THE IMPACT OF CHINESE ENVIRONMENTAL REGULATIONS ON THE EFFECTIVENESS OF GREEN CREDIT POLICY: FROM THE PERSPECTIVES OF PROACTIVE GOVERNMENT AND EFFICIENT MARKET

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Abstract. Green credit is an important practice in China to facilitate enterprises' green transformation through market mechanisms, but its effectiveness remains controversial under the background of "shallow green" development. From the perspective of the synergistic effect between environmental regulations and green credit, this study takes A-share listed companies from 2009 to 2016 as samples, uses the "Green Credit Guidelines" in 2012 as a quasi-natural experiment, and uses the difference-in-differences method to analyze the policy's impact on green technological innovation of heavily polluting enterprises under different environmental regulation levels. It is found that the policy's effectiveness varies with environmental regulation levels: green credit crowds out enterprises' green technological innovation under weak regulations, but forces them to innovate under strong regulations. The conclusion is still valid after a series of robustness tests, and the policy's effects differ by enterprises' property rights, scale, and life cycle. Further tests reveal the green credit policy achieves the "strong Porter hypothesis" under high regulation level, while under weak regulation, heavily polluting enterprises tend to shift investment structures "from the real economy to the virtual economy".
Keywords: *green technological innovation, difference-in-differences model, capital financing mechanism, capital allocation mechanism, heterogeneity analysis*

Introduction

Environmental problems emerging due to economic development are becoming increasingly severe, and pollution control is urgently needed. In the long run, solving this contradiction depends on technological progress, especially green-oriented technological innovation (Acemoglu et al., 2012). This is mainly because general innovation usually only brings economic benefits and cannot improve environmental quality. On the contrary, it may even exacerbate environmental pollution due to the energy rebound effect (Wang and Huang, 2015). Green technological innovation, on the other hand, combines the dual attributes of "emission reduction" and "value-addition", which is conducive to the coordinated development of the economy and the environment. However, due to the external characteristics of environmental problems, enterprises lack the impetus for green technological innovation. In addition, under the traditional development model of banks, heavily polluting enterprises are the main recipients of credit funds and continue to expand their investment scale relying on abundant external funds, which objectively aggravates the continuous deterioration of the ecological environment (Dong et al., 2019; Liu and Wen, 2019). It can be seen that only when financial resources gradually withdraw from polluting industries and are

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more invested in green environmental protection and energy-saving industries can the environmental quality be fundamentally improved.

Against this backdrop, the former China Banking Regulatory Commission issued the "Green Credit Guidelines" policy in 2012, requiring banking financial institutions to intervene in enterprise investment and financing through differential credit, thereby guiding heavily polluting enterprises to shift from passive to active environmental governance. However, in current research on the green credit policy and enterprise green technological innovation, the promotional effect of the policy on the green technological innovation of environmental-friendly enterprises is relatively certain (Li et al., 2018; He et al., 2019; Ding et al., 2022). Nevertheless, there is a controversy between the forcing-effect and crowding-out effect in the research on the impact of the green credit policy on the green technological innovation of heavily polluting enterprises (Lu et al., 2021; Yang and Zhang, 2022). This is essentially due to the "market failure" caused by the externalities of pollution and the public attributes of the ecological environment, which leads to insufficient supply of green technology innovation public goods for enterprises. Against the background of China's "shallow green" development, it is difficult to automatically eliminate this dual externality dilemma through the market mechanism of green credit. In practice, internalizing the external environmental costs through the government's mandatory environmental regulation is considered an important means to correct the market failure of green credit (Li, 2017; Ding and Hu, 2020).

However, current research on the green credit policy pays insufficient attention to government intervention, and the theoretical exploration and empirical analysis of the coordination between environmental regulation and green credit are also inadequate. Under China's environmental decentralization management model, local governments attach different degrees of importance to environmental issues in economic development, and there are significant regional differences in the level of environmental regulation (He and An, 2019). Then, what is the effectiveness of the green credit policy? Will it be affected by the level of government environmental regulation? If so, what is the mechanism by which green credit policies affect the green technology innovation of heavily polluting enterprises under different regulatory levels? Answering these questions attempts to provide an explanation for the uncertainty of the effectiveness of the green credit policy from the perspective of environmental regulation, which is helpful to further improve the capital efficiency of the green credit policy in serving the green transformation of the real economy. In view of this, this article selects A-share listed companies from 2009 to 2016 as research samples, and uses the 2012 "Green Credit Guidelines" as a natural experiment to test the impact of green credit policies on green technology innovation of heavily polluting enterprises through a difference-in-differences model. The analysis of the heterogeneity of environmental regulation level is carried throughout, and the differentiated impacts of green credit policies on green technological innovation under different environmental regulation levels and their underlying mechanisms are deeply explored. This study aims to analyze the synergistic impact mechanism of environmental regulation level and green credit policies on green technology innovation of heavily polluting enterprises, reveal the inherent logic of policy effectiveness differences under different regulatory environments, and provide theoretical basis and empirical support for optimizing the synergistic cooperation between green credit policies and environmental regulatory tools, and enhancing the driving efficiency of policy combinations on enterprise green transformation.

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Literature review and hypotheses

Literature review

Research on the impact of green credit policies on green technology innovation in heavily polluting enterprises

There are two views on the impact of green credit policies on green technology innovation in heavily polluting enterprises in existing research. One type of research suggests that green credit policies will force polluting enterprises to innovate in green technologies. For example, Hu et al. (2021) studied A-share listed companies from 2007 to 2016 and found that green credit policies promote green technology innovation in heavily polluting enterprises, which is more significant under strong financing constraints. Zhang et al. (2022) used A-share listed companies from 2008 to 2017 as samples, and based on 1036 annual observations, found that policies significantly improved the quantity and quality of green technology innovation in heavily polluting enterprises. Wang and Wang (2021) also found that green credit policies restricted industries with more active green innovation performance, using A-share listed companies from 2007 to 2017 as samples. But another type of research questions this. Chen et al. (2019) used A-share listed companies from 2006 to 2015 as a sample and found that policies forced companies to seek other financing channels. Furthermore, based on data from Chinese industrial enterprises from 2004 to 2014, Lu et al. (2021) found that under the cost compliance and credit constraint effects caused by policies, technological innovation in enterprises decreases. Yang and Zhang (2022) used A-share listed companies from 2009 to 2014 as samples and found that policies have a significant inhibitory effect on green technology innovation in heavily polluting enterprises, with credit scale reduction and credit cost increase being the main mechanisms.

Research on the impact of environmental regulations on the implementation of green credit policies

There are two different schools of thought regarding the relationship between government environmental regulations and green credit market mechanisms. The collaborative school represented by Haken (1981) believes that environmental regulations can strengthen the implementation of green credit. This is mainly due to considerations of "reputation risk" and "environmental risk". Environmental regulations will strengthen the enthusiasm of financial institutions to invest in green credit (Luo and Qi, 2021; Liu and Yuan, 2024), and provide policy guidance and institutional guarantees for the development of green credit (Song et al., 2021). However, the school of thought formed by scholars such as Coase opposes government intervention, believing that it is not only costly but also carries the possibility of rent-seeking (Coase, 1960). If market property rights are clear and transaction costs are zero, environmental externalities can be solved solely through market mechanisms. Therefore, green credit can operate efficiently without government regulation (Wang and Wang, 2018; Bian et al., 2022).

After reviewing the literature, it is found that there are differences in existing studies on the impact of green credit policies on green technology innovation of heavily polluting enterprises, and there are also controversial studies on the relationship between environmental regulations and green credit policies. Based on this, this paper

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examines the influence of environmental regulation level on the technological innovation effect of green credit policy by considering both government and effective market.

Hypotheses

Whether the green credit policy can promote the green technology innovation of polluting enterprises depends on two aspects. The first is the implementation of the green credit policy by commercial banks, and the second is the reaction of polluting enterprises to the green credit policy. Existing studies have fully demonstrated the implementation of green credit by commercial banks (Luo and Qi, 2021; Liu and Yuan, 2024), and the response of polluting enterprises to green credit will be affected by the level of environmental regulation (Ding, 2019). In addition, different from the market orientation of developed countries, China's green credit practices a "top-down" development model, which mainly relies on the guidance of government supervision and relevant policies. In essence, it is an institutional change promoted by the government. Therefore, it is necessary to discuss the optimization of the development path of green credit from the perspective of government environmental regulation. Considering the background of China's environmental decentralization system, there are great differences in the implementation of environmental policies by local governments. Therefore, this paper divides local government environmental regulation into two types: loose and strict, and discusses the differentiated impact of green credit policy on green technology innovation of heavily polluting enterprises under different regulatory levels.

In the context of relatively loose environmental regulations of local governments, heavily polluting enterprises can still obtain legal operation by paying fines, making up for procedures and other ways. In this case, banks will suffer small penalties from superior banks or government regulatory authorities for lending to heavily polluting enterprises, but the operating losses given up after implementing green credit will be larger. In addition, the potential intangible benefits are not obvious in the loose regulatory environment, which may lead to weak implementation of green credit for commercial banks pursuing the goal of profit maximization. At the same time, under loose environmental regulations, the pollution attributes of enterprises have not been fully exposed, and the market does not know enough about the investment risks of polluting enterprises. In addition, enterprises can still cover up environmental externalities through "greenwashing" and other behaviors, and local governments may also give certain protection for seeking economic development, so enterprises will not take the initiative to carry out environmental governance. Moreover, faced with financing constraints caused by green credit, heavily polluting enterprises will obtain funds through non-credit channels such as equity and commercial credit (Chen et al., 2019; Guo and Fang, 2022). According to the theory of prioritization financing (Myers and Majluf, 1984), alternative non-credit financing channels will increase the operating costs of enterprises, and eventually force out the green technology innovation of enterprises under the cost-compliance effect.

