# Green credit policy and corporate climate risk exposure

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# Green Credit Policy and Corporate Climate Risk Exposure

**Abstract:** This paper investigates the effects of green credit policies on corporate climate risk exposure and the underlying mechanisms in China. Our results show that after the introduction of green credit policies, enterprises in polluting industry experienced a notable decline in climate risk compared to their counterparts. Further analysis reveals that the effectiveness of green credit policies in mitigating corporate climate risks can be attributed to their capacity to foster green technological innovation, refine investment strategies, facilitate the process of digitalization, and enhance the visibility of environmental issues among analysts. Moreover, we find that the policy in shaping climate risks varies significantly among firms, with particularly pronounced impacts on financially constrained and state-owned enterprises. This study provides critical insights for policymakers aiming to address climate challenges and bolster green financial strategies.

**Keywords:** Green credit policy; climate risk exposure; Green innovation; China

## 1. Introduction

In recent years, global temperatures have repeatedly reached unprecedented levels, with a corresponding surge in the frequency of extreme weather events. The resulting climate risk continuously impact the operational activities of companies (Pankratz et al., 2023) and the sustainable development capabilities of our society (Monasterolo, 2020; Chen et al., 2023). For instance, extreme high temperatures directly result in diminished labor productivity, escalated operating costs, and reduced total output (Zhang et al., 2018; Somanathan et al., 2021; Pankratz et al., 2023). Additionally, associated transition risks like carbon risk affect corporate capital structure, investment decisions, and market value (Nguyen and Phan, 2020; Berkman et al., 2021; Hsu et al., 2023). Effectively achieve low-carbon transformation and proactively addressing climate risk have become unavoidable challenges for global enterprises and various stakeholders.

Recognizing the externalities of climate risk, relying solely on intensive governance by economic entities proves challenging in achieving long-term sustainable development. Confronted with increasingly severe climate issues, financial policies are imperative to promote environmental governance (Sun et al., 2019; Lamperti et al., 2021). Currently, countries worldwide have introduced considerable policies and emission reduction targets to mitigate the climate crisis (Liu et al., 2020; Ren et al., 2022a). As a participant and contributor to global ecological civilization construction, China actively responds to climate governance. The 20th National Congress of the Communist Party of China explicitly states the necessity of improving the system of green finance, promoting the green and low-carbon economic and social development, and actively engaging in global governance to address climate change. Green finance policy emerges as a crucial climate policy to confront with climate risk and achieve sustainable economic growth. Existing literatures have found that in China, the green credit policy plays a unique role in improving environmental quality (Zhang et al., 2021) and assisting heavily polluting enterprises in green transformation (Fan et al., 2021; Hu et al., 2021). In this study, we focus on analyzing the impact of the Green Credit Guidance, a specific policy within green finance, on the climate risk exposure for companies listed on the A-share market in China.

As a hybrid of traditional finance with environmental protection and sustainable development, green finance not only fulfills the fundamental functions of resource allocation and risk management inherent to finance but also aligns with market-oriented environmental regulatory policies. It encourages green development, plays a vital role in promoting the green and low-carbon transformation of economic structures, and contributes to the prevention and mitigation of climate change risk (Fan et al., 2021; Pástor et al., 2021). China has issued various policies to develop green credit and drive economic transformation. Among them, the "Green Credit Guidelines" issued in January 2012 stands as the cornerstone of China's green credit system. Green credit policies, led by the government, implemented by banks, and targeting enterprises, aim to guide financial resources toward the green and environmental sectors, promoting a shift in model of economic growth and an upgrade in economic structure. Therefore, green credit policies serve the dual function of environmental governance and support the real economy, effectively promoting green economic development, and acting an essential means to address climate change and mitigate climate risks.

Despite relevant authorities have successively issued plenty of documents on green finance and addressing climate risks, effectively managing the practical challenges in these areas remains unclear. Concurrently, research in this field is relatively scarce. Existing literature tends to focus on the impact of green finance policies on corporate behavior, such as influencing financing costs (Wen et al., 2021) and promoting green innovation (Hu et al., 2021; Wang and Li, 2022). Another aspect primarily concentrates on the impact of climate risks on enterprises. The effects of climate change on businesses are highly uncertain (Barnett et al., 2020). Some companies face adverse effects, such as cash shortages and reduced stock returns, due to severe climate events like hurricanes and droughts (Dessaint and Matray, 2017; Hong et al., 2019). Other companies experience impacts on their corporate value originating from climate policy uncertainty, environmental regulations, and low-carbon transformation (Bolton and Kacperczyk, 2021; Duan et al., 2021; Mo and Liu, 2023; Hsu et al., 2023). However, research on the relationship between green finance policies and climate risk is limited, with only a few studies investigating it. Wang et al. (2022a) empirically found that the issuance of green bonds can increase a company's attention to climate risk. Zhang et al. (2022) and Mngumi et al. (2022) found that the development of green finance, an increase in the use of renewable energy, and technological innovation can promote a reduction in carbon dioxide emission, mitigating the adverse effects of climate change. Whether green finance will impact enterprise climate risk and what mechanisms underlie such an impact are two questions worthy of the exploration.

In contrast to previous research examining the relationship between financial development and enterprise-related risks, some distinctive aspects emerge when exploring the link between green finance and corporate climate risk exposure. From the perspective of green finance, on a macro level, the introduction of green credit policy not only channels funds towards green industries but also facilitates the transition of high-pollution enterprises into low-pollution or environmentally friendly enterprises. On a micro level, both financial institutions and enterprises actively embrace environmental and social responsibilities, thereby enhancing their public image. However, this also exacerbates the uncertainty of some enterprises' economical expectation and the climate regulatory risk they encounter during the transition phases (Ilhan et al., 2021). Regarding the corporate climate risk exposure, from a macro perspective, efforts to mitigate the impact of climate risk are increasingly becoming a global corporate governance trend, contributing to the long-term development of human society. On a micro level, corporations actively addressing climate risks and pursuing a low-carbon development path tailored to local conditions serve as crucial drivers to enhance their green reputation and competitiveness. This proactive stance aids in mitigate the adverse effects of climate change, accelerating the carbon reduction process and promoting the green transformation.

Based on this, this paper aims to explore the impact of green finance policy on corporate exposure to climate risk. Specifically, utilizing micro-level data from Chinese A-share listed companies, we observe a significant reduction in climate risk among heavily polluting enterprises after the implementation of green credit policy. After adjusting the measurement of the dependent variable, employing propensity score matching, and conducting placebo tests, our results remain robust. Further mechanistic analysis indicates that green credit policies primarily contribute to lowering corporate climate risk by fostering green technological innovation, enhancing investment efficiency, moderating the pace of digital transformation, and increasing analyst attention. Regarding heterogeneity analysis, we find that the reduction in climate risk is more pronounced in companies facing high financing constraints, exhibiting low financialization and agency cost, boasting larger worforces, being state-owned enterprises, and featuring a higher proportion of independent directors and supervisors.

This paper contributes to existing literature in following aspects. Firstly, it innovatively explores the relationship between green credit policies and corporate climate risk exposure, thereby expanding the economic implications of China's 2012 "Green Credit Guidelines." Previous literatures mainly concentrate on its effects on green innovation (Wang and Li, 2022) and financing constraints (Wen et al., 2021). Our research, however, investigates its impact on corporate climate risk exposure.

Secondly, we contribute to the literature on enterprise risk management, particularly in the context of corporate exposure to climate risk. Existing literature often focuses on the impacts of climate risk on businesses, such as capital structure (Ginglinger and Moreau, 2023), financial income (Pankratz et al., 2023), and stock prices (Giolio et al., 2021). Our research, originating from the green credit policy, reveals a mitigating effect on corporate climate risk.

Thirdly, our study contributes to the analysis of the mechanisms between green credit policies and corporate climate risk exposure through following channels: green technology innovation, investment efficiency, digital transformation, and analyst attention. This provides empirical evidence supporting the macro-level policies effectively influencing the decision-making of micro-level entities. Notably, our study emphasizes the importance of climate risk for firms, aligning with investor expectations and concerns regarding climate change (Choi et al., 2020; Krueger et al., 2020).

