RESEARCH ARTICLE

The impact of green credit policy on firms’ green strategy choices: green innovation or green-washing?

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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 Chinese firms’ green strategy choices by using the panel data of A-share listed firms from 2008 to 2019. The results reveal that green credit improves firms’ green innovation overall. In terms of time, the green-washing behavior of listed firms will increase significantly in 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 green innovation of firms in localities under high environmental regulation, economically developed regions, and without other alternative financing channels. Firms located in regions with economically underdeveloped and low environmental regulation are more inclined to adopt the behavior of green-washing environmental information. Besides, after the implementation of the green credit policy, green innovation can improve 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, and environmental information disclosure, and also provide policy implications for improving the quality of green credit policy in the future.

Keywords Green credit policy · Green innovation · Green-washing

Introduction
According to the 2020 Global Environmental Performance Index report, China ranks 120th out of 180 countries with an environmental performance score of 37.3, far below the world average. China has ranked first in power generation and energy consumption in the world for many years, and its high energy consumption has brought lots of pollution problems. High-polluting firms are the largest energy consumption and pollution emission subjects in China, and also the main force in promoting the green transformation of industrial structure and achieving 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 their behaviors through government policy intervention.

High-polluting firms are capital-intensive industries and rely mainly on external bank credit financing to obtain business development funds (Liu et al. 2019; Wang et al. 2020; Yao et al. 2021). Therefore, to urge high-polluting firms to implement green transformation from the 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, guide capital flow to green projects and firms, and limit loans to polluting projects and firms, which is a “carrots and sticks” environmental policy. It aims to internalize the cost of external environmental governance 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, indicating that China’s green credit is developing rapidly and is increasingly important for firms 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 micro-firms, so whether the policy can produce green effects largely depends on high-polluting firms’ response strategies.

A series of studies have been conducted on the impact of the green credit policy on high-polluting firms. For instance, Liu et al. (2019), Li et al. (2021), Peng et al. (2022), and Xu and Li (2020) all believed that green credit policy has a financing penalty effect, which significantly increases the difficulty of debt financing for high-polluting firms. Liu et al. (2017) and Wang et al. (2020) found that the policy inhibits the investment level of polluting firms. Wen et al. (2021) pointed out that the green credit policy under the Green Credit Guidelines in 2012 has a significant negative effect on credit allocation efficiency and upgrading of energy-intensive firms. Yao et al. (2021) demonstrated that the green credit policy has a penalty effect, which significantly reduces the performance of heavily polluting firms. The ultimate goal of green credit is to guide polluting firms to transform and upgrade or exit projects that may cause major polluting problems, rather than directly shutting down these firms. In practice, the promulgation of the green credit policy has brought many financial constraints and greening problems to high-polluting firms, which will undoubtedly have a great negative impact on their production and operation activities. Therefore, an interesting topic worthy of further study is what kind of green strategic behaviors high-polluting firms will choose to cope with the huge development pressure brought by the green credit policy? This remains to be corroborated by more empirical studies.

Some scholars have explored the strategic choices of firms suffering from 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 firm’s reputation was damaged. Lindblom (1994) contend that when firms are threatened by legitimacy, they can adopt the following four strategies: one is to change the public’s perception; the second is to divert public attention through other events; the third is to falsely inform the public of the change of corporate behavior through certain signaling mechanisms; the fourth is to take actions that meet the expectations of the public and society. It can be seen that the ways for firms to deal with negative impacts can be summarized into two points: one is to change the public’s perception of firms through information mechanisms; and the other is to adopt actual improvement behaviors.

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

Therefore, this paper focuses on two corporate behaviors of external green-washing environmental disclosure and internal green innovation. We try to evaluate the effectiveness of China’s green credit policy via a key question, that is, which green behaviors will firms choose under the green credit policy? To answer the question, we undertake an empirical analysis using panel data of listed firms from 2008 to 2019 to test the impact of the green credit policy on green innovation and green-washing. Further, we explore the heterogeneity of this question in terms of time, space, external environment, and corporate resources. And we also consider the economic consequences of different green behaviors adopted by firms to provide empirical guidance for firms to choose appropriate green behaviors. Addressing these problems has important practical implications for many developing countries to enhance the effect of green policies and achieve sustainable economic development.

Our study makes several contributions to previous research. First, we complement 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 firms. Our methodology allows us to open the black box and explain the motivations of the policy that affect corporate green behavior choices, as well as provide guidance for developing countries to improve their green financial systems and ultimately achieve sustainable development. Second, the research results of green innovation and environmental disclosure are supplemented. Although previous literature has separately investigated the impact of green credit policy on green innovation and environmental information disclosure (Liu et al. 2021; Wang et al. 2019), they neither incorporate these two green behaviors into a unified analytical framework nor discuss firms’ choice of two different green behaviors in different environments. This paper discusses the selection strategies of firms for these two green behaviors from the four dimensions of time, space, external environment, and corporate resources, thus supplementing the relevant literature on corporate environmental behavior. Third, our results enrich the research scope of corporate green strategy choice motivation. Relevant documents have begun to notice the instrumental motivation behind corporate environmental behavior (Jiang...
et al. 2021). By collecting the motivations of firms’ green strategy choices under the green credit policy, this paper finds that high-polluting firms will build an environmentally friendly image through green-washing. 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 financing channels and the lack of economic growth momentum. 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 small-scale trials. In February 2012, the CBRC (China Banking Regulatory Commission) issued the “Green Credit Guidelines,” which is considered the core of China’s green credit policy system and the first normative document for green credit. The core content of the Green Credit Guidelines can be summarized in two aspects. First, under the guidance of credit policy, commercial institutions allocate more financial resources to environment-friendly firms or projects through tools such as loan products, loan terms, loan interest rates, and credit lines. Second, commercial institutions set strict financing conditions for polluting firms or projects, firms or projects that violate energy conservation, emission reduction, and environmental protection will be punished by suspending loans, delaying loans, or even withdrawing loans. The essence of the green credit policy is to allocate resources through financial leverage, actively provide credit to support environment-friendly firms and green projects, while restricting credit support to high-polluting and energy-intensive firms and projects, ultimately guiding the green development of the economy.