However, in the strict regulatory environment, the behavioral decisions of commercial banks and heavily polluting enterprises will change. On the one hand, based on the funding guidance effect and green reputation effect of environmental regulations, for commercial banks, the regulatory penalties for lending to heavily polluting enterprises have significantly increased and gradually exceeded the possible

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interest losses. Moreover, the increasing attention of stakeholders to the environment has made the intangible benefits of implementing green credit increasingly apparent. At this time, the supply obstacles of green credit for commercial banks will gradually be alleviated. On the other hand, based on the effects of environmental regulations on infrastructure construction and information disclosure, for heavily polluting enterprises, with the strengthening of environmental regulations and the continuous improvement of environmental policies and laws and regulations, the negative externalities of enterprise pollution are gradually priced correctly. Moreover, the refinement of environmental information disclosure will further increase the financing threshold of the investigated enterprises. At this time, heavily polluting enterprises find it difficult to rely on other means to alleviate financial pressure, and the development model of obtaining government protection by contributing economic output is also unsustainable. Heavily polluting enterprises have to pay attention to their own environmental problems. In addition, considering the implementation of green credit, for enterprises with environmental risks, as long as they meet environmental protection requirements through technological transformation, the credit financing constraints brought by policies can be alleviated (Shen and Ma, 2014). Therefore, in a strict regulatory environment and facing increasing pressure on credit funds, in order to achieve long-term development of enterprises, heavily polluting enterprises will actively increase their investment in green technology innovation in order to obtain innovation compensation. The theoretical model constructed according to the research hypothesis put forward in this paper is shown in *Figure 1*, which is presented as follows:

H: When the level of environmental regulation is low, the green credit policy will inhibit the green technology innovation of heavily polluting enterprises; when the level of environmental regulation is high, the green credit policy will promote the green technology innovation of heavily polluting enterprises.

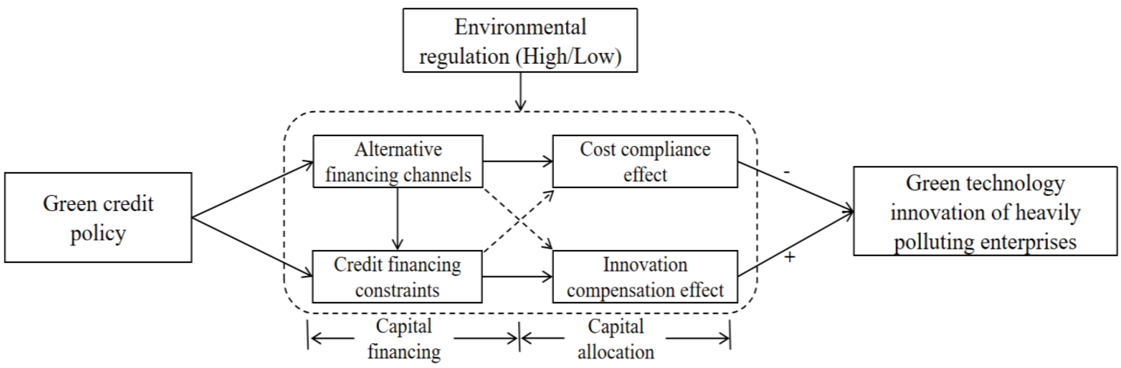

Figure 1. *Logical framework diagram*

Materials and methods

Model construction

This paper uses the difference-in-differences model to examine how the “Green Credit Guidelines” (hereinafter referred to as the “Guidelines”) in 2012 affected the green technology innovation of enterprises. The econometric model is constructed as follows:

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$$\mathrm{PATENT_{it}} = \alpha_0 + \alpha_1(\mathrm{TIME_t} \times \mathrm{TREAT_i}) + \alpha_2 \mathrm{X_{it}} + \mathrm{v_i} + \mathrm{u_t} + \varepsilon_{\mathrm{it}} \qquad \text{(Eq.1)}$$

In *Equation 1*, the subscript i represents the enterprise, t represents the year, PATENT represents the enterprise's green technology innovation, TIME represents the treatment period dummy variable, TREAT represents the treatment group dummy variable, X is a series of control variables, v is an individual fixed effect, u is a time fixed effect, and ε is a random error term. In the model, since the coefficient of TIME and TREAT has been absorbed by individual fixed effects and time fixed effects, this article mainly observes the coefficient of the interaction term $\mathrm{TIME} \times \mathrm{TREAT}$, which measures the net effect of the implementation of green credit policies on corporate green technology innovation. If it is significantly greater than 0, it indicates that the implementation of the Guidelines has significantly promoted green technology innovation in heavily polluting enterprises, and vice versa. In addition, to examine the impact of environmental regulations on the development of green credit and green technological innovation, this study follows the methodology of Ding and Hu (2020), dividing the sample into a high environmental regulation group (ER ≥ mean value of sample regions) and a low environmental regulation group (ER < mean value of sample regions) based on the average level of environmental regulations, and conducting difference-in-differences (DID) tests for each group respectively.

Variable selection

Green technology innovation (PATENT1, PATENT2). Existing studies mainly measure the level of green technology innovation of enterprises in two ways: green total factor productivity (Li and Chen, 2019) and the number of green patents (Qi et al., 2018). The severe shortage of environmental pollution and other relevant data at the enterprise level hinders the effective measurement of enterprises' green total factor productivity. Considering that the number of patents generally provides a more accurate reflection of an enterprise's innovation level, this study selects the count of green patents as a measure for evaluating enterprises' green technology innovation. In addition, considering that there may be a lag in using the number of patent grants to measure the enterprise's green technology innovation, the number of applications can better reflect the innovation ability of the enterprise in the current year. Therefore, this study refers to the practice of Li and Zheng (2016), and measures the enterprise's green technology innovation level with the number of green patent applications. In view of the fact that green invention patents emphasize substantive characteristics and significant advancements, focusing on major green technological innovations. While green utility model patents focus on green technological improvements in product shapes and structures, with relatively lower innovation levels. This study uses the number of green invention patent applications to measure the quality of enterprises' green technological innovation, and takes the number of green utility model patent applications as a comparative indicator to reflect the quantity of green technological innovation. In addition, in order to eliminate the right distribution of green patent application data, this paper adds 1 to the number of green invention patents and green utility model patents and takes the natural logarithm to get PATENT1 (unit: pieces) and PATENT2 (unit: pieces).

Green Credit Policy ($\mathrm{TIME} \times \mathrm{TREAT}$, DID). TIME is a dummy variable for the periods before and after the implementation of the "Guidelines". The value is set as 1 for the period after the implementation of the "Guidelines" (2012 and later) and 0 for

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the period before the implementation (before 2012). TREAT indicates whether an enterprise is a heavily polluting one. If it is a heavily polluting enterprise, the value is 1; otherwise, it is 0. The reason for selecting heavily polluting enterprises as the treatment group is as follows. On the one hand, heavily polluting enterprises are the main targets restricted by green credit, and analyzing changes in their green technological innovation behaviors can more effectively reflect the implementation effects of the Guidelines. On the other hand, compared with non-heavily polluting enterprises, heavily polluting enterprises cause more serious environmental damage due to insufficient green technological innovation. Regarding the classification of heavily polluting enterprises, this study refers to the industry classification standards of the China Securities Regulatory Commission in 2010 and follows the practices of scholars such as Cui and Jiang (2019). Enterprises in eight major industries, including mining, petroleum, and chemistry, are selected as the treatment group. Meanwhile, other listed companies in the same category as the heavily polluting enterprises are used as the control group[1].

Environmental Regulation (ER). In existing studies, there is no unified standard for measuring government environmental regulations, and most of them use environmental governance investment (He and An, 2019), pollutant emission reduction per unit output (Shen et al., 2018) or the number of environmental policies and regulations promulgated (Li and Weng, 2014) as substitutes. Considering the theme of this study, the above environmental regulation indicators have a strong correlation with enterprises' green technology innovation, and there may be a large endogenous problem. In addition, the above indicators mainly focus on a certain aspect of environmental regulation, and it is difficult to reflect the whole picture of government environmental regulation. For this reason, this paper draws on the research of Chen et al. (2018) and uses the proportion of the occurrence frequency of words related to "environmental protection" in the local government work report to represent the government's environmental regulations. This index calculates environmental regulations based on word frequency rather than the number of individual words, which can measure the level of government environmental regulations more comprehensively and accurately. In addition, the government work report is usually determined at the beginning of the year, so the change of the environmental situation in the current year will not affect the government work report that has been formulated before. Therefore, it has the advantage of "exogeneity" to choose the proportion of relevant word frequency in the government work report to measure the level of environmental regulations, which has been adopted by more and more researches in recent years. In addition, drawing on the methodology of Bartik (1991), this study utilized the Database of China Industrial Enterprises to calculate the proportion of heavy industry in prefecture-level cities within the province (unit: %). By multiplying this proportion with the frequency of environmental protection-related terms in the provincial government work report (unit: %), the study derived the level of environmental regulation in prefecture-level cities. In addition to the above measurement methods, this paper, referring to the practice of Shen et al. (2018), also selected the logarithm of the proportion of pollutant discharge charges to regional

[1] According to the *Notice on Public Consultation on the Guidelines for Environmental Information Disclosure of Listed Companies* (Draft for Comment) promulgated by the former Ministry of Environmental Protection in 2010, and combined with the industry classification standards of the China Securities Regulatory Commission (CSRC) in 2001, heavily polluting industries are specifically defined as follows: B (mining), C0 (food and beverages), C1 (textiles, garments, and leather), C3 (paper making and printing), C4 (petroleum, chemicals, plastics, and rubber), C6 (metals and nonmetals), C8 (pharmaceuticals and biological products), and D (production and supply of electricity, gas, and water). Other listed companies in the same category mainly include: C2 (timber and furniture), C5 (electronics), C7 (machinery, equipment, and instruments), and C99 (other manufacturing industries).

