polluting enterprises' green-washing behavior will increase significantly.

Green credit and corporate green innovation

- This article focuses on green credit policy affecting the level of green innovation of high-polluting enterprises through the following paths. First, the green credit policy requires commercial banks to consider the environmental risks of enterprises and projects when granting loans, and not to provide loans for enterprises and projects with high energy consumption and environmental pollution, while providing loans for energy-saving and environmental protection enterprises and projects (Peng et al., 2021). Due to the differentiated credit services of green credit policy, polluting enterprises that rely on bank loans to obtain debt funds must incorporate environmental protection into their business to meet the requirements of bank loans (He et al., 2019; Peng et al., 2021). Empirical evidence indicates that green credit policy makes commercial banks more willing to provide bank loans to enterprises with green innovation, and green innovation plays a stronger role in alleviating financing constraints of heavily polluting enterprises (Francis et al., 2012; Zhang et al., 2020). It also implies that enterprises with poor environmental performance can obtain credit funds and alleviate financing constraints by actively carrying out green innovation activities. Hence, under the differentiated lending mechanism of the green credit policy, high-polluting enterprises can be more stimulated to alleviate the financing constraints caused by the policy through innovative activities.
- Second, In the long term, the debt financing constraint brought by the green credit policy to the heavy polluters from short-term impact gradually becomes a long-term constraint. Zhang et al. (2020) point out that under the constraint of limited resources, the necessary condition for firms to choose green innovation is that the benefits outweigh the costs. From a cost point of view, on the hand, if high-polluting enterprises do not adopt green action after the implementation of the green credit policy, they will suffer not only from environmental costs but also from high financing costs and sunk costs (Hu et al., 2021). On the other hand, since the environmental pressure from green credit policy is long-term, it may be less costly in the short term for enterprises to adopt green-washing, but it is not cost-effective in the long term. From the perspective of innovation benefits, high-pollution enterprises can obtain high innovation benefits through green innovation, such as green reputation, competitive

advantage, legitimacy, credit funds, government subsidies, taxes, and other economic dividends (El-Kassar and Singh, 2019). Thus, for high-polluting firms, there is an incentive for firms to choose green innovative behaviors that can bring long-term competitive advantage to the firm after the implementation of the green credit policy.

Based on the above analysis, the following hypothesis is proposed:

H1: With the green credit, high-polluting enterprises' green innovation behavior will increase significantly.

Sample And Empirical Methodology

Sample selection

Based on the event of "green credit guidelines" issued by CBRC in 2012, this paper collects the panel data of China's 3272 listed companies from 2008 to 2019, constructs a difference-in-difference model, in which the high-polluting enterprises are regarded as the experimental group and other enterprises as the control group. We collect data from several resources. First, data about enterprise environmental information disclosure is collected manually from corporate social responsibility reports, environmental reports, sustainable development reports, and other aspects. Second, data about green innovation are from the Chinese Research Data Services Platform. Third, other data are gathered from China Stock Market & Accounting Research Database. To enable reasonable precision, we exclude firms with special treatment, firms that belong to financial industries, and firms with missing values. All the continuous variables are winsorized at 1% and 99% to exclude the outlier effect.

Definition of variables

Independent variable

High-polluting enterprises under the policy of the "Green Credit Guidelines" (Treat×Post) is the independent variable. Following the industry classification of the China Securities Regulatory

Commission (CSRC), We define the following industries as high-polluting enterprises: thermal power, steel, cement, electrolytic aluminum, coal, metallurgical, chemical, petrochemical, building materials, papermaking, brewing, pharmaceutical, fermentation, textile, leather, and mining. The "Green Credit Guidelines" was launched in 2012, marking the formal implementation of green credit policy, which is the core of China's green credit policy system and has become a key perspective for many scholars to study the green credit policy (Liu et al., 2021; Hong et al., 2021).

Dependent variable

The dependent variable is the level of green innovation, which is indicated by the logarithm of the number of green invention patents applications plus one. Since green patents are often associated with environmental improvements and more broadly indicate the progress of green innovation, we employ

green patents as indicators of corporate green innovation. We measure the scale of green innovation by the natural logarithm of one plus the number of green patents applications.

The other dependent variable is the degree of green-washing. Green-washing refers to the enterprise disclosing untrue environmental information through “confusion”, “hidden”, “exaggeration” and other ways (Kim and Lyon, 2015; Laufer, 2003; Walker and Wan, 2012). Green-washing enterprise creates an environmentally friendly image through symbolic descriptions rather than substantive actions. Clarkson et al. (2008) classify environmental disclosure into soft and hard types. Soft environmental disclosure refers to claims without strong objective evidence. It reflects symbolic corporate environmental behaviors. Correspondingly, hard environmental disclosure is that terms are based on relevant data and can be verified by other institutions. It reflects substantial corporate environmental behavior. Thus, soft disclosure rather than hard disclosure may aggravate green-washing. If the magnitude of soft disclosure is greater than for hard, the firm will be treated as a greenwasher. Referring to Huang et al. (2019), this paper constructs indicators to measure the degree of green-washing of enterprises based on the quality of environmental information disclosure from three aspects: environmental management, resource conservation, and pollution reduction, with a total of 18 indicators. For these 18 indicators, score 0 for those without description, 1 for those with symbolic description, and 2 for those with substantive description. The selective disclosure score (Gwls = 1-number of disclosures/total disclosures) and descriptive disclosure score (Gwle = number of symbolic disclosures/number of disclosures) of enterprise environmental information are obtained by calculation. The geometric average of selective disclosure and descriptive operation is taken to obtain the degree of green-washing of the enterprise (Gwl = $\sqrt{\mathrm{Gwls} \times \mathrm{Gwle}}$).