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

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 still insufficient. Firstly, most studies focus on the direct impact of the policy on corporate financing behavior (Li et al. 2021; Peng et al. 2022). The ultimate goal of the green credit policy is to promote the green development of society. Limited studies have only examined the influence of green credit on corporate environmental activities from the perspective of green innovation. We wanted to know whether, throughout the implementation of the green credit policy (in the short and long term), firms will choose other green behaviors in addition to green innovation to address the 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) and Brammer et al. (2007) classified corporate green activities into external green activities and internal green activities. Some studies have examined the impact of green credit policy on firms’ 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 firms choosing green strategies...
Green credit and corporate green-washing

China’s current green credit policy requires commercial banks to fully consider the firm’s environmental situation 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 the incremental environmental information disclosed by firms. However, at present, China’s environmental information disclosure has the characteristics of incompleteness and concealment. It is difficult for information users to fully and accurately grasp the real environmental conditions of firms, which easily causes capital mismatch in the process of credit allocation by banks (Zhang et al. 2011).

Andersen and Hovring (2020) and Marquis et al. (2016) pointed out that a large number of organizations adopt symbolic strategies as the first choice to address complex institutional pressures, and impression management provides a channel for firms to maintain legitimacy without changing their original business model. Impression management is common in corporate environmental governance and is generally referred to as “green-washing.” Green-washing is a green strategy that hides firms’ poor environmental performance with limited green performance or future commitments to meet the requirements of green regulations and the environmental needs of the public (Kim and Lyon 2015; Laufer 2003; Walker and Wan 2012). 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. Green-washing environmental information has become a strategy for high-polluting firms to gain organizational legitimacy.

In addition, China’s environmental regulation and supervision system is not mature enough, commercial banks cannot fully identify corporate green motives. Huang et al. (2019) pointed out that green-washing can help alleviate banks’ credit discrimination against high-polluting firms and make them easy to obtain debt financing support. Therefore, due to the demand for credit resources, high-polluting firms have a strong initiative to green-wash environmental information to obtain bank loans. From the perspective of costs and benefits, in the short term, there are loopholes in the regulatory system, the cost of the green-washing strategy adopted by firms using oral commitments and symbolic solutions is usually very low, and the private cost of corporate green-washing is lower than the social cost (Lyon and Maxwell 2011). Under the performance-oriented value judgment criteria such as profit margin and market share, green-washing has gradually become the most attractive option for firms.

Therefore, after the promulgation of the green credit policy, heavily polluting firms may respond to the policy pressure by sending green signals to the external market through green-washing environmental information. Based on the above analysis, the following hypothesis is proposed:

H1: With the green credit policy, high-polluting firms’ 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 firms through the following paths. First, the differentiated credit financing method of the green credit policy prompts heavily polluting firms to engage in green innovation to obtain credit funds. China’s green credit policy requires commercial banks to consider the environmental risks of firms and projects when granting loans. Firms or projects with high energy consumption and environmental pollution will not be supported by loans, while for energy conservation and environmental protection firms or projects will be supported by loans and preferential interest rates (Peng et al. 2022). Due to the differentiated credit services of the green credit policy, polluting firms that rely on bank loans to obtain debt funds must incorporate environmental protection into their business activities to meet the requirements of bank loans (He et al. 2019; Peng et al. 2022). Empirical evidence indicates that green credit policy makes commercial banks more willing to provide bank loans to firms with green products, and green innovation plays a strong role in alleviating the financing constraints of heavily polluting firms (Francis et al. 2012; Zhang et al. 2020). This also implies that firms with poor environmental performance can obtain credit funds by actively carrying out green innovation activities. Hence, under the differentiated lending mechanism of the green credit policy, high-polluting firms can be 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 heavily polluting firms from a short-term impact gradually becomes a long-term constraint. Zhang et al. (2020) revealed that under the constraint of limited resources, the necessary condition for firms to choose green innovation is that the benefits outweigh the costs. From the cost perspective, on one hand, if high-polluting firms do not adopt green actions after the implementation of the green credit policy, they will face not only environmental costs but also high financing costs and sunk costs (Hu et al. 2021). On the other hand, because the environmental pressure brought by the green credit policy is long-term, it may be less costly for firms to adopt green-washing in the short term, but it is not cost-effective in the long term. From the perspective of innovation benefits, high-polluting firms can obtain high innovation benefits through green innovation, such as green reputation, competitive advantage, legitimacy, credit funds, government subsidies, tax incentives, and other economic dividends (El-Kassar and Singh 2019). In addition, green innovation can fundamentally alleviate the pressure of environmental regulation arising from the green credit policy and meet the green expectations of various stakeholders.