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pollutant to measure the level of environmental regulations, and conducted a robustness test on this basis.

Control variables. Based on the practices of scholars such as Qi et al. (2018), this paper selected the age of enterprises (AGE, unit: years), performance of enterprises (ROA, unit: %), value of enterprises (TQ, unit: %), cash flow of enterprises (CF, unit: %), growth of enterprises (GROW, unit: %), shareholding ratio of the largest shareholder (FIRST, unit: %) and regional economic development level (GDP, unit: %). As a control variable in the model. The specific variables are defined in *Table 1*.

Table 1. *Variable definition*

Type	Variable	Symbols	Definition
Explained variable	Green invention patent	PATENT1	Natural logarithm of (the number of green invention patent applications + 1) (unit: pieces)
	Green utility model patent	PATENT2	Natural logarithm of (the number of green utility model patent applications + 1) (unit: pieces)
Explanatory variable	Treatment period dummy variable	TIME	1 for the period after the promulgation of the “Guidelines”, 0 for the period before
	Treatment group dummy variable	TREAT	1 if the enterprise belongs to the treatment group, 0 otherwise
Grouping variable	Environmental regulation level	ER	Proportion of environmental protection words (unit: %) * Proportion of heavy industry in the city (unit: %) * 10^4
Control variable	Age of enterprises	AGE	Natural logarithm of the enterprise’s establishment time (unit: years)
	Performance of enterprises	ROA	Net profit after tax / Total assets (unit: %)
	Value of enterprises	TQ	Market value / Total assets (unit: %)
	Cash flow of enterprises	CF	Cash flow from operating activities / Total assets (unit: %)
	Growth of enterprises	GROW	Operating revenue / Total assets (unit: %)
	Shareholding ratio of the largest shareholder	FIRST	Natural logarithm of the shareholding ratio of the largest shareholder (unit: %)
	Regional economic development level	GDP	GDP growth rate of the city where the enterprise is located (unit: %)

Data sources

The data used in this paper mainly comes from the following three aspects. First, for the data of enterprises’ green technology innovation, this paper obtained the patent classification number information of invention patents and utility model patents of all A-share listed companies from the China Research Data Service Platform (CNRDS), and matched it with the “Green List of International Patent Classification” issued by the World Intellectual Property Organization (WIPO). Thus, the number of green patent applications of enterprises can be obtained. Second, the data of environmental regulation came from the provincial government work report, and based on the collection of environmental words, Python software was used to carry out text statistics and processing of the report text. Third, data for other research variables mainly originate from the CSMAR database (https://data.csmar.com/) and the China City

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Statistical Yearbook published from 2010 to 2017. In addition, if the registered place of the listed company is located in a certain city, the macro data of the corresponding year in that city is matched.

This study takes A-share listed companies as samples, which are registered in China and listed on the Shanghai Stock Exchange (Main Board, Science and Technology Innovation Board) or Shenzhen Stock Exchange (Main Board, Main Board, Growth Enterprise Board), subscribing to and trading shares in RMB. Taking the period from 2009 to 2016 as the sample period, this is mainly because China introduced green credit related policies in 2007 and 2008, and the 2012 Guidelines were further strengthened after these policies. Therefore, controlling the sample after 2009 can effectively avoid the impact of previous policies and obtain the net effect of the Guidelines. In addition, this article also excluded financial industry samples, insolvency samples, and ST listed companies that have been specially processed by the exchange based on the original sample. Finally, 15426 annual observation values were obtained for enterprises, including 6239 annual observation values for heavy polluting enterprises and 9187 annual observation values for non-heavy polluting enterprises. In order to eliminate the interference of outliers, this paper truncated the upper and lower 1% quantiles of continuous variables.

Results

Descriptive statistical analysis

Table 2 reports the descriptive statistical analysis results of the variables. In terms of green technology innovation in enterprises, the mean of PATENT1 is 0.4134, with a standard deviation of 0.8259. The mean of PATENT2 is 0.4375, with a standard deviation of 0.8266. It can be seen that there is a significant difference in the number of green technology patent applications among enterprises, and most of the green patent applications belong to green utility model patents. The difference between the maximum value of environmental regulation (ER) of 66.4487 and the minimum value of 6.0911 is significant, indicating that there are prominent regional differences in the level of environmental regulation. The range of values for the remaining variables is consistent with previous research and will not be further elaborated.

Table 2. *Descriptive statistical analysis*

Variables	Obs	Mean	St.d	Min	Med	Max
PATENT1	15426	0.4134	0.8259	0.0000	0.0000	6.7274
PATENT2	15426	0.4375	0.8266	0.0000	0.0000	6.3404
TIME	15426	0.7153	0.4513	0.0000	1.0000	1.0000
TREAT	15426	0.4044	0.4908	0.0000	0.0000	1.0000
ER	15426	31.3112	11.8009	6.0911	28.4871	66.4487
AGE	15426	2.0588	0.8082	0.1284	2.2646	3.2610
ROA	15426	0.0387	0.0628	-2.7463	0.0355	0.5900
TQ	15426	1.8706	0.7227	0.9341	1.6733	3.9870
CF	15426	0.0445	0.0791	-0.8877	0.0431	0.8759
GROW	15426	0.5310	0.2637	0.0694	0.4940	1.2310
FIRST	15426	3.4787	0.4770	2.1759	3.5278	4.4997
GDP	15426	0.1081	0.0468	0.0090	0.0964	0.2651

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Parallel trend test

The validity of the difference-in-differences estimation needs to meet the parallel trend assumption (Bertrand et al., 2004). That is, before the implementation of the "Guidelines" policy, the time trends of the green technology innovation levels of the treatment group and the control group should be as similar as possible. After the implementation of the "Guidelines" policy, significant trend changes will occur between the treatment group and the control group. Therefore, this paper reports the results of the parallel trend test, as shown in *Table 3*. Before the implementation of the Guidelines, there were no significant differences in patent applications for green inventions and green utility models between the treatment group and the control group when considering the entire sample. This lack of significant difference held true even when the sample was grouped according to the level of environmental regulations. However, the differences between the treatment group and the control group became significant from the implementation year of the Guidelines, and obvious differentiation characteristics appeared in the high and low environmental regulations groups. In summary, this study meets the parallel trend assumption of the difference-in-differences model.

Table 3. *Parallel trend test*

	Green invention patents (PATENT1)			**Green utility models (PATENT2)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	ALL	**High ER**	**Low ER**	**ALL**	**High ER**	**Low ER**
BEFORE3	0.0159 (0.0215)	0.0482 (0.0335)	0.0150 (0.0273)	0.0261 (0.0308)	0.0788 (0.0484)	0.0437 (0.0390)
BEFORE2	0.1848 (0.1174)	0.0112 (0.0362)	-0.0153 (0.0249)	0.0213 (0.0223)	0.0511 (0.0440)	-0.0152 (0.0345)
CURRENT	0.1070*** (0.0181)	0.1025*** (0.0283)	-0.0339* (0.0134)	0.2005*** (0.0246)	0.1151* (0.0583)	-0.0212* (0.0095)
AFTER1	0.0766*** (0.0166)	0.1355*** (0.0317)	-0.0385*** (0.0029)	0.1497*** (0.0230)	0.2708*** (0.0243)	-0.0346** (0.0131)
AFTER2	0.0692*** (0.0153)	0.0856*** (0.0225)	-0.0958*** (0.0167)	0.0958*** (0.0228)	-0.0940** (0.0325)	-0.0888*** (0.0127)
AFTER3	0.0423** (0.0149)	0.0430* (0.0203)	-0.0581*** (0.0169)	0.0464*** (0.0117)	0.0542*** (0.0103)	-0.0574*** (0.0159)
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
N	15426	6025	9401	15426	6025	9401
R^2	0.1153	0.1173	0.1272	0.1252	0.1659	0.1285

The numbers in parentheses are standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. (The same below)

Baseline regression analysis

The regression results of the impact of the green credit policy on enterprises' green technology innovation are presented in Columns (1) and (4) of *Table 4*. For green invention patents, the coefficient of the interaction term DID is significantly positive

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(0.0759). For green utility model patents, the coefficient of the interaction term DID is 0.1354, which is significant at the 1% level. Evidently, after the implementation of the "Guidelines", the green technology innovation level of heavily polluting enterprises has been significantly improved. Based on theoretical analysis, this paper further divides the samples according to the level of environmental regulation to examine the differential impacts of the green credit policy on the green technology innovation of heavily polluting enterprises. Columns (2) and (3) of *Table 4* report the regression results based on green invention patents. In Column (2), for the high environmental regulation sample, the coefficient of the interaction term DID (0.1279) is also significantly positive at the 1% level. Moreover, compared with the coefficient in the full sample regression results, the effect of the green credit policy on green technology innovation is greater in the high environmental regulation group. When the level of environmental regulation is low, Column (3) shows that the coefficient of the interaction term DID (-0.0512) is significantly negative at the 5% level, indicating that the implementation of the green credit policy restrains the application for green invention patents of heavily polluting enterprises at this time. Columns (5) and (6) of *Table 4* report the regression results based on green utility model patents. Column (5) shows that in the context of high environmental regulation, the regression coefficient of the interaction term DID (0.2237) is significantly positive at the 1% level, and this promoting effect is stronger than in the general situation. In column (6), the coefficient of DID (-0.0474) is significant at the level of 10%, indicating that under the relaxed regulatory environment, after the implementation of green credit policy, green utility model patent applications of heavily polluting enterprises decreased.