The remaining sections of this paper are organized as follows. In Section 2, we conduct a literature review and propose our research hypotheses. Section 3 introduces the data sources and research design. Section 4 presents our main empirical findings. Section 5 provides the conclusion of the paper.

## 2. Theoretical analysis and hypothesis

It is acknowledged that the losses and impacts brought to the real economy by climate change are increasingly evident. It brings serious adverse effects to the business development, prompting firms to take proactive measures to undertake corresponding risk (Huang et al., 2018; Xu et al., 2022; Zhang and Zhang, 2023). As an important financial regulatory instrument driving green development, green credit policies gradually influence the operational decisions and governance behavior of enterprises (Fan et al., 2021).

Green credit guides fund allocation to achieve sustainable economic development. Specifically, the green credit policy influences corporate production and development decisions through credit channels, achieving a harmonious coexistence of economic development and environmental protection. Green credit offers preferential low-interest rates and higher credit quotas to the green ecological industry, while imposing high-interest rates and lower credit quotas on heavily polluting enterprises. Faced with the dual constraints of credit costs and quotas, managers of heavily polluting enterprises, in order to fully benefit from policy dividends, increase environmental governance investment for green transformation (Begum et al., 2022), continuously aligning themselves with the environmentally friendly production sector.

Green credit serves as a catalyst, stimulating the enthusiasm of heavily polluting enterprises towards adopting environmentally sustainable practices. By guiding the allocation of funds, it steers these enterprises towards embracing greener production methods. This guidance fosters a proactive approach to pollution prevention at the source and encourages investment in green technological innovation, as highlighted in the work of (Sun et al., 2019). Furthermore, the implementation of an elevated credit threshold diminishes the accessibility of credit funds for polluting enterprises, thereby severing a portion of the funding chain associated with "two highs and one leftover" industries. Subsequently, companies may opt to curtail free cash flow and overall investment expenditures. In the pursuit of enhancing investment efficacy, heavily polluting enterprises are prompted to scale back investment allocations towards pollution-centric projects while augmenting the allocation towards green initiatives. This strategic realignment underscores their commitment to pursuing green transformation actively.

Given that the green credit policy leverages fund allocation to achieve green and low-carbon goals, the government continuously encourage financial institutions to engage in green credit businesses. This strategic approach sends a clear signal to enterprises or other stakeholders, fostering an environment conductive to green development and contributing significantly to the realization of ecological governance goals. Therefore, companies undertake structural optimizations and operational transformation aimed at reducing energy consumption and fulfilling their social responsibility by adhering to regulatory behaviors. Drawing upon signal theory, such actions effectively communicate a commitment to sustainable development to the market, thereby garnering favor from investors who prioritize social responsibility, as discussed by (Tang and Zhang, 2020). As entities that balance economic benefits and environmental benefits (Sangiorgi and Schopohl, 2021), the engagement of green investors assists companies in mitigating risks, improving financial performance, and increasing analysts' optimistic expectations of the company. This, in turn, serves as a catalyst for heavily polluting enterprises to voluntarily transition towards green industries, fostering the establishment of a favorable reputation and corporate image. Consequently, this endeavor not only aids in mitigating climate risks but also catalyzes the long-term development of enterprises.

Overall, the green credit policy presents a promising approach to addressing climate change. This policy offers the potential to mitigate corporate climate risk by catalyzing green technology innovation, optimizing investment efficiency, driving digital transformation and drawing heightened attention from analysts. In light of these considerations, this paper proposes hypothesis H1.

Hypothesis H1: The green credit policy could help to decrease the climate risk exposure of polluting firms.

## 3. Data, variables and methodology

### 3.1 Data

This study focuses on all Chinese A-share listed companies from 2004 to 2022. The data for this research are primarily sourced from two main components: first, accounting information, stock returns, and company characteristics are obtained from the China Stock Market and Accounting Research (CSMAR) database; second, data on the number of patent applications and utility model grants are acquired from the China National Research Data Service (CNRDS) platform. Following the approach of Wang and Li (2020), this study matches the obtained data with the International Patent Classification Green List (WIPO) to derive green patent data. Adhering to existing practices in the literature, we exclude observations from abnormal trading listed companies, financial sector companies, and companies with missing control variable information. In this paper, all control variables are winsorized at the 1% and 99% levels. Ultimately, the study comprises 30,121 annual observations.

3.2 Climate risk exposure

Unlike some directly measurable traditional risks, climate risk possesses certain unique characteristics. Current measurements of climate risk by foreign scholars primarily involve keyword-based text analysis (Engle et al., 2020), the construction of virtual variables based on climate risk disclosure (Berkman et al., 2021), and the use of third-party physical climate data (Ginglinger and Moreau, 2019). However, these indicators may pose applicability issues at the enterprise level. Climate risk is generally categorized into physical risk and transition risk (Wang et al., 2022a); in this study, our focus is primarily on the latter. Transition risk-driving factors, such as changes in climate-related policies or technologies, may impact a company's stock returns, exposing its assets to climate risk.

This study defines climate risk exposure as the sensitivity of a company's stock returns to the uncertainty of climate policies, considering it the climate risk faced by the enterprise. While some of the related literature uses machine learning keyword discovery algorithms to measure corporate climate risk exposure (Sautner et al., 2023; Li and Zhang, 2023), there is currently no literature constructing an enterprise-level climate policy uncertainty exposure index. Referring to the literature on constructing economic policy uncertainty exposure at the enterprise level (Bali et al., 2017; Cheng et al., 2021), this paper constructs climate policy uncertainty exposure (climate policy uncertainty exposure, CPUE) as a proxy for enterprise climate risk exposure. Specifically, we use a rolling regression with a 36-month window period:

$$R_{i,\tau} - r_{f,\tau} = \beta_0 + \beta_{i,\tau}^{mkt} MKT_\tau + \beta_{i,\tau}^{smb} SMB_\tau + \beta_{i,\tau}^{hml} HML_\tau + \beta_{i,\tau}^{cpu} CPU_\tau + \varepsilon_{i,\tau} \tag{1}$$

In the above equation, $R_{i,\tau} - r_{f,\tau}$ represents the excess return of stock i in month $\tau$. $MKT_\tau$, $SMB_\tau$ and $HML_\tau$ are the three factors in the Fama–French three-factor model (Fama & French, 1993). $CPU_\tau$ [1]denotes the climate policy uncertainty index in month $\tau$. The coefficient $\beta_{i,\tau}^{cpu}$ signifies the sensitivity of stock I to $CPU_\tau$, which is our primary focus and serves as the explanatory variable indicator (CPUE) in this study.

A negative $\beta_{i,\tau}^{cpu}$ implies that when the CPU increases, the stock returns of the company will decrease (Pástor and Veronesi, 2013). Generally, when a stock's $\beta_{i,\tau}^{cpu}$ is positive, it indicates a strong ability to hedge

[1] The data on the climate policy uncertainty index are available at http://www.policyuncertainty.com/.

against the risk of rising CPU (Bali et al., 2017; Cui et al., 2021). To facilitate the measurement of corporate climate risk exposure, we use the negative results obtained to assess the climate risk faced by the companies. [2]The monthly climate policy uncertainty exposure data are aggregated and averaged to represent the annual climate risk exposure for each enterprise.