Based on the above analysis, according to the signal theory, cost-benefit theory, and legitimacy theory, we believe that green credit will force high-polluting firms to carry out green innovation activities through environmental regulatory signals and long-term credit constraint mechanisms. Thus, the following hypothesis is proposed:

H1: With the green credit policy, high-polluting firms’ 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 uses the data of Chinese A-share listed firms from 2008 to 2019 to explore the impact of the green credit policy on firms’ green strategic choices in a difference-in-differences (DID) framework. According to the DID model, firms are divided into two groups. High-polluting firms most affected by the green credit policy are the treatment group, and other firms as the control group. We collect data from several resources. First, data about corporate environmental information disclosure are collected manually from corporate social responsibility reports, environmental reports, sustainable development reports, and other aspects. Second, data about green innovation are collected 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 and anomalies data. All continuous variables are winsorized at 1% and 99% to exclude the outlier effect. After the above-mentioned processing, we obtained unbalanced panel data of 3272 listed firms with a total of 20168 sample observations, including 5872 observations for the treatment group, and 14,296 observations for the control group. Table 1 lists the sample screening process.

### Definition of variables

#### Independent variable

High-polluting firms 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 firms belonging to the following industries as high-polluting firms: 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 the 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 green credit policy (Hong et al. 2021; Liu et al. 2021).

| Table 1 Sample screening process | Sample size |
|----------------------------------|-------------|
| Sample interval: 2008–2019       |             |
| Initial sample                   | 31,265      |
| Exclude: Observations of financial firms with special industry nature | 2487 |
| Exclude: Firm observations with special treatment | 1515 |
| Exclude: Firm observations with missing data | 6822 |
| Exclude: Firm observations with an asset-liability ratio greater than 1 or less than 0 | 273 |
| Final sample                     | 20,168      |
Dependent variable

The dependent variable is the level of green innovation (Gpat), which is indicated by the logarithm of the number of green patent applications plus one. Since green patents are often associated with environmental improvements and broadly indicate the progress of green innovation, we employ green patents as an indicator of corporate green innovation. We measure the intensity of corporate green innovation by the natural logarithm of the number of green patent applications plus one.

Another dependent variable is the degree of green-washing (Gwl). Green-washing refers to the firm disclosing untrue environmental information through “confusion,” “hidden,” “exaggeration,” and other ways (Kim and Lyon 2015; Laufer 2003; Walker and Wan 2012). Green-washing firms create an environmentally friendly image through symbolic descriptions rather than substantive actions. Clarkson et al. (2008) classified environmental disclosure into soft and hard types. Soft environmental disclosure refers to claims without strong objective evidence. It reflects the firm’s symbolic environmental behaviors. Correspondingly, hard environmental disclosure refers to terms that are based on relevant data and can be verified by other institutions. It reflects the firm’s substantial environmental behavior. Thus, soft disclosure is more likely to exacerbate green-washing than hard disclosure. If the magnitude of soft disclosure is larger than the hard disclosure, the firm will be treated as a green-washer. Referring to Huang et al. (2019), this paper constructs an indicator to measure the degree of green-washing of the firm 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. 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 disclosure is taken to obtain the degree of green-washing of the firm (Gwl = √Gwls × 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 total assets denotes the firm’s size; (2) property rights (State)—state-owned firms 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 firm’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 corporate market value 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 ratio; (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 the green credit policy on firms’ green strategic behavior choices:

\[ Gpat_{i,t}/Gwl_{i,t} = \alpha_0 + \alpha_1 Post_1 \times Treat_i + \alpha X_{i,t} + \sigma_i + \lambda_i + \epsilon_{i,t} \]  

(1)

Among them, Gpat denotes the number of green patent applications of firms. Post is the policy dummy variable. Post is equal to 1 when the year is 2012 and later, otherwise, the value is 0; Treat represents a group dummy variable, which value is 1 when the firm is in the treatment group, otherwise, the value is 0 (high-polluting firm are directly affected by the green credit policy, they are treated as the treatment group, and non-high-polluting firms as the control group). Treat×Post represents a difference-in-difference variable. X denotes a set of characteristic variables of firms. \( \sigma \) and \( \lambda \) denote time fixed effects and firm fixed effects, respectively. In other words, this study uses the two-way fixed-effects model to implement the DID design, which can exclude the interference of other exogenous factors and individual firm heterogeneity issues during the study period. \( \epsilon \) 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 DID model is constructed:

\[ Gpat_{i,t}/Gwl_{i,t} = \alpha_0 + \sum_{t=2012}^{t=2019} \alpha_{PostYear, t} \times Treat_i + \alpha X_{i,t} + \sigma_i + \lambda_i + \epsilon_{i,t} \]  

(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.
Results and analysis

Descriptive statistics

This paper is mainly based on data of 3272 listed firms from 2008 to 2019, and the summary of the main variables is reported in Table 2.