Table 4. *Green technology innovation effects of environmental regulation and green credit policies*

	Green invention patents (PATENT1)			**Green utility models (PATENT2)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	ALL	**High ER**	**Low ER**	**ALL**	**High ER**	**Low ER**
DID	0.0759***	0.1279***	-0.0512**	0.1354***	0.2237***	-0.0474*
	(0.0112)	(0.0228)	(0.0169)	(0.0155)	(0.0273)	(0.0234)
Constant	0.1886**	0.3161***	0.1447*	0.4377***	0.5213***	0.3950***
	(0.0635)	(0.0884)	(0.0708)	(0.0981)	(0.1284)	(0.1121)
CV	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
N	15426	6025	9401	15426	6025	9401
R^2	0.1420	0.1344	0.1324	0.1528	0.1364	0.1425

Robustness test

This study used the 2012 Green Credit Guidelines as a quasi-natural experiment and employed the difference-in-differences method to examine the impact of green credit policies on green technology innovation in heavily polluting enterprises under different regulatory levels. Theoretically, this approach can effectively address endogeneity issues caused by unobservable omitted variables. However, in order to further improve the reliability of the estimation results, this article also conducted sufficient robustness tests. In addition, due to space constraints, only the inspection results based on green invention patents were reported.

Measurement approaches for substituted variables

In order to avoid the potential measurement bias problem that may exist with a single measurement indicator, this paper replaces the core variables. Firstly, the explained variable is replaced with the proportion of the number of green patent applications to the total number of patent applications of the enterprise in that year, and the difference-in-differences model is re-tested. The regression results are shown in columns (1) to (3) of *Table 5*. Secondly, the level of government environmental regulation is measured by the logarithm of the proportion of pollutant discharge charges to regional pollutant. After re-grouping the samples, the regression is conducted again, and the regression results are presented in columns (4) and (5) of *Table 5*. Thirdly, to avoid the impact of the timing of the selection of the green credit policy on the regression results, this paper uses the development level of green credit (GC) as a substitute variable for the time point of the policy shock (TIME) and constructs a continuous difference-in-differences regression model. The indicator for the development level of green credit (GC) in this study draws on the research of Xie and Liu (2019), which is indirectly measured by the ratio of interest expenditure of non-six high-energy-consuming industries in each province to the total interest expenditure of industrial industries in that province. The larger the value of this indicator, the higher the level of green credit development. The regression results are shown in columns (6) to (8) of *Table 5*. As shown above, after replacing the core variables, the coefficient signs and significance of the interaction terms reported under different regulatory levels remain consistent with the previous research, further proving the robustness of the previous research conclusions.

Table 5. *Robustness test: variable replacement*

	Replace green tech innovation variable			**Replace environmental regulation variable**		**Continuous DID**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	ALL	**High ER**	**Low ER**	**High ER**	**Low ER**	**ALL**	**High ER**	**Low ER**
DID	0.1372***	0.1950***	-0.0570*	0.1729***	-0.0778**			
	(0.0164)	(0.0298)	(0.0246)	(0.0306)	(0.0258)			
GC*TREAT						0.3605***	0.4523***	-0.2400**
						(0.0225)	(0.0458)	(0.0888)
Constant	0.4290***	0.6377***	0.3797***	0.2863***	0.1283	0.4325***	0.5459***	0.3545**
	(0.0991)	(0.1380)	(0.1141)	(0.0579)	(0.0674)	(0.1005)	(0.1358)	(0.1133)
CV	YES	YES	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
N	15426	6025	9401	6636	8790	15426	6025	9401
R^2	0.1684	0.1580	0.1582	0.1404	0.1766	0.1589	0.1563	0.1458

Changing the grouping method

In the previous text, the samples were divided into two groups with high and low environmental regulation levels to test the impact of environmental regulation on the green credit policy and the green technological innovation of enterprises. Here, this paper

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attempts to divide the samples into three groups according to the level of environmental regulation, removes the middle group, and re-tests the two remaining groups. The regression results are shown in columns (1) to (2) of *Table 6*. Under the condition of high environmental regulation level, the regression coefficient of the interaction term is 0.2085, which is significant at the 1% level, and this is greater than the coefficient of 0.1279 in the benchmark regression. Under the condition of low environmental regulation level, the coefficient of the interaction term is -0.0687, which is significant at the 10% level, and this coefficient is smaller than -0.0512 in the benchmark regression. It can be seen that after the samples are divided into three groups, the difference in the interaction terms between the high environmental regulation group and the low environmental regulation group becomes larger. This once again confirms the differential impact of the implementation of the green credit policy on the green technological innovation of heavily polluting enterprises under different environmental regulation levels, and also validates the research conclusions of this paper.

Taking into account the long periodicity of green technological innovation

Considering the long periodicity of green technological innovation, this paper follows the approach of He and Tian (2013) and conducts a lag treatment on the explained variable, green invention patents, for periods (T + 1) and (T + 2). The obtained regression results are shown in columns (3) to (8) of *Table 6*. In the regression results for the period (T + 1) in columns (3) to (5), the coefficients of the interaction terms for the full sample, the high environmental regulation group, and the low environmental regulation group are 0.0718, 0.1346, and -0.0489 respectively. In the regression for the period (T + 2) in columns (6) to (8), the corresponding coefficients are 0.0413, 0.1115, and -0.0397 respectively, and all the above results have passed the significance test. It can be seen that this is basically consistent with the benchmark regression, indicating that after further considering the impact of the long periodicity, the research conclusions in the previous text remain robust.

Table 6. *Robustness test: group replacement and long - term green tech innovation*

	Replace the groups		**T + 1**			**T + 2**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	High ER	**Low ER**	**ALL**	**High ER**	**Low ER**	**ALL**	**High ER**	**Low ER**
DID	0.2085***	-0.0687*	0.0718***	0.1346***	-0.0489**	0.0413***	0.1115***	-0.0397*
	(0.0346)	(0.0335)	(0.0125)	(0.0268)	(0.0190)	(0.0123)	(0.0237)	(0.0184)
Constant	0.7413***	0.3374*	0.2255**	0.2873**	0.2098**	0.2235**	0.2359*	0.1860**
	(0.1453)	(0.1386)	(0.0770)	(0.0955)	(0.0662)	(0.0851)	(0.0922)	(0.0696)
CV	YES	YES	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
N	5168	5114	12409	4996	7413	9848	4201	5647
R^2	0.1605	0.1606	0.1328	0.1171	0.1336	0.1231	0.1058	0.1247

Test of propensity score matching-difference-in-differences (PSM-DID)

Due to the different characteristics of heavily polluting enterprises and non-heavily polluting enterprises, the green technological innovation effect of the green credit policy

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may be caused by the characteristics of the enterprises themselves. In order to control the estimation bias brought about by sample selection, this paper further adopts the Propensity Score Matching-Difference-in-Differences (PSM-DID) method to construct counterfactuals, so as to explore how the green technological innovation of heavily polluting enterprises performs under different environmental regulation levels only after the implementation of the “Guidelines” when other factors remain unchanged. Specifically, enterprise age (AGE), enterprise performance (ROA), enterprise value (TQ), enterprise cash flow (CF), enterprise growth (GROW), the shareholding ratio of the largest shareholder (FIRST), and the regional economic development level (GDP) are selected as characteristic variables. The radius matching method (with a radius of 0.001) is used to estimate the propensity score of each individual through the logit model, and the model is re-estimated after the sample matching. According to the balance test results in *Table 7*, it can be seen that after matching, the mean differences of the characteristic variables of the samples in the treatment group and the control group are no longer significant, and the p > Chi2 value changes from 0.000 to 0.860, which further indicates the rationality of the selection of the matching variables and the matching method. The difference-in-differences regression results of the matched data are shown in *Table 8*. Under the full sample and different environmental regulation levels, the coefficient signs of the interaction terms are consistent with the results of the benchmark regression, and are significant at least at the 5% level, which once again confirms the research conclusions of this paper.

