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Research article

The impact of green finance policy on green innovation performance: Evidence from Chinese heavily polluting enterprises

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ABSTRACT

Green innovation (GI) is increasingly recognised as an effective strategy for tackling climate change, mitigating environmental issues, and promoting sustainable development. Using panel data of the Chinese listed firms from 2007 to 2019, this study adopts the difference-in-differences approach to assess the impact of the green finance policy (GFP) initiated by the Chinese government in 2012 on the green innovation performance of firms. The findings reveal that the GFP significantly boosts the green innovation performance of heavily polluting enterprises (HPEs). Notably, this effect is more pronounced in state-owned enterprises and firms with high dependence on external finance. Compared with penalty-based regulations, incentive-based and voluntary environmental regulations demonstrate more significant moderating effects on the relationship between the GFP and green innovation performance for HPEs. We also identify improved efficiency in the usage of green investments as a potential mechanism through which the GFP enhances the green innovation performance of HPEs. Further comparative analysis shows that green enterprises can achieve simultaneous improvement in both the quality and quantity of green innovation, whereas HPEs predominantly exhibit enhancements in innovation quantity. To maximise the GFP's positive effects, it is recommended to facilitate more targeted bank lending towards HPEs to support their structural transformation. Additionally, the coordinated deployment of diverse environmental policy instruments is advised to exploit their synergistic effects.

1. Introduction

Over the past decades, issues related to global warming caused by environmental pollution have triggered wide debate (Francey et al., 2013; Balsalobre-Lorente et al., 2018; Mealy and Teytelboym, 2022; Fan et al., 2023). Over the past few decades, China has experienced high-speed economic growth with rapid industrialisation. However, this growth has resulted in excessive energy consumption and severe environmental pollution (Zhang et al., 2021b). In 2005, China had become the world's largest CO_2 emitter (Wang et al., 2017). The greenhouse effect, exacerbated by excessive CO_2 emissions, presents a significant threat to human survival and production activities (Xu et al., 2021). Consequently, maintaining such an extravagant growth model has become increasingly unsustainable for China (Yang et al., 2023; Wei et al., 2022). The Chinese government, aiming for sustainable development, has set targets like reaching the carbon peak by 2030 and carbon neutrality by 2060 (Liu et al., 2022; Xiong et al., 2022; Zhang et al., 2022a; Stern and Xie, 2023). In particular, there is a growing emphasis on the green transition of heavily polluting enterprises (HPEs) (Wang et al., 2019; Zhou et al., 2019; Hu et al., 2021a).

To meet these targets, the Chinese government implemented various regulatory measures, including command-, market- and voluntary-based measures.[1] Notably, market-based environmental regulation (MER) is gaining prominence due to its flexibility, autonomy, and economic efficiency (Tian and Feng, 2022; Chang et al., 2023). Specifically, MER, exemplified by the green finance policy (GFP), incentivises companies to adopt environmental protection measures. Through the implementation of a series of financial mechanisms, it aims to achieve the dual targets of

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[1] Currently, China mainly has command- (e.g. *Atmospheric Pollution Prevention and Control Law (2015 Revision)*), market- (e.g. *Emission Trading Markets Pilots Policy (2007)* and *Guidelines for Green Credit issued by the China Banking Regulatory Commission (2012)*), and voluntary-based environmental regulation.

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environmental protection and economic development (Sun et al., 2019; Wu and Liu, 2023). The GFP provides loan incentives for green initiatives while imposing constraints on heavily polluting businesses (Wu and Liu, 2023). Financial policies like the GFP effectively use financial market power to foster corporate environmental responsibility, granting firms the autonomy to optimally allocate funds for green transition and environmental protection efforts. Therefore, as a market-based environmental regulation tool, the GFP could gear firms towards green innovation (GI), and contribute to broader economic restructuring and the green transition of the country (Lu et al., 2022; Tan et al., 2022). Despite extensive research on environmental regulations' effects on firms' performance and energy intensity (Hamamoto, 2006; Lin and Xu, 2023; Testa et al., 2011; Wang et al., 2021, 2023), there are limited studies evaluating impacts of GFP on diverse firm-level innovation. This paper aims to fill this gap by analysing the impact of China's GFP on firms' GI, especially focusing on HPEs. This is crucial for understanding China's green economic transition and could provide insights for other economies aiming for carbon neutrality and green development (Tian and Feng, 2022; Su et al., 2022).