Baseline results

This paper explores the green strategy choices of firms affected by green credit policy in terms of internal green technology innovation and external environmental information disclosure. High-polluting firms are regarded as the treatment group and other firms are regarded as the control group. A vital prerequisite of the DID model is that the treatment and the control groups have similar trends before the policy shock (Bertrand et al. 2004). We plot the time trend graph of the treatment group and the control group, as shown in Fig. 1. Before the policy time point, the average growth trends were basically parallel, but after the implementation of the policy, the gap gradually widened, implying that the green credit policy is effective. Specifically, before the implementation of the policy, the average number of green patent applications and the degree of green-washing maintained similar fluctuation trends in the treatment and control groups. After implementing the policy, the overall increase of the number of green patent applications in the treatment group was significantly greater than in the control group, and the degree of green-washing in the treatment group showed a trend of temporary increase and then a significant decline.

Referring to Wang et al. (2020), this study adopts the event-study method to verify the parallel trend. The parallel trend test results in this paper are shown in columns (1) and (2) of Table 3. Before1, Before2, Before3, and Before4 represent that before the implementation of the green credit policy, high-polluting firms take the value of 1, otherwise, the value is 0. Current represents high-polluting firms and belongs to the year when the policy was implemented. After1, After2, After3, and After4 represent that after the implementation of the green credit policy, high-polluting firms 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 green innovation evolution process of the treatment group and the control group was almost the same before the policy implementation, but the gap between the treatment and control groups widened rapidly after the policy was implemented. Similarly, when the dependent variable

| 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 |

Fig. 1 Dynamic trends of the treatment and control groups
Table 3 Baseline results

| Variables | Gpat (1) | Gwl (2) | Gpat (3) | Gwl (4) |
|-----------|----------|---------|----------|---------|
| Post×Treat | 0.100*** (3.082) | − 0.006 (− 0.784) | |
| Before4 | − 0.168 (− 1.190) | 0.015 (0.530) | |
| Before3 | − 0.065 (− 1.010) | 0.025 (1.628) | |
| Before2 | − 0.076 (− 1.244) | 0.013 (0.923) | |
| Before1 | − 0.142** (− 2.215) | 0.021 (1.353) | |
| Current | − 0.086* (− 1.938) | 0.041*** (4.209) | |
| After1 | − 0.051 (− 1.156) | 0.044*** (4.563) | |
| After2 | 0.254*** (4.399) | 0.034*** (2.911) | |
| After3 | − 0.017 (− 0.387) | 0.008 (0.960) | |
| After4 | 0.065* (1.790) | − 0.015** (1.965) | |
| Size | 0.227*** (10.544) | − 0.016*** (− 4.350) | 0.225*** (18.748) | − 0.015*** (− 5.688) |
| State | 0.117** (2.047) | 0.015 (1.441) | 0.117*** (2.937) | 0.016* (1.847) |
| Top | − 0.138 (− 1.221) | − 0.013 (− 0.650) | − 0.136* (− 1.776) | − 0.015 (− 0.883) |
| Roa | − 0.093 (− 0.661) | − 0.027 (− 0.937) | − 0.080 (− 0.648) | − 0.036 (− 1.331) |
| Lev | 0.080 (0.982) | 0.020 (1.270) | 0.080 (1.416) | 0.023* (1.857) |
| Tobin Q | − 0.052** (− 2.096) | 0.013** (2.508) | − 0.056*** (− 2.802) | 0.014*** (3.170) |
| Tangible | 0.068 (0.623) | − 0.027 (− 1.323) | 0.079 (1.124) | − 0.034** (2.244) |
| Cash | − 0.179* (− 1.911) | − 0.006 (− 0.316) | − 0.168* (− 1.872) | − 0.008 (− 0.397) |
| Share | − 0.167 (− 1.407) | − 0.024 (− 1.058) | − 0.164** (− 2.041) | − 0.027 (− 1.528) |
| Dual | 0.006 (0.243) | 0.002 (0.526) | 0.006 (0.337) | 0.003 (0.642) |
| Supn | 0.183** (1.984) | − 0.013 (− 0.781) | 0.180*** (2.875) | − 0.011 (− 0.797) |
| Age | 0.012 (0.450) | − 0.008 (− 1.496) | 0.013 (0.648) | − 0.008* (− 1.947) |
| Firm | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Constant | − 4.787*** (− 10.035) | 1.136*** (14.000) | − 4.800*** (− 18.149) | 1.112*** (19.335) |
| N | 20168 | 20168 | 20168 | 20168 |
| Adj R² | 0.218 | 0.123 | 0.216 | 0.119 |

***, **, 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 into the policy level to regulate corporate environmental behavior, but the actual effect of the policy may have a time lag. To further elucidate the time evolution process of the policy on corporate green strategy choices, this paper introduces policy year dummy variables and uses model (2) to test the dynamic effect of the policy.

Table 4 shows that there is a significant time difference between green credit policy and green innovation and green-washing behavior of high-polluting firms. In terms of the dynamic impact of green credit policy on green innovation, the results are presented in column (1) of Table 4. 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 they are all significant at least at the level of 10%. This result indicates that the level of green innovation of high-polluting firms increased significantly from 2014 to 2019 after the implementation of the green credit policy. In 2012 and 2013, the coefficients of PostYear×Treat are not significant. This result does not support hypothesis 1. As the theoretical analysis above shows, the green credit policy, as a turning point for the change of the intensity of environmental regulation policies, can improve the green innovation level of credit-constrained polluting firms by exerting a long-term credit constraint mechanism and strengthening the signal effect of environmental regulation.
credit policy has some continuity and lag in enhancing the green innovation activities of high-polluting firms.