Control variables

Referring to Hu et al. (2021) and Wang et al. (2019), this paper includes the following variables in the empirical analysis to avoid estimation bias errors due to omitted variables. (1) Firm size (Size). The logarithm of its total assets denotes the firm’s size. (2) Property rights (State). State-owned enterprises are assigned a value of 1, otherwise 0. (3) Ownership concentration (Top). The shareholding percentage of the largest shareholder. (4) Profitability (Roa). The return on assets measures the enterprise’s profitability. (5) Leverage ratio (Lev). The ratio of total liabilities to total assets. (6) Investment opportunities (Tobin Q). The logarithm of the ratio of the market value of the enterprise to the replacement cost of capital. (7) Capital intensity (Tangible). The ratio of tangible assets to total assets. (8) Cash flow (Cash). The ratio of net cash flow from operating activities to total assets. (9) Executive incentive (Share). Management shareholding. (10) Integration of two positions (Dual). A dummy variable that equals 1 if a firm’s chairman and CEO are the same person and 0 otherwise. (11) Size of supervisory board (Supn). The logarithm of the number of supervisors. (12) Firm age (Age). The natural logarithm of the years of establishment of a firm.

Empirical model

We use the following regression model to capture the effect of green credit policy on the green strategic behavior choice of high-polluting enterprises:

$$Gpat_{i,t} / Gwl_{i,t} = \alpha_0 + \alpha_1 Post_t \times Treat_i + \beta X_{i,t} + \sigma_t + \lambda_i + \varepsilon_{i,t} \qquad (1)$$

Among them, *Gpat* denotes the number of green invention patent applications of enterprises. *Post* is the policy dummy variable, *Post* is equal to 1 when the year is in 2012, otherwise, the value is 0; *Treat* represents group dummy variables, which value is 1 when the firm is in the experimental group, otherwise, the value is 0 (as the enterprises in high-polluting industries are directly affected by the green credit guidelines, they are treated as experimental group and non-high-polluting enterprises as control group). *Treat×Post* represents a difference-in-difference variable and α_1 represents the impact of green credit on the experimental group. *X* denotes a set of characteristic variables of enterprises. σ and λ denote time fixed effects and firm fixed effects, respectively. In other words, this study uses the two-way fixed-effects panel model to implement the DID design, which can exclude the interference of other exogenous factors and individual firm heterogeneity issues during the study period. ε is the error term.

Meanwhile, to examine the dynamic policy effects on firms' green behavior choices after the implementation of "Green Credit Guidelines", the following extended difference-in-difference model is constructed :

$$Gpat_{i,t} / Gwl_{i,t} = \alpha_0 + \sum_{t=2012}^{t=2019} \gamma_t PostYear_t \times Treat_i + \beta X_{i,t} + \lambda_i + \varepsilon_{i,t} \qquad (2)$$

In model (2), *PostYear* is a dummy variable for each year after the introduction of " Green Credit Guidelines", and *PostYear×Treat* is a new difference-in-difference variable to test the dynamic effects of the green credit policy.

Empirical results

Descriptive statistics

This paper is mainly based on data of 3272 listed enterprises from 2008 to 2019, and the summary of the main variables is reported in Table 1.

Table 1 Descriptive statistics

Variables	N	Mean	Min	Max	S.D.
Treat	20168	0.291	0	1	0.454
Gpat	20168	0.926	0	4.489	1.179
Gwl	20168	0.713	0.167	0.972	0.214
Size	20168	21.481	18.309	25.344	1.413
State	20168	0.391	0	1	0.488
Top	20168	0.345	0.032	0.742	0.149
Roa	20168	0.038	-0.235	0.195	0.057
Lev	20168	0.432	0.056	0.882	0.205
Tobin Q	20168	0.582	-0.131	2.134	0.476
Tangible	20168	0.218	0.002	0.709	0.164
Cash	20168	0.046	-0.165	0.241	0.070
Share	20168	0.125	0	0.676	0.192
Dual	20168	0.258	0	1	0.437
Supn	20168	1.498	0	2.565	0.206
Age	20168	1.984	0	3.219	0.926

Baseline results

This paper explores the green strategy choices of firms after being affected by green credit policy in terms of internal green technology innovation and external environmental information disclosure. High-polluting enterprises are regarded as the experimental group and other enterprises are regarded as the control group. A vital prerequisite of the DID model is that the experimental and control groups have similar trends before the policy shock (Bertrand et al., 2004). Referring to Wang et al. (2020)'s research, this study employed the event-study method to verify the parallel trend. The results of the parallel trend test in this paper are shown in columns (1) and (2) of Table 2. *Before1*, *Before2*, *Before3*, *Before4* represent before the implementation of the green credit policy, high-polluting enterprises take the value of 1, otherwise, the value is 0. Current represents high-polluting enterprises and belongs to the year when the policy was implemented. *After1*, *After2*, *After3*, *After4* represent after the implementation of the green credit policy, high-polluting enterprises take the value of 1, otherwise, the value is 0. When the dependent variable is *Gpat*, the regression results of *Before4*, *Before3*, and *Before2* are not significant, the coefficient of *Current* is significantly negative, and the coefficients of *After2* and *After4* are significantly positive, indicating that the evolution of green innovation of the experimental group and the control group was almost the same before the policy implementation, but the gap between the experimental and control groups widened rapidly after the policy implementation. Similarly, when the dependent variable is *Gwl*, the regression

results of *Before1* to *Before4* are all insignificant, *Current*, *After1*, and *After2* are significantly positive, but *After4* is significantly negative. All of the above results reflect that the experimental and control groups which meet the parallel trend assumption and the regression results in this study are reasonable to some degree.

Columns (3) and (4) of Table 2 show the DID regression results after controlling for firm and time fixed effects. The independent variable is *Gpat* in column (3) of Table 2, the coefficient of the *Post×Treat* is 0.1, which is significant at the level of 1%. This indicates that compared with other enterprises, high-polluting enterprises have increased green innovation after the implementation of the green credit policy, which confirms hypothesis 2. The independent variable is *Gwl* in column (4) of Table 2, the coefficient of the *Post×Treat* is -0.006, but not significant. This result does not confirm hypothesis 1.