3.3 Empirical methodology

This study develops a differences-in-differences framework to investigate the impact of green credit policy on corporate climate risk exposure. The baseline regression model is as follows.

$$CPUE_{i,t} = \beta_0 + \beta_1 did_{i,t} + \gamma Control_{i,t} + \lambda_t + \mu_j + \varepsilon_{i,t} \tag{2}$$

where $CPUE_{i,t}$ represents the climate risk exposure of the firm, indicating the sensitivity of the stock returns to climate policy uncertainty. $did_{i,t}$ is the interaction term between green credit policy and the industry attributes of the enterprise ($Policy_t \times Treat_j$). $Policy_t$ is a dummy variable representing the pre- and postimplementation periods of the guidelines, taking the value of 1 for the postimplementation period (2012 onwards) and 0 for the preimplementation period (before 2012). $Treat_j$ is a dummy variable that distinguishes whether an enterprise is subject to green credit policy restrictions and utilizes industry-level variation to determine the degree of policy impact. Specifically, we classify enterprises into heavily polluting and nonheavily polluting enterprises based on their industry pollutant emissions. When a company is a heavily polluting enterprise, $Treat_j$ is assigned a value of 1, representing the treatment group in this study. Conversely, when a company is a nonheavily polluting enterprise, the value is set to 0, indicating the control group in this study. $Control_{i,t}$ represents all the control variables we introduced by referencing relevant literature (Krueger, 2020; Wang et al., 2022a; Ren et al., 2022b). These variables include common company characteristic variables such as firm size, leverage, return on assets, cash flow, age of listing, book-to-market ratio, Tobin's q, state ownership, institutional investor ownership, and opacity. The model incorporates industry fixed effects $\mu_j$ and year fixed effects $\lambda_t$, employing a two-way fixed effects panel model for empirical analysis, with clustered standard errors at the enterprise level. The coefficient we interest is the $did_{i,t}$ variable, and a significantly negative coefficient indicates that the implementation of green credit policy significantly contributes to reducing corporate climate risk.

## 4. Empirical results

4.1 Descriptive statistics

[2] For explanatory purposes, we multiply CPUE with 1000.

The descriptive statistical results of the variables in the baseline regression are shown in Table 1. As shown, the mean value of the CPUE is -0.028, specifically, with a minimum value of -21.990 and a maximum value of 24.045, suggesting that firms' climate risks are markedly different from those of other firms.

***<Insert Table 1 about Here>***

4.2 Correlation analysis

Table 2 provides the correlation coefficients among the variables used in the baseline regression. As shown, all correlation coefficients are below 0.6 in absolute value, indicating little concern about significant multicollinearity.

***<Insert Table 2 about Here>***

4.3 Parallel trend test

Figure 1 displays the parallel trends test results for the DID model used in this study. As illustrated in Figure 1, prior to the year 2012, the coefficients of the did variable are mostly nonsignificant, suggesting that the outcomes of our treatment and control groups exhibit similar trends before the intervention. This observation satisfies the parallel trends assumption (He and Wang, 2017). Following the implementation of the policy, the coefficients of "current" and "post_1" are both significantly negative, indicating a substantial reduction in climate risk for enterprises after the introduction of the Green Credit Policy. Subsequent years show positive effects. However, these effects are not statistically significant. Regarding pre_1, there is a downward trend because, prior to 2012, as early as 1992, the United Nations signed the "Climate Change Convention" to address the adverse effects of global warming. Subsequent agreements such as the "Kyoto Protocol" underscore the international commitment to addressing climate change. As we mentioned in the paper, countries frequently emphasize the need for sustainable development, and the introduction of green credit policies amplifies this requirement, which is also our much more primary focus.

***<Insert Figure 1 about Here>***

4.4 Baseline regression

This paper adopts the difference-in-differences (DID) method, which is mainly interested in the changes in climate risk of heavily polluting enterprises relative to other enterprises before and after the promulgation of the Green Credit Guidelines; in other words, the DID method calculates the coefficient of the interaction variable (did) in the model. Table 3 reports the regression results for the effect of the Green Credit policy on corporate climate risk exposure. Column (1) reports the regression results without adding control variables, while column (2) reports the regression results with the addition of control variables. Across different model specifications, the coefficients of the "did" variable are consistently negative at a significance level of 5%. Accordingly, we would like to state that, regardless of whether enterprise-level control variables are included, the implementation of the Green Credit policy has visibly reduced the climate risk of heavily polluting enterprises. The empirical evidence supports Hypothesis H1. [3]Taking column (2) as an example, after the implementation of the green credit policy, for every 1% increase in the standard deviation of the variable indicating heavy-polluting enterprises, the magnitude of companies' climate risk decreases by 14.5% relative to its mean, demonstrating significant economic significance.

***<Insert Table 3 about Here>***

4.5 Robustness check

This section employs various robustness checks and additional analyses to ensure the reliability and validity of the findings obtained from the baseline regression model, which investigates the impact of green credit policy implementation on corporate climate risk. The following methods are employed to enhance the robustness of the study.

First, we adjust the calculation method of the dependent variable. The Fama-French three-factor model was replaced with the Fama-French five-factor model, and the climate risk exposure index was recalculated for regression. Table 4 column (1) reports the regression results. Column (1) shows that the coefficient is significantly negative at the 1% level. [4]After the implementation of the green credit policy, the climate risk for heavy-polluting enterprises will decrease by 21.4%.

Second, we adopt the PSM-DID method. Considering the potential sample selection issues in the previous model, we further utilized the propensity score matching (PSM) method to rematch the experimental group with the control group to reduce sample selection bias. Specifically, 1:4 nearest neighbor matching, kernel matching, and radius matching methods are applied, with enterprise size and other control

[3] 14.5% is calculated as 0.0664*0.380/0.174, where 0.0664 is the estimated coefficient of did in Column (2) of Table 3, 0.380 is the standard deviation of did, and 0.174 is the mean of did.

[4] 21.4% is calculated as 0.0982*0.380/0.174, where 0.0982 is the estimated coefficient of did in Column (1) of Table 4, 0.380 is the standard deviation of did, and 0.174 is the mean of did.

variables serving as covariates for matching. Propensity scores are computed using a logit model for all companies in the full sample. The previous DID model was chosen for retesting. Columns (2)-(4) of Table 4 report the results of the regression. As shown in Table 4, the coefficients remain significantly negative at the 5% level, and the economic significance is generally consistent with the baseline regression. This indicates that the implementation of the green credit policy has indeed reduced corporate climate risk.

***<Insert Table 4 about Here>***

Third, given that the policy shock may not be strictly random, we use the placebo test. We employed two methods for placebo testing. (1) Advance the occurrence time of the policy. Considering that our results may have been caused by other events before the promulgation of the Green Credit Guidelines, we advanced the implementation of the policy by 3 and 4 years, respectively, and 2009 and 2008 were selected as the times of virtual policy occurrence. Table 5 reports the results of the placebo test. In columns (1) and (2) of Table 5, the results indicate that the coefficients of the interaction term are not statistically significant, indicating that virtual policy shocks do not have an impact on corporate climate risk. (2) Patients were randomly divided into experimental groups. We randomly selected 500 times for the interaction term. The coefficient distribution chart, illustrated in coefficient distribution plots, demonstrates a mean close to 0 and a distribution that does not cover the true value. Furthermore, the estimated coefficients generally follow a normal distribution. Hence, our research on these policies has neither been accidental nor caused by other policies or interference factors, reinforcing the robustness of the baseline results mentioned above.

***<Insert Table 5 about Here>***

***<Insert Figure 2 about Here>***

4.6 Mechanism analysis

Based on the above results, this paper finds that the implementation of green credit policies has reduced the corporate climate risk, and this conclusion is robust and credible. However, the specific operational mechanisms behind this impact have not been fully explored. Therefore, this section empirically identifies potential channels in the relationship between green credit policies and the exposure of corporate climate risk. To do so, the paper establishes the following models to test possible mechanisms.

$$did_{i,t} = \delta_0 + \delta_1 channel_{i,t} + \delta_2 Control_{i,t} + \lambda_t + \mu_j + \varepsilon_{i,t} \quad (3)$$

Where $channel_{i,t}$ is the potential mediating mechanism, and other variables are the same as in model (2). If $\delta_1$ is significant, it indicates that the mechanism is established.