***Table 7.** Balance test of propensity score matching*

		Mean		Deviation		T-test	
		Treatment	**Control**	**Deviation rate**	**Reduction rate**	**T**	**p > t**
AGE	U	2.0770	2.0468	3.8	82.9	2.28	0.022
	M	2.0765	2.0713	0.6		0.36	0.717
ROA	U	0.0408	0.0387	4.1	83.1	2.54	0.011
	M	0.0409	0.0406	0.7		0.38	0.701
TQ	U	2.1786	2.2718	-6.1	89.1	-3.68	0.000
	M	2.1718	2.1616	0.7		0.41	0.684
CF	U	0.0559	0.0366	26.8	98.3	16.27	0.000
	M	0.0558	0.0555	0.4		0.26	0.796
GROW	U	0.6582	0.6172	9.3	92.0	5.59	0.000
	M	0.6574	0.6607	-0.7		-0.40	0.686
FIRST	U	3.4965	3.4711	5.5	98.5	3.34	0.001
	M	3.4966	3.4962	0.1		0.04	0.964
GDP	U	0.1088	0.1073	3.3	93.5	2.01	0.044
	M	0.1089	0.1090	-0.2		-0.12	0.906
p > Chi2	U	0.000					
	M	0.998					

Placebo test

This study conducts a time placebo test from two aspects. On the one hand, in order to reduce the interference of other events on the regression results, this study attempts to

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shorten the sample time window and only retains the data of 2011 and 2012 for the test. The results are shown in columns (1) to (3) of *Table 9*. The coefficient values and significance of the interaction terms are consistent with those of the benchmark regression. Thus, it can be seen that after excluding the interference of other events from 2009 to 2010 and from 2013 to 2016, the regression results are still robust. On the other hand, this paper also follows the approach of Topalova (2010) and assumes that the policy is implemented two years in advance (in 2010), and excludes the sample years after the original policy was promulgated, setting the sample period as 2009-2012. In the regression results of columns (4) to (6) of *Table 9*, the coefficients of the interaction terms in the full sample, the high environmental regulation group, and the low environmental regulation group are all not significant. This indicates that after advancing the time point of the policy promulgation, the green technological innovation activities of heavily polluting enterprises have not been significantly affected, which also, in reverse, demonstrates the effectiveness of the evaluation of the implementation effect of the green credit policy in this paper.

Table 8. *Robustness test: propensity score matching - difference-in-differences*

	PSM-DID		
	(1)	**(2)**	**(3)**
	ALL	**High ER**	**Low ER**
DID	0.0620***	0.1509***	-0.0656**
	(0.0122)	(0.0290)	(0.0201)
Constant	0.1598*	0.2528*	-0.1674
	(0.0732)	(0.1095)	(0.0860)
CV	YES	YES	YES
Regional FE	YES	YES	YES
Time FE	YES	YES	YES
Individual FE	YES	YES	YES
N	11952	4638	7314
R^2	0.1338	0.1298	0.1192

Table 9. *Robustness test: time placebo test*

	Keep only the data of 2011 and 2012			**Implement the policy two years earlier**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	ALL	**High ER**	**Low ER**	**ALL**	**High ER**	**Low ER**
DID	0.0463***	0.0944*	-0.0501*	0.0222	0.0225	-0.0025
	(0.0122)	(0.0409)	(0.0223)	(0.0144)	(0.0122)	(0.0197)
Constant	0.2203*	0.6128***	0.1981	0.1408*	0.0852	0.4922***
	(0.0907)	(0.1532)	(0.1015)	(0.0711)	(0.0771)	(0.1270)
CV	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
N	3756	1183	2573	6428	1825	4603
R^2	0.1101	0.1108	0.1156	0.1181	0.1281	0.1157

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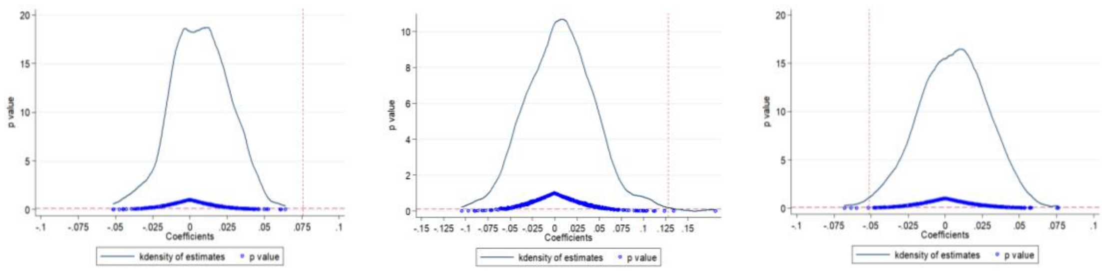
In addition, considering that the treatment group and the control group may be interfered with by other unobservable factors before and after the policy implementation. This paper follows the idea of Li et al. (2021) and conducts a placebo test by randomly selecting the treatment group to construct a “pseudo - policy dummy variable”. First, 550 enterprises are randomly selected and set as the “pseudo” treatment group, and the remaining enterprises are set as the “pseudo” control group, thereby constructing a dummy variable for the placebo test. Second, the abovementioned method is repeated 500 times, and the regression coefficients of the interaction terms from these 500 repetitions are counted. Finally, a scatter plot of the estimated coefficients-P values for the placebo test is drawn based on the 500 regression coefficients. In the placebo test graph, the X-axis represents the magnitude of the estimated coefficients of the “pseudo - policy dummy variable”, and the Y-axis represents the P values. The solid line in the graph represents the distribution of the estimated coefficients in the placebo test, the dots are the P values corresponding to the estimated coefficients in the placebo test, the horizontal dotted line indicates the 10% significance level, and the vertical dotted line represents the true estimated coefficient from the benchmark regression. *Figure 2* shows the scatter plots of the estimated coefficients-P values for the full sample (a), high environmental regulation (b), and low environmental regulation (c) respectively. It can be seen that the estimated coefficients of the regression results are all concentrated around zero, and most of the P values are greater than 0.1. This fully demonstrates that the coefficient estimates of the pseudo policy dummy variable obtained by randomly selecting the treatment group are not significant, indicating that the unobserved random factors will not affect the research conclusions.



(a) (b) (c)

Figure 2. *Scatter plot of estimated coefficients and p-values*

Mechanism test

This study focuses on the impact of external environmental governance factors on the green technological innovation decisions of heavily polluting enterprises. However, the relationship chain between green credit and environmental regulation at the macro-level and enterprise behavior at the micro-level is too long, which may lead to a logical gap. To address this issue, in order to capture the underlying mechanism, based on the theoretical analysis from the two dimensions of capital financing and capital allocation. This section analyzes the causes of the differential impact of the green credit policy on the green technological innovation of heavily polluting enterprises under different environmental regulation levels.

Regarding the capital financing mechanism, this study comprehensively considers methods such as debt financing (DEBT), equity financing (EQ), and commercial credit (COM), while the capital allocation mechanism takes into account environmental

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protection investment (EPI) and R&D expenditure (INNOV). Debt financing (DEBT) is measured by the ratio of the sum of short-term and long-term loans to total assets at the end of the period. Equity financing (EQ) by the ratio of the sum of share capital and capital reserve to total assets at the end of the period. Commercial credit (COM) by the ratio of the sum of accounts payable, notes payable, and advance receipts to total assets at the end of the period. For capital allocation and referring to Xie (2020), 26 items are selected as accounting objects. These items encompass environmental protection facilities and equipment, environmental protection technological transformation, and wastewater treatment facilities, and are sourced from the enterprise's social responsibility, sustainable development, and environmental reports. The purpose of selecting these items is to calculate the environmental investment amount. Environmental protection expenditure (EPI) is measured by the ratio of environmental investment to total assets at the end of the period. Additionally, R&D expenditure (INNOV) is measured by the ratio of R&D expenditure to operating income. Based on this, this section further tests the capital financing and allocation mechanisms through which the green credit policy affects the green technological innovation of heavily polluting enterprises by distinguishing the level of environmental regulation.

Test of the capital financing mechanism

Columns (1) to (3) of *Table 10* report the impact of the implementation of the green credit policy on corporate financing under high environmental regulation. In column (1), the coefficient of the interaction term is -0.0296, which is significant at the 1% level. This indicates that the implementation of the green credit policy significantly inhibits corporate debt financing, which is consistent with the research of Su and Lian (2018). In columns (2) and (3), the coefficients of the interaction terms are both positive but not significant. This shows that enterprises subject to credit constraints will try to find other alternative financing channels. However, under high environmental regulation, the environmental information disclosure of enterprises is relatively complete, and heavily polluting enterprises are gradually exposed to the public. The market's awareness of the pollution attributes of enterprises is also deepening, making it difficult for them to finance through other means. Columns (4) to (6) of *Table 10* present the regression results of the impact of the green credit policy on corporate financing under low environmental regulation. In column (4), the regression coefficient of the interaction term is -0.0089, which is significant at the 5% level, once again verifying the financing constraint effect of green credit policies. However, from the absolute value of the coefficient, the coefficient in the low environmental regulation group is smaller than that in the high environmental regulation group, which may be due to the lack of government environmental regulation support and lower efficiency of green credit allocation. The regression results of columns (5) and (6) show that after the implementation of the green credit policy, the equity financing of heavily polluting enterprises increased by 2.52%, and the commercial credit increased by 9.14%. This indicates that in a relaxed external regulatory environment, heavily polluting enterprises can alleviate their financial pressure through equity financing and commercial credit.