Table 2 Baseline results

	(1)	(2)	(3)	(4)
	Gpat	Gwl	Gpat	Gwl
Post×Treat			0.100***	-0.006
			(3.082)	(-0.784)
Before4	-0.168	0.015		
	(-1.190)	(0.530)		
Before3	-0.065	0.025		
	(-1.010)	(1.628)		
Before2	-0.076	0.013		
	(-1.244)	(0.923)		
Before1	-0.142**	0.021		
	(-2.215)	(1.353)		
Current	-0.086*	0.041***		
	(-1.938)	(4.209)		
After1	-0.051	0.044***		
	(-1.156)	(4.563)		
After2	0.254***	0.034***		
	(4.399)	(2.911)		
After3	-0.017	0.008		
	(-0.387)	(0.960)		
After4	0.065*	-0.015**		
	(1.790)	(-1.965)		
Size	0.227***	-0.016***	0.225***	-0.015***
	(10.544)	(-4.350)	(18.748)	(-5.688)
State	0.117**	0.015	0.117***	0.016*
	(2.047)	(1.441)	(2.937)	(1.847)
Top	-0.138	-0.013	-0.136*	-0.015
	(-1.221)	(-0.650)	(-1.776)	(-0.883)
Roa	-0.093	-0.027	-0.080	-0.036

	(-0.661)	(-0.937)	(-0.648)	(-1.331)
Lev	0.080	0.020	0.080	0.023*
	(0.982)	(1.270)	(1.416)	(1.857)
Tobin Q	-0.052**	0.013**	-0.056***	0.014***
	(-2.096)	(2.508)	(-2.802)	(3.170)
Tangible	0.068	-0.027	0.079	-0.034**
	(0.623)	(-1.323)	(1.124)	(-2.244)
Cash	-0.179*	-0.006	-0.168*	-0.008
	(-1.911)	(-0.316)	(-1.872)	(-0.397)
Share	-0.167	-0.024	-0.164**	-0.027
	(-1.407)	(-1.058)	(-2.041)	(-1.528)
Dual	0.006	0.002	0.006	0.003
	(0.243)	(0.526)	(0.337)	(0.642)
Supn	0.183**	-0.013	0.180***	-0.011
	(1.984)	(-0.781)	(2.875)	(-0.797)
Age	0.012	-0.008	0.013	-0.008*
	(0.450)	(-1.496)	(0.648)	(-1.947)
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Cons	-4.787***	1.136***	-4.800***	1.112***
	(-10.035)	(14.000)	(-18.149)	(19.335)
N	20168	20168	20168	20168
Adj. R^2	0.218	0.123	0.216	0.119

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are reported in parentheses and are based on robust standard errors.

Dynamic effects

The promulgation of the “Green Credit Guidelines” in 2012 marked the formal entry of financial instruments to regulate the environmental behavior of enterprises at the policy level, but the actual effect of the policy may have a time lag. To further clarify how the policy affects the process of enterprise green

strategy choice with time evolution, this paper includes dummy variables of policy years and uses model (2) to test the dynamic effect of the policy.

Table 3 shows that there is a significant time difference between green credit policy and green innovation and green-washing behavior of high-polluting enterprises. In terms of the dynamic impact of green credit policy on green innovation, the results are presented in column (1) of Table 3. The coefficients of *PostYear2014×Treat*, *PostYear2015×Treat*, *PostYear2016×Treat*, *PostYear2018×Treat*, and *PostYear2019×Treat* are 0.352, 0.081, 0.163, 0.1, and 0.142, respectively, and both significance at least at the level of 10%. This result indicates that the level of green innovation of high-polluting enterprises increased significantly from 2014 to 2019 after the implementation of the green credit policy. In 2012 and 2013, the coefficient of *PostYear×Treat* is not significant. The above results reveal that the green credit policy has some continuity and lag on enhancing the green innovation activities of high-polluting enterprises.

Column (2) shows the dynamic influence of green credit policy on enterprises' green-washing behavior. The coefficient of the interaction term *PostYear2012×Treat* and *PostYear2013×Treat* are positive at the 1% level of significance, the coefficients interaction term *PostYear2014×Treat* and *PostYear2015×Treat* are not significant. However, the coefficient of *PostYear2016×Treat*, *PostYear2018×Treat*, and *PostYear2019×Treat* are significantly negative at least at the level of 5%. This reveals that although the overall effect of green credit policy on corporate green-washing behavior is not statistically significant, in terms of the time dimension, the first two years after the implementation of the policy significantly induces high-polluting enterprises to choose green-washing behavior, over time corporate green-washing behavior will be detected and the benefits of green-washing to firms are much lower than the costs of environmental regulation, which in turn inhibits the green-washing behavior of high-polluting enterprises.

The reason for the above-mentioned results is that, at the early stage of the implementation of green credit policy, high marginal of enterprise green innovation and insufficient banking supervision lead to high-polluting enterprises are more inclined to adopt green-washing with lower cost to meet the requirements of legality. However, with the development of time, the environmental information of enterprises is easier monitored and observed, and the supervision of enterprises by commercial banks is becoming more severe. When an enterprise's green-washing is exposed, it will induce criticisms and negative evaluations and hinder the enterprise's survival and development (Testa et al., 2018; Leonidou and Skarmeas, 2017). Symbolic green-washing behavior is ineffective and cannot essentially improve the environmental condition of enterprises. Therefore, from the long-term development perspective, it is more in line with the cost-benefit principle to carry out green innovation.