4.6.1 Channel 1: green technology innovation

Facing the rapid deterioration of the climate environment, numerous studies point that enterprises engaging in green technological innovation contribute to addressing climate risk (Hu et al., 2021; Wang and Li, 2022). But undertaking green innovation activities faces significant potential risks. Moreover, green innovation activities have long return period and strong environmental externalities, necessitating sustained and long-term financial support (Huang et al., 2019). Meanwhile, China's financial system has traditionally been dominated by indirect financing (mainly through banks), coupled with limited internal financing for businesses. Bank credit has gradually become a crucial source of funds for corporate innovation activities. The introduction of green credit policy directly imposes requirements on businesses for green transformation. The Porter hypothesis suggests that in the face of intensified environmental regulations, firms are likely to increase their research and development innovation efforts (Porter and Linde, 1995). Green credit aims to provide financial support to the environmental protection industry while restricting loans to heavily polluting sectors. This differentiated credit policy is a concrete manifestation of environmental regulations in the financial market.

Under the influence of the green credit policy, on the one hand, financial institutions, in allocating funds to heavily polluting industries, may force them to undergo green transformation by increasing credit costs (Hoepner et al., 2016) and reducing credit scales, thereby encouraging investments in green technological innovation (Wen et al., 2021). On the other hand, for environmental enterprises, green credit supports their green development. Financial institutions provide ample funds at lower credit rates, alleviating the challenge of high investment required for green innovation. This, in turn, increases the scale of credit acquisition for environmental firms and reduces credit costs (Wen et al., 2021), and encouraging them to take green technological innovation.

To test this mechanism, referring to previous studies on the treatment of green innovation (Wang and Li, 2022), we use the number of green patent applications and granted patents to measure corporate green innovation. Table 6 reports the regression results of the impact of green credit policy on green technological innovation in columns (1)-(6). It can be observed that in all six regressions, the coefficient of the "did" is positive, indicating that the green credit policy has a promoting effect on green technological innovation in heavily polluting enterprises. In the first three regressions, the coefficient passes the significance test, indicating that the implementation of the green credit policy significantly increases the number of green patent applications in heavily polluting enterprises. In column (5), the coefficient does not pass the significance test, suggesting that the increase in the number of green invention patent grants in heavily polluting enterprises is not significant. However, in columns (4) and (6), the coefficient is significantly positive at the 1% level, with coefficients of 0.1611 and 0.1374, respectively. This implies that after the implementation of the green credit policy, the total number of green patent grants in the heavily polluting industry increases by 16.11%, and the number of green utility model patent grants increases by 13.74%. In conclusion, the implementation of the green credit policy has promoted green technological innovation in heavily polluting enterprises.

4.6.2 Channel 2: investment efficiency

Moreover, the introduction of green credit policies may drive improvements in corporate investment efficiency. From the perspective of principal-agent dynamics, green credit policy adds green requirements upon traditional credit. This raises the loan threshold for heavily polluting enterprises. Simultaneously, with the escalating issues of climate change, there is a gradual enhancement of environmental awareness across society. Consequently, heavily polluting enterprises face increasing financing constraints, leading to a reduction in their disposable free cash flow (Ren et al., 2022b). Change in bank credit funds can influence corporate investment behaviors. Facing high-cost environmental regulations, companies become more sensitive to the availability of internal cash flows (Zhao et al., 2023). Shareholders and managers jointly intensify their awareness of green investment and consider sustainable transformation. From the perspective of credit allocation, green credit policy, by configuring credit funds, internalize the negative externalities of corporate pollution behavior, elevating the opportunity cost of environmentally harmful production for companies (Zahan et al., 2021). To avoid the generation of opportunity costs and internalize the social costs of pollution, companies enhance their green performance, seeking transformation and consequently boosting investment efficiency (Zahan et al., 2021).

To examine this potential channel, [5]we follow Richardson's (2006) model for measuring investment

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[5] $Inv_{i,t}$ represents the actual new investment expenditure of enterprise i in year t, calculated as the difference between total investment and maintenance investment divided by total assets at the beginning of the year. Total investment includes capital expenditure, merger and acquisition expenditure, and research and development expenditure, while maintenance investment includes asset disposal gains and reset investments. $Growth_{i,t-1}$ is the revenue growth rate from the previous period,

efficiency with $Inv_{i,t} = \alpha_0 + \alpha_1 Growth_{i,t-1} + \alpha_2 Cash_{i,t-1} + \alpha_3 Age_{i,t-1} + \alpha_4 Size_{i,t-1} + \alpha_5 Return_{i,t-1} + \alpha_6 Inv_{i,t-1} + \Sigma Year + \Sigma Ind + \nu_{i,t}$. We use the absolute value of the model's regression residuals to measure investment efficiency, denoted as "InefficInvestDegree." This variable reflects the degree of inefficiency in a firm's investment. Notably, since InefficInvestSign is a dummy variable, we estimate it using the logit method during regression. Considering the possibility of both overinvestment and underinvestment by firms, following Richardson (2006), this study defines the variable InefficInvestSign. If the regression residual from Model (5) is greater than 0, InefficInvestSign takes the value of 1, indicating overinvestment; otherwise, it takes the value of 0, indicating underinvestment. Table 6 reports the regression results in columns (7)-(8). It can be observed that after the implementation of green credit policies, the level of inefficient investment by companies significantly decreases, with a reduction of 51.9% in overinvestment, leading to an improvement in investment efficiency.

4.6.3 Channel 3: digital transformation

Additionally, digital transformation is one of the most influential trends shaping corporate development currently (George et al., 2020) and plays an important role in improving environmental performance. Green credit incorporates ecological environmental elements into financial decisions, sending a signal to enterprises about green development, with carbon reduction gradually becoming a main point of corporate management. In this context, achieving digital transformation has potential emission reduction effects (Shapiro and Walker, 2018). At the macro level, the penetration and application of digital technologies such as Information and Communication Technology (ICT) enable relevant entities to access environmental information such as corporate energy consumption and carbon emissions. This allows real-time tracking and supervision, addressing pollution control issues in the production process promptly. It achieves greening through digitization, enhancing the capacity and resilience in addressing climate change. At the micro level, if corporates leverage ICT or employ robots for production process automation, achieving refined management in each step and optimizing production structures, it can reduce energy consumption in the manufacturing process, contributing to the process of reducing carbon emissions and improving energy efficiency (Lange et al., 2020; Huang et al., 2022).

To identify the role of digital transformation, drawing on the study by Jiang et al. (2022), this paper

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$Cash_{i,t-1}$ is the cash assets from the previous period, $Age_{i,t-1}$ is the company's age from the previous period, $Size_{i,t-1}$ is the asset size from the previous period, $Return_{i,t-1}$ is the annual stock return rate from the previous period, and $Inv_{i,t-1}$ is the previous period's new investment. $\Sigma Year$ and $\Sigma Ind$ represent yearly and industry dummy variables, respectively.

characterizes the degree of digital transformation from the perspective of frequency statistics of terms related to digital transformation in the annual reports of listed companies. Table 6 reports the regression results in the column (9). The coefficient is significantly negative at the 5% level, indicating that the degree of digital transformation of enterprises has decreased by 29.4%. This is because digital transformation requires a substantial amount of funding and resources and green transformation is also a high-cost activity as mentioned earlier. To achieve both digital and green transformations, enterprises need sufficiently abundant resources. From the perspective of fund displacement effects, in the context of increasing global climate change concerns and continuous emphasis on green development in national policies, compared to digital transformation, enterprises are more inclined to increase green investments to achieve green transformation, indirectly suppressing digital transformation.

#### 4.6.4 Channel 4: analyst attention

It is well known that analysts serving as crucial information intermediaries in the external market, can influence companies’ investment and financing decisions (Guo et al., 2019). They exert a certain level of supervision and constraint on companies (Chen et al., 2015). From the perspective of signaling theory, in the context of green credit policy, analysts may increase their attention to companies’ pollution behavior, social responsibility, and climate risk disclosure (Schiemann and Tietmeyer, 2022). The heightened attention increases the supervisory pressure faced by heavily polluting enterprises. This prompts managers to make decisions that better align with market expectations, with green transformation being a significant aspect.