Test of the capital allocation mechanism

Table 11 presents the test results of the capital allocation mechanism through which the green credit policy affects enterprises' green technological innovation under

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different environmental regulations. Columns (1) and (2) show that the coefficients of the interaction terms are 0.2678 and 1.7089 respectively, and both are significant at the 1% level. It can be seen that in the context of high-level environmental regulation, enterprises will actively increase their environmental protection investment and R&D expenditure. However, in columns (3) and (4), the regression coefficients of the interaction terms are significantly negative. That is, under lax environmental regulation, after the implementation of the green credit policy, enterprises' environmental protection investment and R&D expenditure are crowded out.

Table 10. *Mechanism test based on capital financing*

	High ER			**Low ER**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	DEBT	**EQ**	**COM**	**DEBT**	**EQ**	**COM**
DID	-0.0296***	0.0097	0.0023	-0.0089**	0.0252*	0.0914***
	(0.0077)	(0.0135)	(0.0064)	(0.0030)	(0.0105)	(0.0077)
Constant	0.0550*	0.7442***	0.0503**	0.0600***	-0.0515	0.0877***
	(0.0217)	(0.0806)	(0.0171)	(0.0029)	(0.8388)	(0.0163)
CV	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
N	5403	6025	6025	9024	9401	9401
R^2	0.2536	0.1237	0.2112	0.2059	0.1355	0.2052

Table 11. *Mechanism test based on capital allocation*

	High ER		**Low ER**	
	(1)	**(2)**	**(3)**	**(4)**
	EPI	**INNOV**	**EPI**	**INNOV**
DID	0.2678***	1.7089***	-0.5190***	-0.6013*
	(0.0364)	(0.2517)	(0.0301)	(0.2387)
Constant	18.3016***	13.0881***	17.8995***	11.4160***
	(0.1510)	(1.1424)	(0.1183)	(0.9352)
CV	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
N	3269	4565	4730	6121
R^2	0.2038	0.1119	0.1976	0.1917

Heterogeneity test

To further explore the green technological innovation effect of green credit policies, based on existing research, this paper comprehensively considers characteristics such as the property rights nature, scale, and life cycle of enterprises, so as to distinguish which

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type of enterprises is more significantly influenced by green credit policies on their green technological innovation under different regulatory levels.

Heterogeneity in property rights

This paper divides the total sample into three categories: state-owned enterprises, private enterprises, and foreign-funded enterprises, and performs regression estimation for Model (1). The specific results are shown in *Table 12*. As can be seen from Columns (1) to (3) of *Table 12*, when the level of environmental regulation is high, the coefficients of the interaction term DID are all significantly positive at the 1% level, which is consistent with the benchmark regression results. However, in terms of the specific values of the cross-term coefficients, there are differences in policy effects. The cross-term coefficient of foreign-funded enterprises is 0.2034. To comply with local environmental standards, they rely on mature green technology reserves to accelerate technology transfer or R&D investment in China, so the policy effect is the most significant. The regression coefficient of the state-owned enterprise is 0.2027, which is mainly due to its natural mutual assistance relationship with the government, which enables state-owned enterprises to assume more policy responsibilities and social missions. The cross-term coefficient of private enterprises is 0.1184. Although they are highly sensitive to market competition, their policy impact is minimal due to limitations in technology and financing capabilities. When the level of environmental regulation is low, the impacts show obvious differentiation, as shown in Columns (4) to (6). The cross-term coefficient of state-owned enterprises is -0.0255. Since traditional business profits dominate and alternative financing channels are diverse, the crowding-out effect is not significant. The regression coefficient of private enterprises is -0.0834, which is significant at the 1% level. Under the impact of comprehensive financing costs brought by alternative financing channels, the crowding-out effect of green credit policies on their green technological innovation is the most obvious. The cross-term coefficient of foreign-funded enterprises is -0.0522 and does not pass the significance test. Considering that foreign-funded enterprises can avoid environmental costs through transfer pricing and global financing networks, their degree of inhibition is less than that of private enterprises.

Table 12. *Heterogeneity in enterprise property rights*

	High ER			Low ER		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	State-owned	**Private**	**Foreign-funded**	**State-owned**	**Private**	**Foreign-funded**
DID	0.2027***	0.1184***	0.2034***	-0.0255	-0.0834***	-0.0522
	(0.0105)	(0.0268)	(0.0105)	(0.0274)	(0.0199)	(0.0478)
Constant	0.2558	0.2868**	0.6793	0.0779***	0.2701**	0.1777
	(0.1711)	（0.1042）	（0.4683）	(0.0121)	(0.0829)	(0.3021)
CV	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
N	2324	3296	242	4505	4242	427
R^2	0.1338	0.1483	0.1196	0.1794	0.1167	0.1315

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Heterogeneity in scale

To investigate whether there are differences in the green technological innovation effect of the green credit policy under different environmental regulation levels among enterprises of different scales. This paper divides the sample into large scale enterprises and small-scale enterprises using the median of total assets as the boundary and conducts grouped regression. From the regression results in *Table 13*, it can be seen that the coefficient of the interaction term in column (1) is not significant, while the regression coefficient of the interaction term in column (2) is 0.2465, which is significant at the 1% level. This indicates that when the environmental regulation pressure is high, the implementation of the green credit policy significantly improves the green technological innovation level of small-scale enterprises, but has no significant impact on the green technological innovation of large-scale enterprises. This may be because small scale enterprises are more sensitive to market changes and can respond more quickly and seek green transformation projects to drive green technological innovation. In contrast, large scale enterprises have complex internal operation and management systems, with greater difficulty and longer time required for transformation. In addition, the coefficient of the interaction term in column (3) is -0.0954, which is significant at the 1% level, and the coefficient of the interaction term in column (4) is -0.0384, which is significant at the 5% level. It can be seen that under low environmental regulation level, the implementation of the green credit policy inhibits the green technological innovation level of both large scale and small-scale enterprises, which also verifies the robustness of the research conclusions of this paper to a certain extent.

Table 13. *Heterogeneity in enterprise scale*

	High ER		**Low ER**	
	(1)	**(2)**	**(3)**	**(4)**
	Large-scale	**Small-scale**	**Large-scale**	**Small-scale**
DID	0.0529	0.2465***	-0.0954***	-0.0384**
	(0.0755)	(0.0526)	(0.0265)	(0.0119)
	(0.0770)	(0.2504)	(0.1590)	(0.2078)
Constant	0.2225***	0.5187***	0.1394***	0.2331***
	(0.0125)	(0.0187)	(0.0161)	(0.0283)
CV	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
N	2901	3124	4812	4589
R^2	0.1219	0.1890	0.1301	0.1060

Heterogeneity in enterprise life cycle

From the perspective of the enterprise life cycle, there are significant differences in investment and financing strategies, innovation motivation, and innovation willingness at different development stages. Therefore, this paper draws on Dickinson's (2011) cash flow pattern method and divides the enterprise life cycle into three stages: the growth

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stage, the maturity stage, and the decline stage based on the positive-negative combinations of the net cash flows from operating, investing, and financing activities[2]. The regression results are shown in *Table 14*. In the high environmental regulation group in columns (1) to (3), after the implementation of the green credit policy, the green technological innovation level of enterprises in the growth stage increased by 7.19%, and that of enterprises in the maturity stage increased by 19.18%, while the impact on enterprises in the decline stage was not significant. This indicates that under government regulatory pressure, compared with enterprises in the decline stage, the green credit policy significantly promotes the green technological innovation of enterprises in the growth and maturity stages, and the promotion effect is greater for mature enterprises. This is mainly because enterprises in the growth and maturity stages are in a period of rapid development. They are good at seizing opportunities presented by green policies and actively seeking investment opportunities for green transformation, so they have a stronger willingness for green technological innovation. In addition, due to the lack of R&D experience, the innovation success rate of growth stage enterprises is relatively low. However, after accumulating previous innovation experience, the failure probability of mature enterprises is significantly reduced, resulting in a greater improvement in the green technological innovation level. Columns (4) to (6) present the regression results for the low environmental regulation group. The regression coefficients of the interaction terms for enterprises in the growth and maturity stages are -0.0599 and -0.0300 respectively, but neither passes the significance test. The regression coefficient of the interaction term for enterprises in the decline stage is -0.0822, which is significant at the 1% level. It can be seen that in an external environment with low environmental regulation, the green credit policy has a greater crowding out effect on the green technological innovation of enterprises in the decline stage.

Table 14. *Heterogeneity in enterprise life cycle*

	High ER			**Low ER**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Growth	**Maturity**	**Decline**	**Growth**	**Maturity**	**Decline**
DID	0.0719*	0.1918***	-0.0055	-0.0599	-0.0300	-0.0822***
	(0.0351)	(0.0416)	(0.0336)	(0.0349)	(0.0259)	(0.0241)
Constant	0.2478*	0.4563***	0.4331**	0.1103	0.0749	0.2816**
	(0.1196)	(0.1265)	(0.1587)	(0.1116)	(0.0944)	(0.1005)
CV	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
N	2908	2100	1017	4282	3409	1710
R^2	0.1718	0.1578	0.1181	0.1810	0.1607	0.1304

[2] The growth phase is characterized by negative net cash flows from operating and investing activities alongside positive net cash flows from financing activities, reflecting the need for external financing to support expansion. The maturity phase is marked by positive net cash flows from operating activities and negative net cash flows from both investing and financing activities, indicating stable operations and returns to investors. The decline phase is defined by negative net cash flows from operating and financing activities, coupled with positive net cash flows from investing activities (largely dependent on asset disposals), signaling operational recession and rising financial risks.