Column (2) shows the dynamic influence of green credit policy on firms' green-washing behavior. The coefficients of interaction terms PostYear2012×Treat and PostYear2013×Treat are positive at the 1% significant level, while the coefficients of interaction terms PostYear2014×Treat and PostYear2015×Treat are not significant. However, the coefficients 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 the 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 induce high-polluting firms to choose green-washing behavior. Over time, corporate green-washing behavior will be detected and the benefits of green-washing to firms are far lower than the costs of environmental regulation, which in turn inhibits the green-washing behavior of high-polluting firms.

The reason for the above-mentioned results is that, at the early stage of the implementation of the green credit policy, heavily polluting firms were discriminated against in credit financing, which led to firms cannot carry out R&D activities in the short term due to a lack of funds. In addition, at the early stage of the policy, there is a situation of rising marginal costs and declining returns for commercial banks, which led to the weak implementation of the green credit policy by banks because they could not obtain more profits. Therefore, at this stage, due to the lack of funds and lax supervision, heavily polluting firms tend to adopt low-cost green-washing behaviors. However, with the development of time, corporate environmental information is easily monitored and observed, governments and commercial organizations can identify corporate green-washing behaviors, and firms that use symbolic green actions are increasingly skeptical by stakeholders. When a firm's green-washing is exposed, it will trigger criticisms and negative evaluations, hindering the firm's survival and development (Leonidou and Skarmeas 2017; Testa et al. 2018). In addition, as commercial banks strengthen the implementation of the policy, the credit discrimination faced by heavily polluting firms has become more and more prominent. Symbolic green-washing behavior is ineffective and cannot essentially improve the environmental condition of firms. Therefore, from the perspective of long-term development, heavily polluting firms must earnestly undertake their environmental responsibilities in order to survive and develop, thus forcing firms to increase investment in environmental protection, carry out green technology innovation, and reduce or not choose green-washing behavior.

Heterogeneity analysis

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 5. 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 of the number of independent and joint green patent applications by firms. Specifically, the introduction of the green credit policy significantly increased the number of green patents applied by high-polluting firms jointly and independently by 0.086 and 0.041, respectively. The results in columns (3) and (4) show that after the implementation of the policy, the number of green invention patents of firms did not increase significantly (α = 0.010, p > 0.1), while the number of green utility patent applications increased significantly (α = 0.105, p < 0.01). In other words, the
green credit policy only promotes the increase of green innovation quantity, but lacks the improvement of innovation quality. On the one hand, invention patents require a large amount of resource input, while the promulgation of the green credit policy causes banks to refuse or reduce loans to high-polluting firms, which reduces the funds available to these firms for innovation activities. On the other hand, the green technology knowledge accumulated by high-polluting firms is relatively lacking, and the innovation environment, R&D equipment, and personnel are also relatively poor. Under the circumstance of high financial pressure and limited innovation resources, high-polluting firms will give up the green invention patent innovation with long cycle and high risk, and prefer to carry out the green utility patent innovation with low cost, short cycle, and low risk.

**Intensity of environmental regulation**

The effects of 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 significantly affect the implementation effect of the green credit policy. Hence, the heterogeneity of regional environmental regulation intensity on the relationship between green credit and corporate 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 5 reports the heterogeneous impact of environmental regulation. In the high environmental regulation group, the green credit policy promotes corporate green innovation and reduces green-washing behavior. In contrast, firms in the low environmental regulation group are more inclined to green-wash environmental information. The estimation coefficient shows that the policy will increase the number of green patent applications by 0.104 and reduce the degree of green-washing by 0.027 for high-polluting firms in high environmental regulation areas, while increasing the

| Table 4 Results of dynamic effects test |
|----------------------------------------|
| Variables | (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 |
| | (1.740) | (–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 |
| Constant   | –4.838*** | 1.141*** |
| | (–18.277) | (19.832) |
| N          | 20168 | 20168 |
| Adj. $R^2$ | 0.218 | 0.123 |

***, **, 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.

6 Sixteen provinces, including Beijing, Hebei, Liaoning, Jiangsu, Zhejiang, Shandong, Guangdong, Shanxi, Henan, Heilongjiang, Hunan, Guangxi, Inner Mongolia, Guizhou, Shanxi, and Xinjiang, are classified as high-environmental regulation areas, and firms in these areas are classified in the high environmental regulation group. Fifteen provinces, including Shanghai, Tianjin, Fujian, Jilin, Hubei, Sichuan, Ningxia, Gansu, Anhui, Jiangxi, Hainan, Yunnan, Chongqing, Qinghai, and Tibet, are defined as low environmental regulation areas, and firms located in these areas are assigned to the low environmental regulation group.
green-washing degree by 0.025 for high-polluting firms in low environmental regulation areas. This suggests that the higher the intensity of regional environmental regulation, the more pronounced the green incentive effect of the green credit policy. Regions with high intensity of environmental regulation have higher efficiency in law enforcement, which provides good environmental support for the implementation of the green credit policy. Green credit and environmental