Based on the external corporate governance theory, heavily polluting enterprises engage in green activities, as a positive externality, signals to the market the company's commitment to low-carbon transformation. This attracts the long-term attention and stock holdings from investors and institutional investors who embrace green principles (Flammer, 2021), along with increased attention from analysts. In this scenario, analysts are inclined to make optimistic predictions about the company, contributing to stock price increases (Tsang et al., 2022). Although the possibility of greenwashing activities, such as companies make false green marketing to attract attention (Zhang, 2023), analysts tracking the company's green governance process significantly reduces the extent of greenwashing (Liu et al., 2023). This is because analysts play a role in reducing information asymmetry between companies and the public, simultaneously exert supervision and constraint. As a result, companies regulate their behavior, actively assume social responsibility, enhance their green reputation, and mitigate the negative impacts of risk events.

To verify our hypothesis, we measure analyst attention by taking the logarithm of the sum of one and the number of securities analysts providing investment ratings and earnings forecasts for each company annually. Table 6 reports the regression results in the column (10). After the implementation of the green credit policy, analyst attention to heavily polluting enterprises increases by 15.3%. The increase in analyst attention often plays a supervisory and constraining role in corporate governance. In the context of green development, this, in turn, promotes enterprises to regulate their behavior, engage in innovative activities, and drive the realization of green transformation.

***<Insert Table 6 about Here>***

4.7 Heterogeneity analysis

In this section, we further discuss the potential heterogeneity results based on differences in corporate characteristics.

4.7.1 Financing constraints

Firstly, we identify the impact of the green credit policy on the climate risk of enterprises with varying financing constraints. Table 7 reports our results. For the sample of companies with low financing constraints, the coefficient of the did variable, while negative, is not significant. However, in the sample with high financing constraints, the coefficient is significantly negative at the 1% level. From an economic perspective, on average, for companies facing higher financing constraints, the implementation of green credit policy leads to a 34.8% reduction in climate risks. This indicates a stronger impact of green credit policy on lowering climate risks for such businesses, providing a valuable complement to our earlier discussions on the underlying mechanisms. Specifically, heavily polluting enterprises with high financing constraints lack internal cash flow and find it difficult to obtain sufficient external financing (Nguyen and Phan, 2020); however, the green credit policy further strengthens financing constraints. Therefore, enterprises will actively carry out pollution control to achieve green transformation to gain financial support and sustainable development.

***<Insert Table 7 about Here>***

4.7.2 Financialization level

Secondly, we categorize the sample into low-financialization and high-financialization groups to investigate the influence of the green credit policy on the climate risk of enterprises. To measure the level of financialization, we adopt the methodology proposed by Demir (2009), utilizing the proportion of financial assets held by the firm as an indicator of the degree of financialization. Table 8 reports the results. For the sample with high financial support, the coefficient of the did variable is not significant. In contrast, it is plainly negative in the low financialization sample. In economic terms, for companies with high-financialization, the implementation of green credit policy results in a 20.8% reduction in climate risks. Drawing from reservoir theory, a higher degree of financialization in enterprises implies an expanded portfolio of financial assets and enhanced resilience against risks, thus making them less sensitive to the impacts of green credit policies.

***<Insert Table 8 about Here>***

4.7.3 Agency cost

Thirdly, we take the asset turnover rate as the first type of agency cost and the level of capital occupation by major shareholders as the second type of agency cost to examine the impact of the green credit policy on enterprises' climate risk at different agency cost levels. Table 9 shows the results. According to columns (1) and (2), in the sample group with higher asset turnover and lower agency costs, the coefficient of the did variable is significantly negative. From columns (3) and (4), we find in the sample group with fewer funds occupied by large shareholders, the coefficient is negative. Taking the example of column (3), from an economic standpoint, for companies with minimal capital occupation by major shareholders, the implementation of green credit policy results in a 22.4% reduction in climate risks. Our finding underscores how reduced agency costs enhance the positive impact of green credit policy on climate risk reduction. The less capital occupied by major shareholders, the smaller the agency conflict and the lower the agency costs of the firm., leading to a lower level of inefficient investments, aligning with the earlier-discussed mechanism of investment efficiency.

***<Insert Table 9 about Here>***

4.7.4 Number of employees in enterprises

Fourthly, considering the high correlation between employee scale and business development, we group the sample into enterprises with fewer employees and more employees. Table 10 shows the results. With more employees, the coefficient is significantly negative, revealing a more pronounced effect of the Green

Credit policy on decreasing corporate climate risk for enterprises with more employees. In economic terms, for companies with a larger number of employees, the implementation of green credit policy results in a 28.3% reduction in climate risks. Generally, the number of employees in a company is mostly positively related to its size. Firms with more employees often possess more abundant resources, more robust infrastructure, and more sophisticated technology and are better equipped to conduct research activities such as green innovation. Additionally, a larger employee scale also means greater electricity consumption (Wang et al., 2022b), prompting these firms to be more conscious of energy efficiency and climate risk management.

***<Insert Table 10 about Here>***

4.7.5 Property right nature

Next, we divide the sample into state-owned enterprises and non-state-owned enterprises to discuss the impact of the green credit policy on their climate risk. According to the results reported in Table 11, we see that the coefficient is not significant for the sample of non-state-owned enterprises, while it is significantly negative for the sample of state-owned enterprises. From an economic standpoint, for state-owned enterprises, the implementation of green credit policies results in a 19.1% reduction in climate risks. Given the richer resources, enhanced responsiveness to policy cues, and amplified societal obligations that state-owned enterprises bear (Lin and Wu, 2022), they naturally exhibit a heightened capability and incentive to tackle and navigate climate-related challenges. In response to climate change, it is vital to give full scope to the state-owned enterprises in transitioning development modes and achieving high-quality economic growth, supporting green development.

***<Insert Table 11 about Here>***

4.7.6 Percentage of independent directors and number of supervisors

We choose the proportion of independent directors and the number of supervisors to group the sample to investigate the impact of the green credit policy on corporate climate risk. Table 12 reports the results. In columns (1) and (3), the coefficients are negative but not significant for the groups with a low proportion of sole directors and fewer supervisors. Conversely, for the groups with a high proportion of sole directors and more supervisors, the coefficients are negative and pass the significance test. From an economic perspective, for enterprises with more independent directors and more supervisors, the implementation of the green credit policy results in a respective reduction of 20.2% and 17.9% in climate risks separately. Firms with more robust corporate governance structures have more positive responses to green credit policy. The green credit policy has a more expressive impact on diminishing climate risk for such enterprises. Because independent directors and supervisory boards play supervisory and managerial roles in enterprises' decision-making and deputy activities. The more they are, the more enterprises can engage in positive social responsibility actions, thereby improving environmental performance.

***<Insert Table 12 about Here>***

## 5. Conclusion

This study takes the introduction of China's "Green Credit Guidelines" in 2012 as a starting point and employs panel data from Chinese A-share listed companies spanning from 2004 to 2022 to investigate the influence of the Green Credit Policy on CER exposure. This research further analyses the inherent mechanisms involved. Heterogeneity analysis was also performed. We conceptualize climate risk exposure as the challenges faced by enterprises due to climate-related factors. Empirical results reveal several key findings. First, after the implementation of the Green Credit Policy, the climate risk of heavily polluting enterprises significantly decreased compared to that in the pre policy period. Second, the reduction in climate risk is attributed to the green credit policy stimulating green technological innovation, enhancing investment efficiency, reducing digital transformation costs, and increasing analyst attention. Third, heterogeneity analysis demonstrates that the magnitude of the reduction in climate risk varies for heavily polluting enterprises with different characteristics. The impact of the Green Credit policy is more pronounced for heavily polluting enterprises with high financing constraints, while its effect is less significant for those with high financialization levels and high agency costs than for those with low financialization levels and low agency costs. The influence of the Green Credit policy on climate risk is more evident in state-owned enterprises and companies with a high number of employees, a high proportion of independent directors, and a large number of supervisors. Finally, after conducting a series of robustness tests, the results of this study remain robust.