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Further test

Further test based on the strong porter hypothesis

As shown by the abovementioned tests, under strong environmental regulation, the implementation of the green credit policy promotes the green technological innovation of heavily polluting enterprises, which verifies the Porter Hypothesis. It is worth considering that, due to different degrees of innovation, the Porter Hypothesis is further divided into the "Weak Porter Hypothesis" and the "Strong Porter Hypothesis". The green technological innovation promoted by the implementation of the green credit policy satisfies the Weak Porter Hypothesis. Then, in a strict regulatory environment, will the implementation of the green credit policy ultimately lead to an improvement in enterprise competitiveness or enterprise performance through innovation compensation? That is, does it also realize the Strong Porter Hypothesis?

In response, this paper selects the total factor productivity (TFP) of enterprises as a substitute indicator for enterprise competitiveness and performance, and uses the total factor productivity of enterprises in period T and period T + 1 as the explained variables to conduct a regression on the difference-in-differences model. In addition, for the sake of robustness, the total factor productivity of enterprises measured by the LP method and the OP method is also tested. The regression results are shown in *Table 15.* In columns (1) and (3), the coefficients of the interaction terms are significantly positive, indicating that the implementation of the green credit policy under strict environmental regulation significantly improves the current period total factor productivity of enterprises. In columns (2) and (4), the coefficients of the interaction terms are also positive and significant at the 1% level, and their values are larger than the regression results for the current period total factor productivity. It can be seen that under high level environmental regulation constraints, the green credit policy realizes the Strong Porter Hypothesis.

Table 15. *Further test based on the Porter hypothesis*

	TFP_LP		TFP_OP	
	(1)	(2)	(3)	(4)
	T	T + 1	T	T + 1
DID	0.2130***	0.3132***	0.2201***	0.3030***
	(0.0269)	(0.0255)	(0.0264)	(0.0266)
Constant	7.0758***	7.5042***	6.2541***	6.6689***
	(0.2655)	(0.2330)	(0.2346)	(0.2175)
CV	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
N	5978	4978	5978	4978
R^2	0.4039	0.2314	0.3787	0.2183

Further test based on investment structure

The results of the mechanism test above indicate that in a lax regulatory environment, the restriction of credit financing prompts enterprises to increase noncredit

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financing, and at this time, environmental investment and R&D expenditure are crowded out. According to this logic, the increased equity financing and commercial credit will force enterprises to seek other investment opportunities. Therefore, it is worth further exploring where the funds of heavily polluting enterprises are invested. This paper follows the approach of Jiang et al. (2022) and considers both the financial asset investment and real sector investment of enterprises to identify the specific investment directions. Among them, financial asset investment is measured by the ratio of a firm's financialized assets to total assets. Meanwhile, financial assets are divided into two categories. One is short term financial assets, including trading financial assets (TFA) and derivative financial assets (DFA), and the other is long term financial assets, namely investment real estate (IRE). In terms of real sector investment, the percentages of net inventory (INV), net fixed assets (FIX), and net intangible assets (INTAN) to total assets are selected for measurement.

From the regression results in *Table 16*, it can be seen that in columns (1) to (3), the coefficients of the interaction terms are all significantly positive. This indicates that in a lax regulatory environment, after the implementation of the green credit policy, heavily polluting enterprises will significantly increase their investment in financial assets. Moreover, by comparing the regression coefficient values of different types of financial assets, it is found that the increase in short term financial assets is greater than that in long term financial assets. This may be because the increase in non-credit channel financing raises the comprehensive financing cost of heavily polluting enterprises. To mitigate the adverse impact of the increased financing cost, enterprises tend to invest in financial assets that can yield relatively high returns in the short term. In addition, in columns (4) to (6), the regression results based on real asset investment show that after the implementation of the green credit policy, the inventory investment of heavily polluting enterprises decreases significantly, while there is no obvious change in fixed asset and intangible asset investment. Therefore, it can be known that in a lax environmental regulatory environment, in the face of the financing pressure caused by the green credit policy, heavily polluting enterprises reduce their production scale.

Table 16. *Further test based on investment structure*

	Financial asset investment			**Real sector investment**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	TFA	**DFA**	**IRE**	**INV**	**FIX**	**INTAN**
DID	0.0867*	0.0329*	0.0277***	-1.0774**	-0.1289	0.3369
	(0.0404)	(0.0155)	(0.0023)	(0.3335)	(0.4751)	(0.1990)
Constant	0.3341	0.1391***	0.0400*	16.3531***	22.2816***	4.7133***
	(0.2590)	(0.0104)	(0.0194)	(0.3126)	(0.3454)	(0.1272)
CV	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
N	8580	5289	8897	9390	9401	9401
R^2	0.1053	0.1023	0.1048	0.1180	0.1458	0.1143

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Discussion

The level of environmental regulations has a differentiated impact on the green technology innovation effect of green credit policies

This study analyzes the impact of green credit policies on green technological innovation in heavily polluting enterprises using the difference-in-differences method and finds that the policy's effectiveness significantly depends on the level of environmental regulation. In regions with high-level environmental regulation, green credit policies effectively promote enterprises' green technological innovation. In regions with low-level environmental regulation, however, the policies have a restraining effect. This finding highlights the critical synergistic role of environmental regulation in enhancing the effectiveness of green credit policies, providing an important basis for policy-making.

The mechanisms of capital financing and allocation through which green credit policies influence enterprises' green technological innovation under different levels of environmental regulations

The mechanism test reveals that green credit policies drive green technological innovation by influencing enterprises' capital financing and allocation. Under high-level environmental regulation, the policies restrict the debt financing of polluting enterprises, forcing them to increase investment in environmental protection and R&D expenditure, thereby promoting green technological innovation. In contrast, under low-level environmental regulation, enterprises can alleviate financing pressures through alternative financing channels, leading to a crowding-out effect on environmental protection investment and R&D expenditure. The results of this mechanism test provide an in-depth explanation of the pathways through which green credit policies influence enterprises' green technological innovation under different levels of environmental regulation.

Heterogeneous characteristics of the green technological innovation effect of green credit policies under the influence of environmental regulations

The heterogeneity test shows significant differences in the effectiveness of green credit policies across different enterprise characteristics. Foreign-funded enterprises and state-owned enterprises demonstrate stronger motivation for green technological innovation under high-level environmental regulation, while private enterprises show relatively weaker motivation. Additionally, small-scale enterprises and those in the growth and maturity stages experience significant improvements in green technological innovation under high-level environmental regulation. These findings reveal the important role of enterprise characteristics in influencing the effectiveness of green credit policies and provide a basis for policymakers to adjust policies in a differentiated manner.

The long-term effects and potential risks of green credit policies under the influence of environmental regulations

This study deeply explores the long-term effects and potential risks of green credit policies from the perspectives of the Porter Hypothesis and investment structure. The test based on the Porter Hypothesis shows that under high-level environmental

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regulation, green credit policies not only promote green technological innovation but also enhance enterprises' total factor productivity, verifying the "strong Porter Hypothesis". However, under low-level environmental regulation, the policies lead enterprises to shift funds from the real economy to the virtual economy, increasing investment in financial assets. This finding reveals the risk of "displacement from the real to the virtual economy" that green credit policies may bring when effective environmental regulation is lacking, reminding policymakers to comprehensively consider environmental regulation and policy implementation effects to achieve sustainable development goals.

Conclusion

The green technology innovation effect of green credit policies in the context of China's "shallow green" development is questionable. In this study, the 2012 "Green Credit Guidelines" were used as a quasi-natural experiment, and A-share listed companies from 2009 to 2016 were selected as samples to investigate the differential impact and mechanism of this policy on green technology innovation decisions of heavily polluting enterprises under different environmental regulation levels. The results showed that environmental regulation level significantly moderated the policy effect, while strict regulation promoted green technology innovation of heavily polluting enterprises. Loose regulation inhibited it, and this conclusion still holds true after robustness tests such as variable replacement and grouping replacement. In terms of the mechanism of action, strict regulation forces enterprises to increase environmental protection investment by intensifying credit constraints and blocking non credit financing channels, while loose regulation allows enterprises to obtain financing through alternative channels such as equity and commercial credit, but the increase in financing costs leads to the crowding out of environmental protection expenditures. In addition, the policy effects vary depending on the property rights, scale, and life cycle of enterprises. Under high regulation, policies not only promote green technology innovation, but also improve the total factor productivity of enterprises, verifying the "strong Porter hypothesis". Under loose regulation, enterprises may reduce their production scale in pursuit of short-term performance, and there may be a tendency for investment to shift from real to virtual.