### Table 5 Results of heterogeneous effects

| Panel A Heterogeneity test of green patent type |  |  |  |  |
| --- | --- | --- | --- | --- |
| (1) | (2) | (3) | (4) |
| Variables | Gpat | Gpat | Gpat | Gpat |
| PostxTreat | 0.086*** | 0.041** | – 0.010 | 0.105*** |
| (2.648) | (1.970) | (– 0.362) | (3.705) |
| Controls | Yes | Yes | Yes | Yes |
| Constant | – 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) |
| Variables | Gwl | Gpat | Gpat | Gwl |
| PostxTreat | 0.104** | – 0.027*** | 0.067 | 0.025** |
| (2.194) | (– 2.699) | (1.443) | (2.344) |
| Controls | Yes | Yes | Yes | Yes |
| Constant | – 5.179*** | 1.188*** | – 4.366*** | 1.052*** |
| (– 13.474) | (14.631) | (– 11.620) | (12.319) |
| N | 10883 | 9285 | 9285 | 9285 |
| Adj. $R^2$ | 0.227 | 0.122 | 0.199 | 0.112 |

| Panel C Heterogeneity test of space |  |  |  |  |
| --- | --- | --- | --- | --- |
| (1) | (2) | (3) | (4) |
| Variables | Gwl | Gpat | Gpat | Gwl |
| PostxTreat | 0.113*** | – 0.019** | 0.083 | 0.023** |
| (2.632) | (– 2.118) | (1.628) | (1.969) |
| Controls | Yes | Yes | Yes | Yes |
| Constant | – 4.764*** | 1.179*** | – 5.376*** | 1.227*** |
| (– 12.207) | (14.222) | (– 10.811) | (10.606) |
| N | 13779 | 6352 | 6352 | 6352 |
| Adj. $R^2$ | 0.209 | 0.231 | 0.231 | 0.138 |

| Panel D Heterogeneity test for alternative financing channel |  |  |  |  |
| --- | --- | --- | --- | --- |
| (1) | (2) | (3) | (4) |
| Variables | Gpat | Gwl | Gpat | Gwl |
| PostxTreat | 0.000 | – 0.009 | 0.149*** | – 0.006 |
| (0.008) | (– 0.825) | (3.415) | (– 0.655) |
| Controls | Yes | Yes | Yes | Yes |
| Constant | – 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 |

***, ** 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.
regulation form a strong combination in function, influencing the green strategic behavior of firms from two directions. Therefore, under coercive pressure, firms will have to adopt substantial environmental behaviors to increase green innovation and reduce green-washing. Conversely, in regions with low environmental regulation, the efficiency of law enforcement is poor and environmental departments are loose in environmental supervision, which leads to ineffective implementation of the green credit policy in this region.

Spatial heterogeneity

The green credit policy through the financial market sends signals to firms, so the green credit policy would be affected by the development level of the regional financial. Based on regional per capita GDP, 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 the green credit policy has a positive effect on green innovation of firms in the economically developed regions, and has a negative effect on green-washing behavior of firms. Columns (3) and (4) show that the green credit policy has no influence on the innovation behavior of firms in economically underdeveloped regions, but it strengthens the green-washing behavior of firms. The estimation coefficient shows that the policy will increase the number of green patent applications by 0.113 and reduce the degree of green-washing by 0.019 for high-polluting firms in economically developed regions, while increasing the green-washing degree by 0.023 for high-polluting firms in economically underdeveloped regions. The possible reason is that in economically underdeveloped areas, governments and firms regard economic benefits as the priority, and in these areas, high-polluting firms are the largest contributors to the regional economy. To boost economic growth, local governments have loosened regulations on the environment and commercial institutions have low loaning standards for high-polluting firms, resulting in a lack of incentive for firms to innovate. In economically developed regions, it is the tertiary industry that drives economic growth, and the public has a strong demand for environmental protection, which in turn promotes the implementation of the green credit policy in this region to be more effective, and firms will adopt green innovation and reduce green-washing behavior.

Alternative financing channel

Trade credit is a well-known alternative financing channel for firms facing credit financing constraints, firms can use the trade credit when the commercial bank financing becomes unavailable (Chen et al. 2019; Wen et al. 2021). Thus, we believe that trade credit will have a significant impact on the forms of green activities chosen by firms after the implementation of the green credit policy, which needs to be further explored. Referring to Wen et al. (2021), trade credit is measured by the ratio of accounts payable to the total assets of the firm. We further classified firms into high and low trade credit, where firms are classified as high if their index value is higher than the median of industry years and as low otherwise. Panel D summarizes the group test results of corporate trade credit. The results show that the green credit policy has a direct and effective effect on green innovation only in firms with low trade credit. Trade credit is an important alternative financing method for firms. After the implementation of the green credit policy, high-polluting firms with high trade credit can easily obtain funds from external stakeholders through trade credit without being restricted by the capital allocation of commercial institutions, thereby reducing the incentive for high-polluting firms to take green actions to respond to green policy. For high-polluting firms that lack alternative financing, they are more affected by the policy due to a lack of capital sources, and they will engage in more green innovation activities to obtain credit funds from commercial institutions.