Table 3 Results of dynamic effects test

	(1)	(2)
	Gpat	Gwl
PostYear2012×Treat	0.011	0.022**
	(0.253)	(2.330)
PostYear2013×Treat	0.046	0.025***
	(1.046)	(2.588)
PostYear2014×Treat	0.352***	0.015
	(6.231)	(1.232)
PostYear2015×Treat	0.081*	-0.011
	(1.746)	(-1.078)
PostYear2016×Treat	0.163***	-0.034***
	(3.654)	(-3.559)
PostYear2017×Treat	0.049	-0.011
	(1.158)	(-1.212)
PostYear2018×Treat	0.100**	-0.020**
	(2.427)	(-2.182)
PostYear2019×Treat	0.142***	-0.027***
	(3.438)	(-2.964)
Size	0.227***	-0.016***
	(18.884)	(-6.174)
State	0.119***	0.015*
	(2.983)	(1.725)
Top	-0.139*	-0.013
	(-1.807)	(-0.791)
Roa	-0.097	-0.026
	(-0.790)	(-0.960)
Lev	0.082	0.019
	(1.455)	(1.560)
Tobin Q	-0.051**	0.013***

	(-2.544)	(2.979)
Tangible	0.068	-0.027*
	(0.971)	(-1.769)
Cash	-0.180**	-0.007
	(-2.002)	(-0.351)
Share	-0.168**	-0.024
	(-2.092)	(-1.397)
Dual	0.006	0.002
	(0.327)	(0.624)
Supn	0.183***	-0.014
	(2.926)	(-1.000)
Age	0.012	-0.008*
	(0.587)	(-1.885)
Firm	Yes	Yes
Year	Yes	Yes
Cons	-4.838***	1.141***
	(-18.277)	(19.832)
N	20168	20168
Adj. R^2	0.218	0.123

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are reported in parentheses and are based on robust standard errors.

Analysis of heterogeneity

Green patent type

This paper subdivides the types of green patents into green invention patents and green utility patents according to patent attributes, joint applications green patents and independent applications green patents according to patent application categories. The results are shown in Panel A of Table 4. Columns (1) and (2) show that the regression results of *Post×Treat* are both significantly positive, indicating that the implementation of the green credit policy significantly contributes to the increase in the number of independent and joint green patent applications by firms. The results in columns (3) and (4) show that

after the implementation of the green credit policy, the number of green invention patents of enterprises did not increase significantly ($t=-0.362$, $p>0.1$), while the number of green utility patent applications increased significantly ($t=3.705$, $p<0.01$). In other words, the green credit policy only promotes the increase of the quantity of green innovation of enterprises but lacks the improvement of the quality of innovation.

Intensity of environmental regulation

Environmental policies vary widely among different regions in China. The effectiveness of the green credit policy requires the support of relevant laws and regulations, and environmental regulation, as an important institutional arrangement to solve the current environmental pollution problem, will certainly significantly affect the implementation effect of green credit. Hence, the heterogeneity of regional environmental regulation intensity on green credit and enterprise green activities should be analyzed. Based on the discharge of industrial wastewater, industrial smoke, and industrial sulfur dioxide, we calculated the environmental regulation index of different regions using the entropy method. The median value of the environmental regulation index of each province is used as the criterion to divide the whole sample into two groups: high environmental regulation and low environmental regulation. Panel B of Table 4 reported the heterogeneous impact of environmental regulations. In the high environmental regulation group, the green credit policy promotes green innovation of enterprises and reduces green-washing behavior. In contrast, enterprises in the low environmental regulation group prefer the behavior of green-washing environmental information. This suggests that the higher the intensity of regional environmental regulation, the more pronounced the green incentive effect of the green credit policy.

Spatial heterogeneity

The green credit policy through the financial market sends signals to enterprises, so the green credit policy would be affected by the development level of the regional financial. Based on the per capita GDP of provinces where the listed company is located, we further classified the sample as economically developed regions if its provinces with an index value higher than the average value and as economically underdeveloped regions otherwise. The results in columns (1) and (2) of Panel C show that green credit policy has a positive effect on green innovation of enterprises in the economically developed regions, and has a negative effect on green-washing behavior of enterprises. Columns (3) and (4) show that green credit policy has no influence on the innovation behavior of enterprises in economically underdeveloped regions, but strengthens the green-washing behavior of enterprises.

Alternative financing channel

Trade credit is a well-known alternative financing channel for enterprises facing credit financing constraints, the enterprise uses the trade credit after the commercial bank financing became unavailable (Chen et al., 2019; Wen et al., 2021). Thus, we believe that the trade credit will significantly affect the forms of green activities after the implementation of the green credit policy, which needs further explored in depth. Referring to Wen et al. (2021), trade credit is measured by the ratio of accounts payable to the

total assets of a firm. We further classified firms as having a high or a low trade credit, where firms were classified as high if their index value was above the median of industry years and as low otherwise. Panel D summarized the grouped test results of trade credit for enterprises. The results show that green credit policy has a direct and effective effect on green innovation only in enterprises with low trade credit.

Table 4. Results of heterogeneous effects

Panel A Heterogeneity test of green patent type

	(1)	(2)	(3)	(4)
	joint applications green patents	independent applications green patents	green invention patents	green utility patents
	Gpat	Gpat	Gpat	Gpat
Post×Treat	0.086***	0.041**	-0.010	0.105***
	(2.648)	(1.970)	(-0.362)	(3.705)
Controls	Yes	Yes	Yes	Yes
Cons	-4.552***	-1.474***	-3.816***	-3.502***
	(-17.233)	(-8.799)	(-16.705)	(-15.250)
N	20168	20168	20168	20168
Adj. R^2	0.170	0.165	0.198	0.066

Panel B Heterogeneity test of environmental regulation intensity

	(1)	(2)	(3)	(4)
	High environmental regulation		Low environmental regulation	
	Gpat	Gwl	Gpat	Gwl
Post×Treat	0.104**	-0.027***	0.067	0.025**
	(2.194)	(-2.699)	(1.443)	(2.344)
Controls	Yes	Yes	Yes	Yes
Cons	-5.179***	1.188***	-4.366***	1.052***
	(-13.474)	(14.631)	(-11.620)	(12.319)
N	10883	10883	9285	9285
Adj. R^2	0.227	0.122	0.199	0.112

Panel C Heterogeneity test of space

	(1)	(2)	(3)	(4)
	Economically developed regions		Economically undeveloped regions	
	Gpat	Gwl	Gpat	Gwl

Post×Treat	0.113***	-0.019**	0.083	0.023**
	(2.632)	(-2.118)	(1.628)	(1.969)
Controls	Yes	Yes	Yes	Yes
Cons	-4.764***	1.179***	-5.376***	1.227***
	(-12.207)	(14.222)	(-10.811)	(10.606)
N	13779	13779	6352	6352
Adj. R^2	0.209	0.103	0.231	0.138
Panel D Heterogeneity test for alternative financing channel				
	(1)	(2)	(3)	(4)
	High trade credit		Low trade credit	
	Gpat	Gwl	Gpat	Gwl
Post×Treat	0.000	-0.009	0.149***	-0.006
	(0.008)	(-0.825)	(3.415)	(-0.655)
Controls	Yes	Yes	Yes	Yes
Cons	-4.942***	1.054***	-4.784***	1.223***
	(-11.442)	(11.498)	(-12.331)	(14.032)
N	10050	10050	10118	10118
Adj. R^2	0.202	0.117	0.209	0.112

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are reported in parentheses and are based on robust standard errors.