Based on the above analysis, to further stimulate the technological innovation vitality of China's green credit policy, the following policy recommendations are put forward. First, the effective implementation of the green credit policy requires the coordination of environment related policies. Therefore, the government should strengthen top level design to provide institutional guarantees for the implementation of the green credit policy. It should accelerate the improvement of enterprises' environmental information disclosure, build an environmental information sharing platform to reduce information asymmetry in the implementation of green credit, and set different environmental regulation levels and methods for different types of enterprises. Achieving full coordination between the government and the market is the key to making up for market failures and ensuring the long-term effectiveness of the green credit policy. Second, commercial banks should be encouraged, supported, and guided to develop green credit business to give full play to the resource allocation function of the financial market. Commercial banks should continue to increase the scale of green credit, continuously enrich and innovate green credit products and services, and strengthen the credit

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tracking mechanism to avoid the possible “green washing” behavior of enterprises. This ensures the continuity and stability of the technological innovation effect of green credit, enabling green financial tools to play a greater role in promoting the green transformation of enterprises. Third, in the context of the country’s vigorous development of the green and low carbon economy, heavily polluting enterprises should accelerate their adaptation to the new situation of green credit regulation and proactively improve their green technological innovation level. The green credit policy can not only force enterprises to engage in green technological innovation but also ultimately improve their total factor productivity through the innovation compensation effect. Therefore, enterprise management should have a forward-looking understanding of the value of green innovation, reduce resource waste caused by traditional investment projects, and continuously integrate the green concept into enterprise operations, aiming to obtain innovation compensation through green technological innovation.

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REFERENCES

[1] Acemoglu, D. (2002): Directed technical change. – The Review of Economic Studies 69(4): 781-809.
[2] Bartik, T. (1991): Boon or Boondoggle? The Debate Over State and Local Economic Development Policies. – W. E. Upjohn Institute for Employment Research, Kalamazoo, MI.
[3] Bertrand, M., Duflo, E., Mullainathan, S. (2004): How much should we trust differences-in-differences estimates. – The Quarterly Journal of Economics 119(1): 249-275.
[4] Bian, C., Chu, Z. P., Sun, Z. L. (2022): Policy simulation of environmental regulation, green credit and enterprise green technology innovation—from the perspective of evolutionary game of government intervention. – Management Review 34(10): 122-133.
[5] Chen, X. X., Shi, Y. Y., Song, X. Z. (2019): Green credit constraints, trade credit and enterprise environmental governance. – Studies of International Finance 392(12): 13-22.
[6] Chen, Z., Kahn, M. E., Liu, Y., Zhang, L. (2018): The consequences of spatially differentiated water pollution regulation in China. – Journal of Environmental Economics and Management 88: 468-485.
[7] Coase, R. H. (1960): The problem of social cost. – Journal of Law and Economics 3(1): 1-44.
[8] Cui, G. H., Jiang, Y. B. (2019): The impact of environmental regulation on enterprise environmental governance behavior—a quasi-natural experiment based on the new Environmental Protection Law. – Economic Management Journal 41(10): 54-72.
[9] Dickinson, V. (2011): Cash flow patterns as a proxy for firm life cycle. – The Accounting Review 86(6): 1969-1994.
[10] Ding, J. (2019): Green credit policy, credit resource allocation and enterprise strategic response. – Economic Review 218(4): 62-75.
[11] Ding, J., Hu, R. (2020): Regional environmental regulation and the effectiveness of the green credit policy — From the perspective of credit financing of heavily polluting enterprises. – Soft Science 34(12): 61-67.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_74297456

[12] Ding, J., Li, Z. F., Huang, J. B. (2022): Can the green credit policy promote enterprise green innovation?—From the perspective of policy effect differentiation. – Journal of Financial Research (12): 55-73.
[13] Dong, Q. M., Wen, S. Y., Liu, X. L. (2019): Credit allocation, pollution, and sustainable growth: theory and evidence from China. – Emerging Markets Finance and Trade 56(12): 2793-2811.
[14] Guo, J. J., Fang, Y. (2022): Green credit, financing structure and enterprise environmental investment. – The Journal of World Economy 45(8): 57-80.
[15] Haken, H. (1981): Introduction to Synergetics. – Scientific Research Department of Northwest University, Xi'an, pp. 67-73 (translated by Zhang, J. Y., Guo, Z. A.).
[16] He, A. P., An, M. T. (2019): Local government competition, environmental regulation and green development efficiency. – China Population, Resources and Environment 29(3): 21-30.
[17] He, J., Tian, X. (2013): The dark side of analyst coverage: the case of innovation. – Journal of Financial Economics 109: 856-878.
[18] He, L. Y., Liang, X., Yang, X. L., Zhong, Z. Q. (2019): Can green credit promote technological innovation of environmental-protection enterprises? – Studies of Financial Economics 34(5): 109-121.
[19] Hu, G., Wang, X., Wang, Y. (2021): Can the green credit policy stimulate green innovation in heavily polluting enterprises? Evidence from a quasi-natural experiment in China. – Energy Economics 98(3): 105134.
[20] Jiang, P. C., Jiang, H. L., Wu, J. H. (2022): Is inhibition of financialization the sub-effect of the green credit policy? Evidence from China. – Finance Research Letters 47: 102737.
[21] Li, C., Gan, Y. (2021): The spatial spillover effects of green finance on ecological environment — Empirical research based on spatial econometric model. – Environmental Science and Pollution Research 28(5): 5651-5665.
[22] Li, P. S., Chen, Y. Y. (2019): Environmental regulation, enterprise bargaining power and green total factor productivity. – Finance & Trade Economics 40(11): 144-160.
[23] Li, S., Weng, W. G. (2014): China's local environmental regulation and total factor productivity growth—an empirical analysis based on the actual efficiency of local legislation and administrative regulations. – Journal of Finance and Economics 40(2): 19-29.
[24] Li, W. J., Zheng, M. N. (2016): Substantive innovation or strategic innovation?—the impact of macro-industrial policies on micro-enterprise innovation. – Economic Research Journal 51(4): 60-73.
[25] Li, X. X. (2017): Analysis of the relationship between profitability and public-welfare of green finance. – Financial Forum 22(5): 3-11.
[26] Li, Z. H., Liao, G. K., Wang, Z. Z., Liu, X. Q., Chen, Y. F. (2018): Green loan and subsidy for promoting clean production innovation. – Journal of Cleaner Production 187: 421-431.
[27] Liu, X. H., Yuan, Q. J. (2024): Does public environmental concern promote the development of green finance?—Empirical evidence from 284 cities in China. – Audit & Economy Research 39(03): 107-116.
[28] Liu, X. L., Wen, S. Y. (2019): Should China's financial institutions assume environmental responsibilities?—Basic facts, theoretical model and empirical test. – Economic Research Journal 54(3): 38-54.
[29] Lu, J., Yan, Y., Wang, T. X. (2021): Research on the micro-effects of the green credit policy—from the perspectives of technological innovation and resource re-allocation. – China Industrial Economics 394(1): 174-192.
[30] Luo, Z., Qi, B. C. (2021): The industrial transfer and upgrading effect of environmental regulation and the coordinated development effect of banks—evidence from the water pollution control in the Yangtze River Basin. – Economic Research Journal 56(2): 174-189.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_74297456

[31] Myers, S. C., Majluf, N. S. (1984): Corporate financing and investment decisions when firms have information that investors do not have. – Journal of Financial Economics 13(2): 187-221.
[32] Qi, S. Z., Lin, S., Cui, J. B. (2018): Can the environmental rights trading market induce green innovation?—Evidence based on the green patent data of Chinese listed companies. – Economic Research Journal 53(12): 129-143.
[33] Shen, C., Li, S. L., Huang, L. X. (2018): Research on the influence mechanism of heterogeneous environmental regulation on China's industrial green transformation—an empirical analysis based on the mediating effect. – Nankai Economic Studies 203(5): 95-114.
[34] Shen, H. T., Ma, Z. B. (2014): Regional economic development pressure, enterprise environmental performance and debt financing. – Journal of Financial Research 404(2): 153-166.
[35] Song, M., Xie, Q., Shen, Z. (2021): Impact of green credit on high-efficiency utilization of energy in China considering environmental constraints. – Energy Policy 153: 22.
[36] Su, D. W., Lian, L. L. (2018): Does green credit affect the investment and financing behavior of heavily polluting enterprises? – Journal of Financial Research 462(12): 123-137.
[37] Topalova, P. (2010): Factor immobility and regional impacts of trade liberalization: evidence on poverty from India. – American Economic Journal: Applied Economics 2(4): 1-41.
[38] Wang, F. R., Wang, K. S. (2018): "Green" policies and the allocation efficiency of green finance—an empirical study based on Chinese manufacturing listed companies. – Finance & Economics 362(5): 1-14.
[39] Wang, M., Huang, Y. (2015): China's environmental pollution and economic growth. – China Economic Quarterly 14(2): 557-578.
[40] Wang, X., Wang, Y. (2021): Research on the promotion of green innovation by the green credit policy. – Management World 37(6): 173-188 + 11.
[41] Xie, D. M. (2020): Local supervision, vertical supervision and enterprise environmental protection investment—an empirical study based on A-share listed heavily polluting enterprises. – Accounting Research 397(11): 170-186.
[42] Xie, T. T., Liu, J. H. (2019): How does green credit affect China's green economic growth? – China Population, Resources and Environment 29(9): 83-90.
[43] Yang, L. Y., Zhang, Z. Y. (2022): The impact of the green credit policy on enterprise green innovation. – Studies in Science of Science 40(2): 345-356.
[44] Zhang, S., Wu, Z., He, Y., Hao, Y. (2022): How does the green credit policy affect the technological innovation of enterprises? Evidence from China. – Energy Economics 113: 106236.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_74297456