In conclusion, our study innovatively analyses the relationship between green credit policy and corporate climate risk exposure, systematically examining the nature of their connection and the underlying mechanisms involved. This approach tentatively dissects the internal logic between green financial policy and climate risk. Ultimately, this paper provides new evidence on the impact of green credit on corporate climate risk, contributing to the policy significance of national climate adaptation and mitigation efforts. Simultaneously, this study offers new insights for financial markets in addressing climate risk. On the one hand, China should continue to advance the development of green credit, using financial strength to safeguard the environment. This will effectively alleviate corporate climate risk and contribute to enhancing their value. On the other hand, companies should prioritize the advancement of green and low-carbon technological innovations, continuously improving the sustainability of investment returns, and achieving green transformation. This will help enhance both the financial and environmental performance of companies, strengthening their core competitiveness to address climate risk.

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**Table 1** Descriptive statistics

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | N | mean | sd | min | max |
| CPUE | 30,121 | -0.028 | 0.573 | -21.990 | 24.046 |
| did | 30,121 | 0.174 | 0.380 | 0.000 | 1.000 |
| size | 30,121 | 22.292 | 1.278 | 19.865 | 26.273 |
| lev | 30,121 | 0.460 | 0.197 | 0.069 | 0.897 |
| roa | 30,121 | 0.036 | 0.063 | -0.226 | 0.220 |
| cashflow | 30,121 | 0.051 | 0.070 | -0.154 | 0.253 |
| age | 30,121 | 2.397 | 0.549 | 1.386 | 3.367 |
| bm | 30,121 | 0.640 | 0.259 | 0.119 | 1.190 |
| tobinq_1 | 30,121 | 1.992 | 1.292 | 0.840 | 8.391 |
| soe | 30,121 | 0.485 | 0.500 | 0.000 | 1.000 |
| investor | 30,121 | 48.215 | 23.850 | 0.541 | 95.121 |
| opacity | 30,121 | 1.312 | 1.059 | 0.000 | 4.000 |

Note: “N” indicates the total number of firm-years. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Appendix provides variable definitions.

**Table2** Correlation coefficients

| | CPUE | did | size | lev | roa | cashflow | age | bm | tobinq_1 | soe | investor | opacity |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CPUE | 1 | 0.021* | 0.031* | 0.003 | -0.036* | -0.046* | 0.049* | 0.032* | -0.032* | -0.005 | -0.024* | 0.010* |
| did | 0.022* | 1 | 0.134* | 0.003 | -0.011* | 0.076* | 0.111* | 0.091* | -0.091* | 0.002 | -0.034* | 0.052* |
| size | 0.046* | 0.144* | 1 | 0.378* | 0.066* | 0.068* | 0.357* | 0.475* | -0.475* | 0.201* | 0.334* | -0.106* |
| lev | 0.014* | 0.003 | 0.384* | 1 | -0.373* | -0.153* | 0.216* | 0.394* | -0.394* | 0.242* | 0.179* | -0.085* |
| roa | -0.036* | 0.002 | 0.093* | -0.340* | 1 | 0.419* | -0.135* | -0.281* | 0.281* | -0.110* | 0.166* | -0.098* |
| cashflow | -0.043* | 0.066* | 0.067* | -0.161* | 0.406* | 1 | -0.036* | -0.080* | 0.080* | 0.005 | 0.160* | -0.058* |
| age | 0.048* | 0.107* | 0.340* | 0.220* | -0.097* | -0.034* | 1 | 0.207* | -0.207* | 0.356* | 0.161* | -0.061* |
| bm | 0.042* | 0.094* | 0.492* | 0.383* | -0.218* | -0.094* | 0.215* | 1 | -1.000* | 0.274* | 0.153* | -0.051* |
| tobinq_1 | -0.046* | -0.068* | -0.363* | -0.318* | 0.216* | 0.108* | -0.131* | -0.823* | 1 | -0.274* | -0.153* | 0.051* |
| soe | 0.006 | 0.002 | 0.220* | 0.241* | -0.062* | 0.001 | 0.355* | 0.273* | -0.196* | 1 | 0.408* | -0.236* |
| investor | -0.014* | -0.035* | 0.357* | 0.189* | 0.168* | 0.144* | 0.185* | 0.147* | -0.055* | 0.426* | 1 | -0.235* |
| opacity | 0.005 | 0.052* | -0.111* | -0.083* | -0.114* | -0.052* | -0.063* | -0.049* | 0.045* | -0.236* | -0.235* | 1 |

Note: The table reports the correlation matrix of variables in the baseline regression, displaying the correlation coefficients between each pair of variables. The upper triangular matrix presents the Spearman correlation coefficients, while the lower triangular matrix presents the Pearson correlation coefficients. *, * *, and * ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table** 3 Baseline results

| | (1) | (2) |
|---|---|---|
| VARIABLES | CPUE | CPUE |
| did | -0.0640** | -0.0664** |
| | (-2.10) | (-2.21) |
| size | | 0.0013 |
| | | (0.09) |
| lev | | 0.1036* |
| | | (1.88) |
| roa | | -0.0290 |
| | | (-0.31) |
| cashflow | | -0.1427** |
| | | (-2.12) |
| age | | 0.0810** |
| | | (2.07) |
| bm | | -0.0631 |
| | | (-1.24) |
| tobinq_1 | | -0.0404*** |
| | | (-4.87) |
| soe | | 0.0349 |
| | | (1.35) |
| investor | | 0.0000 |
| | | (0.03) |
| opacity | | -0.0084 |
| | | (-1.49) |
| Constant | -0.0115 | -0.1034 |
| | (-0.63) | (-0.38) |
| Observations | 30,121 | 30,121 |
| R-squared | 0.049 | 0.053 |
| Ind FE | YES | YES |
| Year FE | YES | YES |

Note: This table reports ordinary least square regressions of corporate climate risk exposure on the Green Credit Policy. Dependent variables are corporate climate risk exposure index. For explanatory purposes, the dependent variable is multiplied by 1000. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, * *, and * ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 4** Substitute outcome regression and PSM regression.

| | (1) Cpue_5factors | (2) Nearest neighbor matching | (3) Kernel matching | (4) Radius matching |
|---|---|---|---|---|
| VARIABLES | CPUE | CPUE | CPUE | CPUE |
| did | -0.0982*** | -0.0664** | -0.0664** | -0.0664** |
| | (-3.33) | (-2.21) | (-2.21) | (-2.21) |
| Constant | -0.3015 | -0.1034 | -0.1034 | -0.1034 |
| | (-1.11) | (-0.38) | (-0.38) | (-0.38) |
| Observations | 30,121 | 30,121 | 30,121 | 30,121 |
| R-squared | 0.059 | 0.053 | 0.053 | 0.053 |
| Control | YES | YES | YES | YES |
| Ind FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

Note: Dependent variables corporate climate risk exposure, which are measured by corporate climate risk exposure index. For explanatory purposes, the dependent variable is multiplied by 1000. Columns (1) report the regression that we adjust the calculation method of the dependent variable, the climate risk exposure index was recalculated by the Fama-French five-factor model. Columns (2)–(4) report PSM regressions, specifically, 1:4 nearest neighbor matching, kernel matching, and radius matching methods are applied, with enterprise size and other control variables serving as covariates for matching. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, * *, and * ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 5** Regressions with policy time-leading.

| | (1) | (2) |
|---|---|---|
| VARIABLES | CPUE | CPUE |
| did_placebo2009 | -0.0209 | |
| | (-0.62) | |
| did_placebo2008 | | -0.0190 |
| | | (-0.54) |
| Constant | -0.1351 | -0.1381 |
| | (-0.50) | (-0.51) |
| Observations | 30,121 | 30,121 |
| R-squared | 0.053 | 0.053 |
| Control | YES | YES |
| Ind FE | YES | YES |
| Year FE | YES | YES |