Economic consequences analysis: why make such a green choice

The above research found that the green credit policy significantly increases firms’ green innovation, but has no significant effect on green-washing on the whole. From the perspective of time, firms will choose green-washing in the early stage of the policy implementation, and then reduce green-washing behavior and increase green innovation. We argue that this may be because over time, firms’ green-washing behavior will be identified and bring a series of negative impacts to firms, while the accumulation of innovative output can add the competitive advantage of firms, which eventually motivates firms to choose innovative behavior and reduce green-washing behavior. To detect the mechanism, we try to verify how the performance of high-polluting firms is affected by a series of green activities under the pressure of the 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 high-polluting firms using the following model:

1 Shanghai, Beijing, Guangdong, Zhejiang, Suzhou, Fujian, Tianjin, Liaoning, Shandong, and Inner Mongolia belong to economically developed regions, while Hebei, Hainan, Shanxi, Henan, Anhui, Hebei, Jilin, Heilongjiang, Jiangxi, Hunan, Guangxi, Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Qinghai, Ningxia, and Xinjiang are economically underdeveloped regions.
The coefficients of \( Gpat \times Treat \) and \( Gwl \times Treat \) are not significant when the CSR with one lag period is used as the dependent variable. When CSR is lagged by two periods as the dependent variable, the coefficient of \( Gpat \times Treat \) is significant and positive at the level of 10%, and the coefficient of \( Gwl \times Treat \) is significant and negative. The above results show that the green credit policy significantly improves corporate social responsibility performance by prompting high-polluting firms to engage in green innovation activities, but this effect has a lagged effect, while green-washing behavior adopted by firms does not improve corporate social responsibility performance.

### Environmental performance

\( EP \) represents the environmental performance of the firm. Emission fee per unit of operating revenue is used as environmental performance proxy variable, with smaller values indicating better environmental performance of the firm. Emission fee data was collected through the management fee details in the firm’s annual report. By screening the keyword “emission fee” in the detailed items of management fees, we can get the emission fee data, and then add up the emission fee by year to obtain the total amount of the annual emission fee paid by the firm. The results of panel B show that neither of the two green behaviors of firms have an impact on the environmental performance in the lag period after the implementation of the green credit policy. When \( EP \) is lagged by two periods as the dependent variable, the regression coefficient of \( Gpat \times Treat \) is significantly negative, reflecting that after the implementation of the policy, high-polluting firms increase the output of green credit policy. When \( EP \) is lagged by two periods as the dependent variable, the regression coefficient of \( Gpat \times Treat \) is significantly positive, indicating that firms’ behavior of green-washing environmental information does not improve firms’ environmental performance. Instead, it will lead the government to increase the punishment of firms for pollution.

### Financial performance

\( ROE \) denotes the financial performance of the firm. Empirical results are shown in panel C of Table 6. The coefficient of \( Gpat \times Treat \) is significantly positive, indicating that increasing green innovation can improve the financial performance of heavily polluting firms. The coefficient of \( Gwl \times Treat \) is significantly negative, which reflects that the green-washing behavior adopted by firms significantly reduces corporate financial performance.

### Robustness test

To verify the robustness of the baseline regression results, the following tests are conducted.
Propensity score matching 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-differences method (DID) are combined to solve this problem. First, we use the Probit model to estimate the propensity scores. Referring to previous research literature, eight observable variables, including the number of employees (Staff), the ownership concentration of companies (Top), return on assets (Roa), investment opportunities (Tobin Q), capital intensity (Tangible), cash flow (Cash), size of the supervisory board (Supn), and region (Area) are selected as matching indexes of the PSM model. Second, since the treatment group has 5872 samples and the control group has 14,296 samples, we use the 1:2 nearest neighbor matching, radius matching, and kernel matching to match the treatment group (high-polluting firms) with the control group (non-high-polluting firms). We implement a balance test to ensure no significant difference between the treatment and control groups after matching. Table 7 shows the results of the balance test. Fig. 3 shows the density function diagram before and after matching. As shown in Fig. 3 and Table 7, the treatment 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 8. Regardless of which propensity score matching method is chosen, the coefficient of Treat×Post is significantly positive at least at the level of 5%, which further verifies the reliability of the conclusion in this paper.

### Table 7 Balance test

| Variables | Unmatched/matched | Mean | %Bias | t-test | p>|t| |
|-----------|-------------------|------|-------|--------|------|
|           | Treated | Control |       |        |       |
| 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 |

Fig. 3 Density before and after matching
Difference-in-differences-in-differences

As the government has promulgated other environmental regulation policies after 2012, these policies will also affect firms’ choice of green behavior. Therefore, how to distinguish the 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 firms following green standards, theoretically the degree of firms’ external financing demand will directly affect the effectiveness of the green credit policy.

Table 8  Results of endogenous test

| Variables       | (1) Nearest-neighbor matching | (2) Kernel matching | (3) Radius matching | (4) DDD | (5) DDD |
|-----------------|------------------------------|---------------------|---------------------|--------|--------|
| 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    |
| Constant        | – 6.329***                   | – 4.776***          | – 4.813***          | – 4.790*** | 1.112*** |
| (– 16.079)      | (– 18.038)                   | (– 18.008)          | (– 18.108)          | (19.332) |
| N               | 11,526                       | 20,143              | 19,994              | 20,168  | 20,168 |
| Adj. R²         | 0.231                        | 0.215               | 0.216               | 0.216   | 0.120  |