Analysis of economic consequences: Why make such a green choice

The previous findings suggest that green credit policy significantly increases enterprises' green innovation but has no significant effect on green-washing on the whole. From the perspective of time, enterprises will choose green-washing at the early stage of policy implementation, and then reduce green-washing behavior and increase green innovation. We argued that this may be firms' green-washing behavior will be identified over time and bring negative impact to the firm, while the accumulation of innovative output can add competitive advantage to the firm, which eventually motivates the firm to choose innovative behavior and reduce green-washing behavior. To detect the mechanism, we try to verify how the performance of high-polluting enterprises is affected by a series of green activities under the pressure of green credit policy. Three indicators of corporate social performance, environmental

performance, and financial performance are selected to examine the impact of the green credit policy on the economic consequences of different green behaviors of heavy polluters using the following model:

$$CSR_{i,t+1} / EP_{i,t+1} / ROA_{i,t+1} = \alpha_0 + \alpha_1 \sum_{t=2012}^{2019} Treat_{i,t} \times Gpat_{i,t} (Treat_{i,t} \times Gwl_{i,t}) + \beta X_{i,t} + \sigma_t + \lambda_i + \varepsilon_{i,t} \quad (3)$$

Social Performance

CSR denotes corporate social responsibility score, which is measured by the social responsibility score published by the Hexun website. The result is shown in Panel A of Table 5. The coefficients of *Gpat×Treat* and *Gwl×Treat* are not significant when the social responsibility of the firm lagged one period is used as the dependent variable. When the social responsibility of the firm lagged two periods as the dependent variable, the coefficient of *Gpat×Treat* is significant and positive at the level of 10%, the coefficient of *Gwl×Treat* is significant and negative. The above results show that the “Green Credit Guidelines” have significantly improved *CSR* by prompting high-polluting enterprises to engage in green innovation activities, but this effect has a lagged effect, while green-washing behavior adopted by firms does not improve *CSR*.

Environmental Performance

EP represents the environmental performance of the firm. Emission fee per unit of operating revenue is used as environmental performance proxy variable, and a smaller value means the better environmental performance of enterprises. The results of Panel B show that neither of the two green behaviors of firms has an impact on the environmental performance in the latter period after the implementation of the green credit policy. In terms of environmental performance with two lags, the regression coefficient of *Gpat×Treat* is significantly negative, reflecting that after the implementation of the policy, high-polluting enterprises increase the output of green innovation can reduce corporate emission fees. The coefficient of *Gwl×Treat* is significantly positive, indicating that the enterprise’s behavior of green-washing environmental information will not improve the environmental performance of the enterprise. Instead, it will lead the government to increase the punishment of enterprise pollution due to violations.

Financial Performance

ROE denotes the financial performance of a company. Empirical results are shown in Panel C of Table 5. The coefficient of *Gpat×Treat* is significantly positive, indicating that increasing green innovation can improve the financial performance of heavy pollution enterprises. The coefficient of *Gwl×Treat* is significantly negative, reflecting that the adoption of green-washing behavior by firms significantly reduces their financial performance.

Table 5. Results of economic consequences

Panel A Consequences test for corporate social responsibility performance				
	(1)	(2)	(3)	(4)
	CSR_{t+1}	CSR_{t+2}	CSR_{t+1}	CSR_{t+2}
Gpat×Treat	-0.002	0.022*		
	(-0.209)	(1.826)		
Gwl×Treat			0.078	-0.097*
			(1.402)	(-1.696)
Controls	Yes	Yes	Yes	Yes
Cons	0.268	1.092***	0.441**	1.143***
	(1.319)	(5.113)	(2.166)	(5.333)
N	17737	14716	17737	14716
Adj. R^2	0.150	0.106	0.150	0.105
Panel B Consequences test for environmental performance				
	(1)	(2)	(3)	(4)
	EP_{t+1}	EP_{t+2}	EP_{t+1}	EP_{t+2}
Gpat×Treat	-0.009	-0.042*		
	(-0.289)	(-1.678)		
Gwl×Treat			0.254	0.382***
			(1.567)	(3.108)
Controls	Yes	Yes	Yes	Yes
Cons	0.372	-0.876*	0.312	-0.867**
	(0.688)	(-1.915)	(0.578)	(-1.978)
N	13067	10066	13067	10066
Adj. R^2	0.007	0.008	0.007	0.008
Panel C Consequences test for financial performance				
	(1)	(2)	(3)	(4)
	ROE_{t+1}	ROE_{t+2}	ROE_{t+1}	ROE_{t+2}
Gpat×Treat	0.018**	0.015**		

	(2.447)	(2.269)		
Gwl×Treat			-0.093***	0.004
			(-2.600)	(0.117)
Controls	Yes	Yes	Yes	Yes
Cons	0.087	0.912***	0.125	0.927***
	(0.664)	(7.782)	(0.952)	(7.873)
N	17731	13293	17731	13293
Adj. R^2	0.017	0.026	0.018	0.025

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are reported in parentheses and are based on robust standard errors.

Robustness test

To verify the robustness of the baseline regression results, the following tests are conducted.