Note: The table reports regression results conducted with policy time advanced by 3 years and 4 years, respectively. The explanatory variables are did_placebo2009 and did_placebo2008, where they are measured as 1 if the year is greater than 2009 (or 2008) and 0 otherwise. For explanatory purposes, the dependent variable is multiplied by 1000. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, * *, and * ** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 6** Channel test

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | lntotal | lninva | lnuma | lntotalg | lninvg | lnumg | InefficInvest Degree | InefficInvest Sign | lndcg | IAnaAttention |
| did | 0.1966*** | 0.0751* | 0.1991*** | 0.2046*** | 0.0433 | 0.1861*** | -0.0074*** | -0.2376*** | -0.1346** | 0.0696** |
| | (4.17) | (1.80) | (5.17) | (4.88) | (1.49) | (4.94) | (-3.08) | (-3.42) | (-2.46) | (2.02) |
| Constant | -7.5681*** | -6.0021*** | -5.1644*** | -6.1315*** | -2.9942*** | -5.2293*** | -0.0049 | -3.0195*** | -0.3579 | -12.3100*** |
| | (-15.19) | (-13.17) | (-12.74) | (-13.27) | (-8.86) | (-12.41) | (-0.15) | (-7.38) | (-0.96) | (-36.55) |
| Observations | 30,121 | 30,121 | 30,121 | 30,121 | 30,121 | 30,121 | 30,121 | 30,119 | 17,408 | 30121 |
| R-squared | 0.276 | 0.215 | 0.207 | 0.270 | 0.131 | 0.227 | 0.049 | 0.031 | 0.128 | 0.402 |
| Control | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Ind FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Note: The table reports regression results of the green credit policy on green technological innovation, enterprise investment efficiency, enterprise digital transformation, and analyst attention. Columns (1) - (3) report the regression results for green patent applications, with the dependent variables being the total number of green patent applications, the number of green invention patent applications, and the number of green utility model patent applications, respectively. Columns (4) - (6) report the regression results for green patent authorization, with the explained variables being the total number of green patent authorizations, the number of green invention patent authorizations, and the number of green utility model patent authorizations, respectively. All are measured by taking the logarithm with each value increased by 1. Columns (7)-(8) present the outcomes where the dependent variables are the degree of inefficient investment by the enterprise and the inefficiency investment indicator, respectively. Specifically, the degree of inefficient investment is measured by constructing an investment efficiency model and taking the absolute value of its regression residuals. The inefficiency investment indicator variable takes a value of 1 to indicate over-investment and 0 to indicate insufficient investment. Column (9) represents the outcome where the dependent variable is the degree of enterprise digital transformation. Column (10) represents the outcome where the dependent variable is analyst attention, measured by taking the logarithm of the number of securities analysts for the enterprise with member increased by 1. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 7** Heterogeneity in financing constraints

| | (1) Low financing constraints | (2) High financing constraints |
|---|---|---|
| VARIABLES | CPUE | CPUE |
| did | -0.0199 | -0.1592*** |
| | (-0.27) | (-3.30) |
| Constant | -0.2393 | 0.5816 |
| | (-0.53) | (1.19) |
| Observations | 17,134 | 12,987 |
| R-squared | 0.033 | 0.072 |
| Control | YES | YES |
| Ind FE | YES | YES |
| Year FE | YES | YES |

Note: The table presents regression results on the impact of the green credit policy on enterprise climate risk exposure at different levels of financing constraints. Financing constraints are measured using the SA index. Column (1) represents the outcome for samples with low financing constraints, specifically, samples where the SA index is below its mean value. Column (2) represents the outcome for samples with high financing constraints, namely, samples where the SA index is above its mean value. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 8** Heterogeneity in financialization level

| VARIABLES | (1)<br>Low financialization | (2)<br>High financialization |
| --- | --- | --- |
| | CPUE | CPUE |
| did | -0.0952** | -0.0130 |
| | (-2.56) | (-0.21) |
| Constant | -0.3361 | -0.4028 |
| | (-0.88) | (-0.81) |
| Observations | 13,835 | 16,286 |
| R-squared | 0.067 | 0.050 |
| Control | YES | YES |
| Ind FE | YES | YES |
| Year FE | YES | YES |

Note: The table reports regression results on the impact of the green credit policy on enterprise climate risk exposure at different levels of financialization. Financialization levels are measured by the proportion of financial assets held by the enterprise, specifically calculated as the sum of trading financial assets, derivative financial assets, net amount of loans and advances, net amount of available-for-sale financial assets, net amount of held-to-maturity investments, and net amount of investment properties divided by total assets. Column (1) represents the outcome for samples with low financialization levels, i.e., samples where the degree of financialization is below its mean value. Column (2) represents the outcome for samples with high financialization levels, i.e., samples where the degree of financialization is above its mean value. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 9** Heterogeneity in agency cost

| VARIABLES | (1) Low asset turnover | (2) High asset turnover | (3) Few funds occupied | (4) More funds occupied |
|---|---|---|---|---|
| | CPUE | CPUE | CPUE | CPUE |
| did | 0.0018 | -0.0996*** | -0.1025** | -0.0173 |
| | (0.03) | (-2.59) | (-2.04) | (-0.42) |
| Constant | 0.1534 | -0.3798 | 0.3728 | -0.3459 |
| | (0.37) | (-0.90) | (0.77) | (-0.95) |
| Observations | 15,060 | 15,061 | 15,053 | 15,068 |
| R-squared | 0.040 | 0.072 | 0.050 | 0.065 |
| Control | YES | YES | YES | YES |
| Ind FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

Note: The table presents regression results on the impact of the green credit policy on enterprise climate risk exposure at different levels of agency costs. Columns (1)-(2) represent the outcomes for the first type of agency costs, measured by asset turnover ratio. Column (1) is for samples with asset turnover ratios below their mean values, while Column (2) is for samples with asset turnover ratios above their mean values. Columns (3)-(4) represent the outcomes for the second type of agency costs, measured by the level of funds occupied by large shareholders. Column (3) is for samples where the degree of funds occupied by large shareholders is below its mean value, and Column (4) is for samples where the degree of funds occupied by large shareholders is above its mean value. All continuous variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 10** Heterogeneity in corporate employees' number

| VARIABLES | (1)<br>Fewer employees | (2)<br>More employees |
|---|---|---|
| | CPUE | CPUE |
| did | -0.0691 | -0.1297*** |
| | (-1.27) | (-3.32) |
| Constant | -0.6475 | 0.1627 |
| | (-1.37) | (0.38) |
| Observations | 15,052 | 15,069 |
| R-squared | 0.038 | 0.083 |
| Control | YES | YES |
| Ind FE | YES | YES |
| Year FE | YES | YES |

Note: The table reports regression results on the impact of the green credit policy on enterprise climate risk exposure for businesses of different employee scales. The specific measure for the number of employees in the enterprise is the logarithm of the number increased by 1. Column (1) represents the outcomes for samples with fewer employees, i.e., samples where the number of employees is below its mean value. Column (2) is designated for samples with more employees, i.e., samples where the number of employees is above its mean value. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 11** Heterogeneity in property right nature

| | (1) | (2) |
|---|---|---|
| VARIABLES | Non-state-owned | State-owned |
| | CPUE | CPUE |
| did | -0.0145 | -0.0874** |
| | (-0.21) | (-2.56) |
| Constant | -0.2131 | -0.1496 |
| | (-0.46) | (-0.39) |
| Observations | 15,515 | 14,606 |
| R-squared | 0.046 | 0.083 |
| Control | YES | YES |
| Ind FE | YES | YES |
| Year FE | YES | YES |

Note: The table reports regression results on the impact of the green credit policy on enterprise climate risk exposure based on different property rights. Specifically, the samples are divided into state-owned enterprise samples and non-state-owned enterprise samples. Column (1) represents the outcomes for non-state-owned enterprise samples. Column (2) represents the outcomes for state-owned enterprise samples. For explanatory purposes, the dependent variable is multiplied by 1000. All continuous variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