***, **, 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.
on firms. Using the method of Huang et al. (2019), the difference between firm growth and endogenous growth rate (FID) is used to reflect the degree of external financing demand of firms. $FID = (Asset_t - Asset_{t-1}) / Asset_t - Roe / (1 - Roe)$, $Asset$ denotes total assets and $Roe$ denotes return on net assets. The higher $FID$ value indicates that the firm is more dependent on external financing and more influenced by the green credit policy. Based on this, the $FID$ greater than the industry annual average is set to 1; otherwise, the $FID$ is set to 0. Thus, we add the dummy variable of external financing demand of firms to the original DID model to construct a DDD model to further test the robustness of the relationship between the green credit policy and firms’ green behaviors. The results are presented in columns (4) and (5) of Table 8. The regression result of $Post \times Treat \times FID$ cross term on $Gpat$ is significantly positive at the level of 10%, while the regression result on $Gwl$ does not pass the significance test. It can be seen that the test results are consistent with the previous results, suggesting that our findings are robust.

### 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 a proxy variable for corporate 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 firms. The results in columns (1) to (3) of Table 9 show that the coefficients of $Treat \times Post$ all pass the significance test whether the green innovation ratio or the lag green innovation time is selected as the dependent variable.

#### Replacement model

Considering that there are some samples with the number of green patents is 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 columns (4) and (5) of Table 9. Unsurprisingly, a positive and statistically significant relationship between green credit and green innovation still exists, which proves that our research conclusions have good robustness.

### Exclude some samples

To observe the continuity of firms’ behavior before and after the implementation of the green credit policy, firms listed after 2012 are removed from this paper. As these listed firms lack data on corporate green behaviors before the implementation of the policy, including these data in the sample may lead to biased results. The results in columns (6) and (7) of Table 9 show that the regression result of $Gpat$ is still significant, while the regression result of $Gwl$ does not pass the significance test.

### Conclusions and recommendations

#### Conclusions

Through the empirical research of China’s green credit policy, this paper provides experience for developing countries to improve their green financial system and ultimately achieve sustainable development. The above regression studies the impact of the green credit policy on the green behavior of high-polluting firms from the four dimensions: 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 firms’ green innovation and has not increased corporate green-washing behavior. However, from the perspective of the dynamic effect of the policy, after the implementation of the green credit policy, high-polluting firms are more inclined to adopt the behavior of green-washing environmental information rather than green innovation in the short term, but over time, the green-washing behavior of firms will be identified, which in turn force firms to choose green innovation behavior. (2) Heterogeneity analysis has shown that firms 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 the green innovation strategy. However, firms located in economically underdeveloped regions and low environmental regulation regions are more inclined to choose the green-washing strategy. (3) Economic consequence analysis finds that the increase of green innovation by firms after the implementation of the green credit policy significantly improves corporate financial, environmental, and social performance, while green-washing behavior reduces corporate financial, environmental, and social performance.

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Recommendations

There are several practical recommendations from our findings, as shown below. First, firms should realize that although green innovation will crowd out the operating funds of firms to some extent, from the perspective of long-term development, firms engaging in green innovation activities can achieve a win-win for both the environment and the economy. At the same time, firms must limit short-sighted green-washing behaviors, which will ultimately damage corporate value and hinder social progress. Besides, firms should also take the initiative to adapt to the situation of green finance regulation, positively respond to the green credit policy, and independently improve innovation capacity. Second, government departments should further improve the green credit policy system. At present, the environmental information disclosure of listed firms in China is not standardized and the disclosure ratio is relatively low. The
government should strengthen the environmental information disclosure policy, increase the punishment for environmental violations, and inhibit corporate green-washing behavior. Our research shows that green credit policy can significantly increase the green innovation of high-polluting firms. Hence, the Chinese government should continue to strengthen the incentive mechanism of green credit and improve the enthusiasm of financial institutions to carry out green credit. Finally, according to the characteristics of different regions, adopt different strategies to implement the green credit policy to maximize the green effect of the policy. Continuing to maintain the implementation of the green credit policy in economically developed regions and high environmental regulation regions is important to promote the transformation and upgrading of high-polluting firms. It is very necessary to expand the coverage and implementation of green credit in economically underdeveloped areas and areas with low environmental regulation. Meanwhile, the improvement of corporate environmental performance should be used as the criteria for credit disbursement, so as to avoid excessively strengthening the financial constraints of polluting firms and hindering the realization path of corporate technological innovation.

Limitations and further research

Our study also has some limitations and offers new avenues for future research. First, the indicators selected in this paper to measure the degree of green-washing of firms have some deficiencies. Since 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, it is necessary to construct a more scientific, comprehensive, and accurate indicator of corporate green-washing. Second, firms have multiple strategic choices to cope with environmental pressures. We only compared the difference between internal green innovation and external green-washing environmental information selected by firms after the implementation of the green credit policy, and only made a preliminary analysis of their links with the policy. Other green behaviors of firms are not included, which may not fully reflect the impact of the green credit policy on firms. Continuing to explore the relationship between the policy and corporate other green behaviors will further extend the findings of this research. Third, due to the availability of data, the sample in this paper is limited to listed firms, which are usually large firms. Since firms with different sizes have great differences in resource acquisition and business philosophy, it is also worthwhile to further study whether the green credit policy has different impacts on the green behavior of small and medium-sized firms. Follow-up studies can expand the empirical sample and re-verify the conclusion.

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

Declarations

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