Propensity score matching method and difference-in-differences

Since the sample may have endogeneity problems arising from selection bias, to ensure the robustness of the study findings, the propensity score matching method (PSM) and the difference-in-difference method (DID) are combined to solve this problem. First, we use the Probit model to estimate the propensity scores. Referring to the previous research literature, eight observable variables, including the number of employees (Staff), the ownership concentration of companies (Top), the return on assets measures the enterprise's profitability (Roa), investment opportunities (Tobin Q), capital intensity (Tangible), cash flow (Cash), size of the supervisory board (Supn), and firm's region (Area) are selected as the matching indexes of the PSM model. Second, since there have 5872 samples in the experimental and 14296 samples in the control group, we use the 1:2 nearest neighbor matching, radius matching, and kernel matching to match the experimental group (high-polluting enterprises) with the control group (non-high-polluting enterprises). We implement a balance test to ensure no significant difference between the treatment and control groups after matching. Table 6 shows the results of the balance test. Figure 1 shows the density function diagram before and after matching. As shown in figure 1 and Table 6, the experimental group and the control group are obviously different before matching, but have the same trend after matching. The results of PSM-DID are shown in columns (1) to (3) of Table 7. Regardless of which propensity score matching method is chosen, the coefficient of *Treat×Pos*t is significantly positive at least at the level of 5%, which further verifies the reliability of the conclusion in this paper.

Table 6 Balance test

Variable	Unmatched matched	mean Treated	Control	%bias	t-test t	p>|t|
Staff	U	7.8368	7.6135	17.7	11.23	0.000
	M	7.8368	7.8202	1.3	0.73	0.468
Top	U	0.3476	0.3437	2.6	1.69	0.092
	M	0.3476	0.3436	2.7	1.46	0.146
Roa	U	0.0421	0.0365	9.8	6.31	0.000
	M	0.0421	0.0431	-1.7	-0.97	0.333
Tobin Q	U	0.5300	0.6041	-15.7	-10.05	0.000
	M	0.5300	0.5652	-7.4	-4.16	0.000
Tangible	U	0.3006	0.1839	73.6	48.65	0.000
	M	0.3006	0.3015	-0.6	-0.29	0.776
Cash	U	0.0577	0.0415	23.7	15.01	0.000
	M	0.0577	0.0586	-1.4	-0.78	0.433
Supn	U	1.5287	1.4853	20.5	13.67	0.000
	M	1.5287	1.5239	2.3	1.16	0.245
Area	U	14.086	13.349	9.7	6.23	0.000
	M	14.086	14.062	0.3	0.17	0.865

Difference-in-differences-in-differences

Since the government has enacted other environmental regulation policies after 2012, these policies will also affect enterprises' choice of green behavior. Therefore, how to distinguish green credit policy from other environmental policies is the key problem to be solved in this paper, and we use the DDD method to overcome this problem. Because green credit requires commercial banks to grant loans to enterprises following green standards, theoretically the degree of external financing demand of enterprises will directly affect the effect of green credit policy on enterprises. Using the method of Huang et al. (2019) to reflect external financing demand by using the difference between enterprise growth and endogenous growth rate (FID). FID= $(Asset_t - Asset_{t-1})/Asset_t - Roe_t/(1-Roe_t)$, Asset denotes total assets, Roe denotes return on equity, the higher FID value indicates that the firm is more dependent on external funding and more influenced by green credit policy. Based on this, the FID greater than the annual industry average is set to 1; otherwise, the FID is set to 0. Thus, we add the dummy variable of external financing demand of enterprises to the original DID model to construct a DDD model to further test the robustness of the relationship between the green credit policy and enterprises' green behaviors. The results are shown in (4) and (5) of Table 7. The regression results of *Post×Treat×FID* cross term on *Gpat* are significantly positive at the level of 10%, while regression results on *Gwl* do not pass the significance test. The empirical results are basically consistent with the above main regression results, indicating that the results of this paper are robust.

Table 7. Results of endogenous test

	(1)	(2)	(3)	(4)	(5)
	Nearest-neighbor matching	Kernel matching	Radius matching	DDD	DDD
	Gpat	Gpat	Gpat	Gpat	Gwl
Post×Treat	0.096**	0.098***	0.098***	0.053	-0.008
	(2.320)	(2.999)	(2.991)	(1.253)	(-0.896)
Post×Treat×FID				0.099*	0.006
				(1.794)	(0.462)
Post×FID				0.030**	0.001
				(2.214)	(0.428)
Treat×FID				-0.074	-0.003
				(-1.477)	(-0.308)
Size	0.289***	0.224***	0.226***	0.225***	-0.015***
	(15.998)	(18.633)	(18.575)	(18.759)	(-5.685)
State	0.171***	0.121***	0.124***	0.118***	0.016*
	(2.978)	(3.014)	(3.053)	(2.964)	(1.854)
Top	-0.144	-0.141*	-0.141*	-0.132*	-0.015
	(-1.341)	(-1.831)	(-1.825)	(-1.719)	(-0.872)
Roa	-0.327*	-0.088	-0.157	-0.056	-0.034
	(-1.751)	(-0.713)	(-1.207)	(-0.453)	(-1.273)
Lev	0.086	0.078	0.077	0.053	0.021*
	(1.060)	(1.368)	(1.341)	(0.931)	(1.727)
Tobin Q	-0.017	-0.057***	-0.054***	-0.052***	0.014***
	(-0.580)	(-2.833)	(-2.694)	(-2.587)	(3.206)
Tangible	0.099	0.082	0.085	0.096	-0.033**
	(1.054)	(1.167)	(1.196)	(1.369)	(-2.165)
Cash	-0.157	-0.169*	-0.159*	-0.139	-0.006
	(-1.151)	(-1.874)	(-1.754)	(-1.539)	(-0.316)
Share	-0.054	-0.173**	-0.181**	-0.172**	-0.027
	(-0.463)	(-2.157)	(-2.241)	(-2.139)	(-1.552)

Dual	0.020	0.005	0.002	0.004	0.002
	(0.762)	(0.296)	(0.095)	(0.245)	(0.620)
Supn	0.212**	0.180***	0.181***	0.181***	-0.011
	(2.465)	(2.887)	(2.884)	(2.890)	(-0.794)
Age	-0.037	0.011	0.009	0.012	-0.008**
	(-1.297)	(0.564)	(0.431)	(0.584)	(-1.963)
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Cons	-6.329***	-4.776***	-4.813***	-4.790***	1.112***
	(-16.079)	(-18.038)	(-18.008)	(-18.108)	(19.332)
N	11526	20143	19994	20168	20168
Adj. R^2	0.231	0.215	0.216	0.216	0.120

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are reported in parentheses and are based on robust standard errors.