**Table 12** Heterogeneity in Percentage of independent directors and number of supervisors

| VARIABLES | (1)<br>Low proportion of inddirect | (2)<br>High proportion of inddirect | (3)<br>Fewer supervisors | (4)<br>More supervisors |
|---|---|---|---|---|
| | CPUE | CPUE | CPUE | CPUE |
| did | -0.0713 | -0.0926** | -0.0564 | -0.0818* |
| | (-1.63) | (-1.98) | (-1.27) | (-1.84) |
| Constant | -0.3506 | 0.1124 | 0.0415 | -0.3577 |
| | (-0.80) | (0.31) | (0.12) | (-0.65) |
| Observations | 15,476 | 14,645 | 20,722 | 9,399 |
| R-squared | 0.067 | 0.042 | 0.044 | 0.086 |
| Control | YES | YES | YES | YES |
| Ind FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

Note: The table reports regression results on the impact of the green credit policy on enterprise climate risk exposure based on different corporate governance structures. Specifically, the measures selected are the proportion of independent directors in the company and the number of supervisors. Columns (1)-(2) present the results of regressions for different proportions of independent directors. Column (1) represents outcomes for samples where the proportion of independent directors is below its mean value. Column (2) represents outcomes for samples where the proportion of independent directors is above its mean value. Columns (3)-(4) display the results of regressions for different proportions of supervisors. Column (3) represents outcomes for samples where the proportion of supervisors is below its mean value. Column (4) represents outcomes for samples where the proportion of supervisors is above its mean value. For explanatory purposes, the dependent variable is multiplied by 1000. All control variables are winsorized at the 1% and 99% levels to reduce outliers and data noise. Robust standard errors are clustered at the firm levels and reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

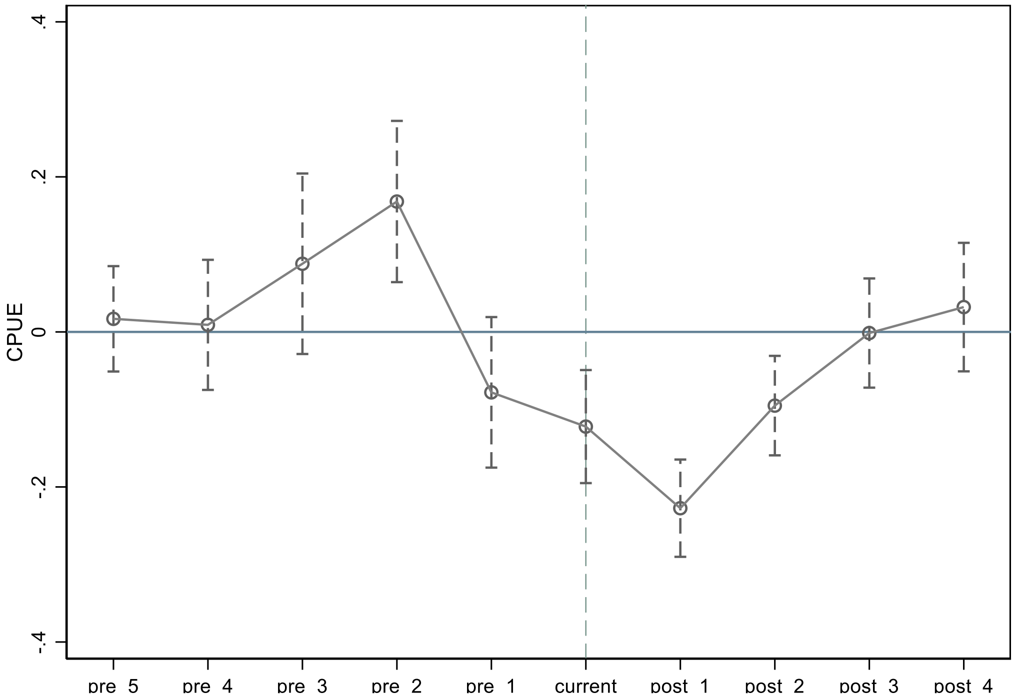


**Fig. 1** Parallel trends in enterprise climate risk exposure. The horizontal axis represents relative years, with the 2012 'Guidelines' serving as the dividing line. Here, we consider 5 periods before (pre) and 5 periods after (post) policy implementation. To avoid multicollinearity issues, we dropped post_5. The vertical axis represents the confidence interval of the enterprise climate risk exposure index, with the dashed line indicating the year of green credit policy implementation.

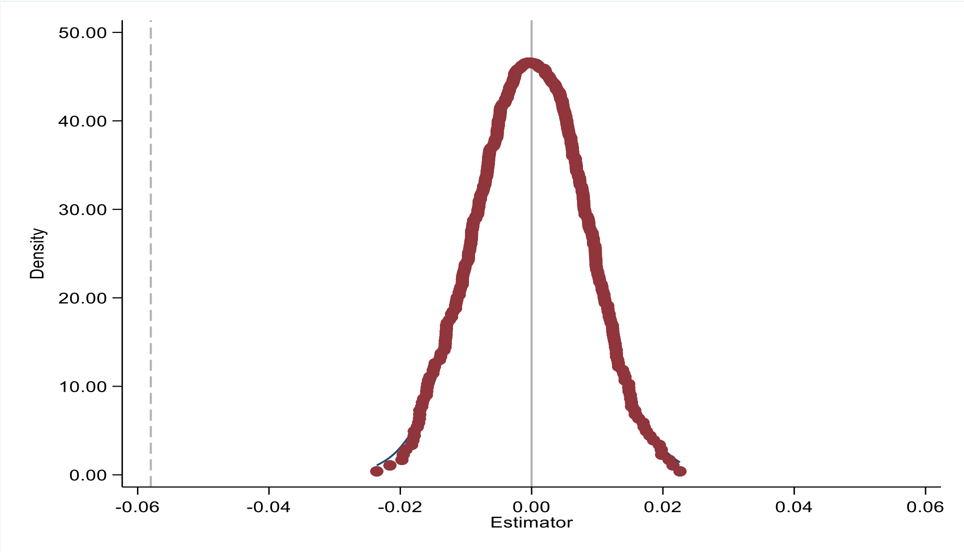


**Fig. 2** Kernel density plot of the coefficients for the placebo test's explanatory variable (did regression). The horizontal axis represents the estimated coefficients, ranging from (-0.06, 0.06). The vertical axis represents the density of the coefficients, ranging from (0, 50). The vertical dashed line serves as the reference, indicating the true estimated coefficient value. The densely-packed red solid circles represent the p-values. The vertical solid line represents the estimated coefficient, which has a value of 0. Most of the simulated estimated coefficients are clustered around 0, diverging significantly from the true regression coefficients.

**Appendix A. Variable Definitions**

| Type | Variables | Symbol | Definition |
|---|---|---|---|
| Dependent variables | Climate risk exposure | CPUE | Climate policy uncertainty exposure index |
| Explanatory variables | Green credit policy | did | The interaction term between green credit policy and the industry attributes of the enterprise |
| Control variables | Enterprise size | size | The natural logarithm of asset at the beginning of the year. |
| | Leverage | lev | Ratio of firm's total liabilities to total assets at the end of the year. |
| | Net profits to total assets | roa | Ratio of firm's net profits to total assets. |
| | Net cash flows | cashflow | Net cash flows from operating activities divided by total assets |
| | Listing age | age | Taking the logarithm of the difference between the current year and the year the company was established, after adding 1. |
| | Book-to-market ratio | bm | Book-to-market ratio, defined as the book value of equity divided by its market value. |
| | Toin Q value | tobinq1 | The market value of assets divided by the book value of assets. |
| | Property ownership | soe | Property rights nature |
| | Institutional investors | investor | The shareholding ratio of institutional investors. |
| | Company transparency | opacity | Company transparency: 1 = Excellent, 2 = Good, 3 = Pass, 4 = Fail. |