Other robustness tests

Replacing variables

Referring to Hong et al. (2021) and Liu et al. (2021), we use the ratio between the number of green patents and the total number of patents (*GPatratio*) as proxy variables for enterprises' green innovation. In addition, considering the high risk of innovation and the relatively long time required for patent research and development, we select the number of green patent applications in t+1 and t +2 years to measure the green innovation of enterprises. The results in columns (1) to (3) of Table 8 show that the regression results of the *Treat×Post* cross-product term pass the significance test for both the proportion and the lagged innovation time.

Replacement model

Considering that there are some samples with the number of green innovation being 0, and the value of enterprise green-washing degree is between 0 and 1. Therefore, this paper uses the Tobit model to replace the fixed effect model to test the main fundamental regression. The results are shown in (4) and (5) of Table 8. It can be seen that the test results are consistent with the previous results, suggesting that our findings are robust.

Exclude some samples

To observe the continuity of enterprises' behavior before and after the implementation of the green credit policy, enterprises listed after 2012 are removed from this paper. As these listed enterprises lack data on the green behaviors of enterprises before the implementation of the policy, the inclusion of these data in the sample may lead to deviations in the results. The results in columns (6) and (7) of Table 8 show that the regression result of *Gpat* is still significant, while the regression result of *Gwl* does not pass the significance test.

Table 8. Results of other robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GPatratio	$GPat_{t+1}$	$GPat_{t+2}$	GPat	Gwl	GPat	Gwl
Post×Treat	0.009*	0.145***	0.136***	0.292***	-0.004	0.102***	-0.006
	(1.863)	(3.263)	(3.302)	(2.591)	(-0.362)	(3.101)	(-0.774)
Post				1.860***	-0.053***		
				(8.458)	(-3.174)		
Treat				-0.270**	-0.080***		
				(-2.159)	(-7.063)		
Size	0.021***	0.176***	0.134***	0.656***	-0.045***	0.228***	-0.014***
	(10.608)	(11.169)	(7.441)	(21.271)	(-17.873)	(18.082)	(-5.093)
State	-0.009	0.192***	0.168***	0.071	-0.014**	0.155***	0.015*
	(-1.362)	(3.419)	(2.668)	(0.854)	(-1.997)	(3.667)	(1.660)
Top	-0.020	-0.111	-0.091	-0.902***	-0.020	-0.167**	-0.012
	(-1.516)	(-1.177)	(-0.867)	(-4.272)	(-1.166)	(-2.038)	(-0.667)
Roa	-0.075***	0.258	0.566***	-1.548***	-0.065*	-0.172	-0.050*
	(-3.560)	(1.586)	(2.763)	(-3.699)	(-1.826)	(-1.277)	(-1.687)
Lev	-0.051***	0.114	-0.015	-0.278	0.070***	0.065	0.024*
	(-5.382)	(1.556)	(-0.183)	(-1.559)	(4.792)	(1.082)	(1.811)
Tobin Q	-0.010***	0.006	-0.012	0.219***	0.006	-0.047**	0.019***
	(-3.745)	(0.222)	(-0.424)	(3.155)	(1.087)	(-2.182)	(3.890)
Tangible	0.012	-0.013	0.006	-0.341*	-0.169***	0.063	-0.034**
	(1.010)	(-0.141)	(0.065)	(-1.649)	(-10.078)	(0.863)	(-2.078)
Cash	0.002	-0.207*	0.085	-1.145***	-0.030	-0.180*	-0.018
	(0.138)	(-1.889)	(0.703)	(-3.692)	(-1.153)	(-1.856)	(-0.862)
Share	-0.018	-0.092	-0.042	0.416**	0.030**	-0.117	-0.023
	(-1.337)	(-0.891)	(-0.361)	(2.319)	(2.000)	(-1.293)	(-1.160)
Dual	0.001	0.035	-0.006	0.023	0.005	0.005	0.002
	(0.354)	(1.539)	(-0.231)	(0.376)	(1.006)	(0.251)	(0.438)
Supn	0.001	0.141*	0.170*	0.116	-0.031**	0.175***	-0.005

	(0.085)	(1.786)	(1.956)	(0.691)	(-2.202)	(2.686)	(-0.349)
Age	0.018***	0.054**	0.007	-0.257***	0.006*	0.022	-0.010*
	(7.128)	(2.040)	(0.241)	(-6.709)	(1.849)	(0.902)	(-1.918)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cons	-0.350***	-3.716***	-2.657***	-14.505***	1.758***	-4.869***	1.082***
	-8.140	(-10.708)	(-6.719)	(-21.756)	(32.755)	(-17.455)	(17.614)
N	19985	14693	12186	20168	20168	16470	16470
Adj. R^2	0.031	0.185	0.159	-	-	0.228	0.124

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are reported in parentheses and are based on robust standard errors.

Conclusions And Recommendations

Conclusions

Based on the empirical research on China's green credit policy, this paper provides experience for developing countries to improve the green financial system and ultimately achieve sustainable development. The above regression studies the impact of green credit on the green behavior of high-polluting enterprises from the four dimensions of baseline regression analysis, dynamic effect analysis, heterogeneity analysis, and economic consequences analysis. The results show that: (1) On the whole, green credit has significantly increased high-polluting enterprises' green innovation and has not increased corporate green-washing behavior. However, in terms of the dynamic effect of the policy, in the short term after the implementation of the green credit policy, high-polluting enterprises are more inclined to adopt the behavior of green-washing environmental information rather than green innovation, but over time the green-washing behavior of enterprises will be identified, which in turn force enterprises to choose green innovation behavior. (2) Heterogeneity analysis has shown that enterprises located in economically developed areas and high environmental regulation areas, and lacking alternative financing channels are more sensitive to the green credit policy and prefer to choose green innovation. However, enterprises located in economically underdeveloped regions and low environmental regulation areas prefer to choose green-washing. (3) Economic consequence analysis finds that increased green innovation by enterprises after the implementation of the green credit policy significantly improves financial, environmental, and social performance, but the impact of the one-period lag is not significant and the two-period lag is more significant, while green-washing behavior reduces corporate financial, environmental, and social performance.

Recommendations

There are several practical recommendations from our findings, as shown below. First, enterprises should realize that although green innovation would crowd out the operating funds of enterprises to a certain extent, from the perspective of long-term development, enterprises engaging in green innovation activities can achieve a win-win for the environment and the economy. At the same time, enterprises must limit short-sighted green-washing behaviors, which will ultimately damage corporate value and hinder social progress. Besides, enterprises should also take the initiative to adapt to the situation of green finance regulation, actively connect with the new green credit policies, and independently improve innovation capacity. Second, government departments should further improve the green credit policy system. At present, the environmental information disclosure of listed companies in China is not standardized and the disclosure ratio is low. The government should strengthen the environmental information disclosure policy, increase the punishment for environmental violations, and inhibit the green bleaching behavior of enterprises. this paper shows that green credit policy can significantly increase the green innovation of high-pollution enterprises. Hence, Chinese financial institutions should continue to strengthen the incentive mechanism of green credit and improve the enthusiasm of financial institutions to carry out green credit. Finally, green credit policies should be implemented using different strategies in regions with different characteristics to maximize their green effect. It is important to maintain the strength of green credit policy in economically developed regions and high environmental regulation regions to transform and upgrade high-pollution enterprises. It is very necessary to expand the coverage and implementation of green credit in economically underdeveloped areas and areas with low environmental regulations. Meanwhile, the environmental performance improvement of enterprise loan projects should be used as the criteria for credit disbursement, to avoid excessively strengthening the financial constraints of polluting enterprises and hinder the realization path of technological innovation of enterprises.

Lastly, the limitations of this paper mainly include the following aspects. Firstly, the indicators selected to measure green-washing have some deficiencies. Given there is no official index for measuring green-washing, it is a challenge for us to conduct a comprehensive measurement for green-washing. In future research, there can be a need to construct more scientific, comprehensive, and accurate indicators of corporate green-washing. Secondly, although we compare the difference between internal green innovation and external environmental disclosure, we have only done a preliminary analysis of their links to the green credit policy that may be because of the sample and model settings, which may not reflect its full impact. Continuing to discuss the relationship between the policy and corporate green behavior will further extend the findings of this research. Third, due to the availability of data, this paper limits the sample to listed companies in China, the listed firms are usually large enterprises. Whether the role of green credit policy is different for small and medium-sized enterprises' green behavior. Follow-up studies can expand the empirical sample and re-verify the conclusion.

Declarations

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Author contribution Ling He proposed the research topic, designed the research proposal, and wrote the original manuscript; Shengdao Gan collected the research data required for the thesis and collated it; Tingyong Zhong reviewed, supervision, corrected mistakes.

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Data availability The datasets used during the current study are available from the corresponding author on reasonable request.

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Consent to participate Not applicable.

Consent to publish Not applicable.

Competing interests The authors declare that they have no competing interests.

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Figures

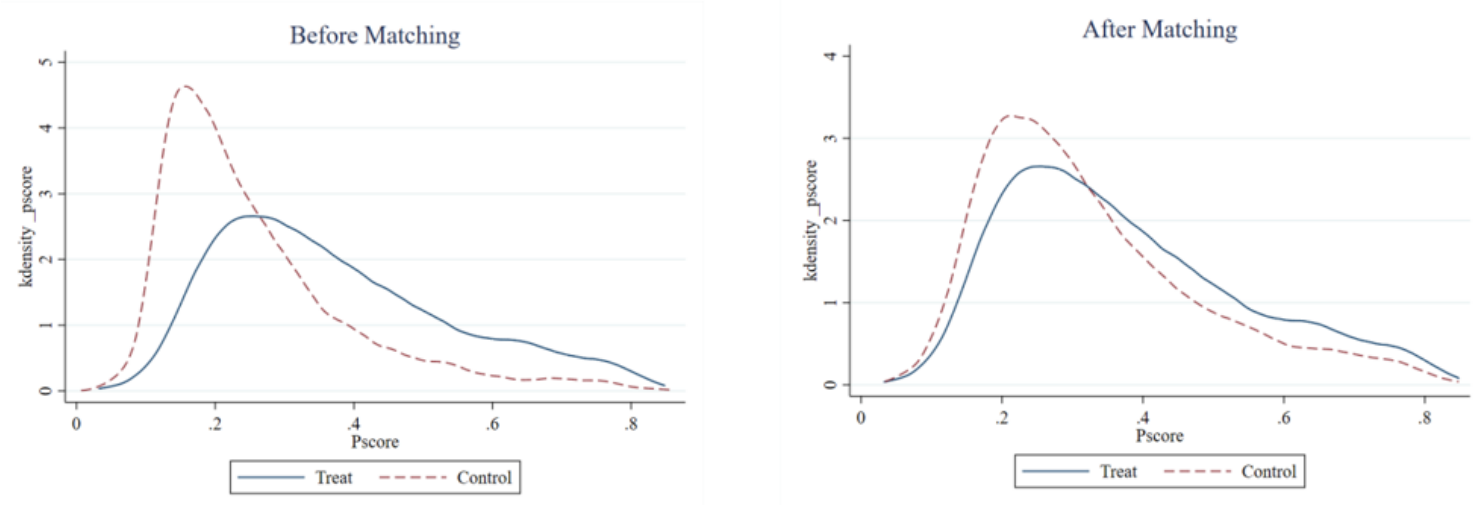

Figure 1

Density before and after matching