Fossil fuels, despite being pivotal for industrial and economic growth (Awada and Mestre, 2023), present significant environmental challenges. Consequently, enterprises' GI performance, encompassing sustainable technological, product or service advancements, is gaining focus (Liu and Wang, 2023; Cheng et al., 2021; Ma et al., 2021; Vasileiou et al., 2022). It is considered an effective way to balance economic development and environmental governance (Rennings, 2000; Walker et al., 2015; Shahbaz et al., 2018; Chen et al., 2023). In particular, GI helps reduce energy use and emissions, cutting production costs and mitigating adverse environmental impacts, thus fostering an increase in eco-friendly product market share and propelling the industry's broader green transformation (Huang et al., 2019; Li et al., 2023). Additionally, the Chinese government has implemented many environmental policies to accelerate green transformation, particularly targeting HPEs (Wang and Li, 2022). It is therefore argued that GI offers firms competitive edges through early adoption benefits, government support, and technological leadership (Gupta and Barua, 2018).[2] As a result, government-enacted environmental regulations are crucial for enhancing firms' GI (Stern and Valero, 2021), with this effect intensified by digital media's supervisory role (Li et al., 2023; Liu et al., 2023).

Regarding the connection between environmental regulations and GI, the Porter Hypothesis (PH) posits that flexible environmental regulations can enhance innovation's environmental advantages (Porter, 1991). Consequently, this study offers empirical evidence supporting the PH, drawing from samples in the world's largest developing economy. In China, the GFP has become a key environmental regulation (Yao et al., 2021). When faced with GFP, HPEs are significantly affected due to financial constraints and their need for substantial profit gains (Hu et al., 2021b). Also, green enterprises respond to GFP by investing in GI to retain the competitive advantage. Furthermore, existing studies primarily focus on the effects of a single policy on firms' innovation (Tang et al., 2020; Xu and Li, 2020; Su et al., 2022), neglecting the synergistic impact of different environmental regulations. However, this synergistic effect is a crucial component of the PH, and the findings will be significant for China and other economies with similar economic characteristics in shaping effective environmental policies.

Given the significance of research objectives, this study examines the relationship between GFP and GI using panel data on Chinese listed companies from 2007 to 2019, particularly focusing on whether GFP promotes GI among HPEs under heterogeneous conditions. Further, China has implemented different types of environmental regulations and these policies may have synergistic effects. Then, understanding how these regulations affect the relationship between GFP and GI may be worthwhile. We also explore: what are the impacts of GFP on green enterprises? Are these impacts consistent with those on HPEs?

This study contributes to the literature in the following aspects. First, while some studies examine the impact generated by GFP on HPEs' performance (Cui et al., 2022; Peng et al., 2022), little has been done to explore the relationship between GFP and GI of HPEs and their greener peers. Despite being less polluting, GFP could still promote green firms' GI to strengthen competitiveness. However, responses from green firms vary according to the regulatory initiatives imposed and their chosen GI strategies. This research offers valuable insights by comparing the diversified responsive channels chosen by these two types of enterprises for the future green transition of HPEs.

Second, previous studies have explored the GI and GFP but failed to identify internal mechanisms (Wang et al., 2022c; Chang et al., 2023). This study delves into the nuances of GI, differentiating between its quality and quantitative increments, and further investigates firms' preferences and the rationale behind them.[3] More critically, the study adds to the field by identifying several possible mechanisms through which the GFP improves firms' innovation performance, such as the ownership structure and external financing dependence.

Third, while GFP is an important MER within China's environmental regulation framework, studies suggest that different regulatory tools can synergistically impact firms' innovation capabilities and emissions reduction efforts (Fabrizi et al., 2018; Yuan, 2019). This study reveals that both the command- and voluntary-based regulatory tools significantly moderate the relationship between the GFP and GI. These observations have led to valuable policy implications, underscoring the importance of an integrated approach in environmental regulations to stimulate GI effectively.

Fourth, while assessing the impact of GFP on GI, changes in channel factors (e.g. efficiency of green capital utilisation) should also be considered. However, existing studies failed to identify such channels (Zhu, 2022; Wang et al., 2022c). This study fills this gap by revealing that the efficiency of green capital utilisation is one such channel through which more GI is generated with the same amount of capital investment.

Fifth, the study adopts a novel Word Embedding model to improve variable measurement accuracy and the robustness of results. Traditional methods, like manually identifying synonyms (Loughran and McDonald, 2011), may introduce bias due to subjective nature. In contrast, employing the Word Embedding model, a technique grounded in machine learning, addresses this limitation (Li et al., 2021). The approach allows for a more precise measurement of variables like incentive-based environmental regulation and green investment.[4]

The rest of this study is organised as follows. Section 2 provides an overview of the literature and develops the hypotheses. Section 3 describes the variables and methodology. Section 4 discusses the empirical results. Finally, section 5 presents the conclusions of this study.

2. Literature review and hypothesis development

2.1. The Porter Hypothesis

The Porter Hypothesis (PH) suggests that stringent but properly

[2] For example, when an enterprise achieves technological innovation that meets the requirements of environmental regulations, it can apply for patent protection. In the context of strict environmental regulations, this behaviour can encourage other enterprises to purchase its innovation, which can bring high profits to the enterprise (Porter, 1991).

[3] Green innovation quality focuses more on the quality of green innovation and is more related to newly created inventions (Zhang et al., 2023). While green innovation increment focuses more on the quantity of green innovation and tends to build on existing technologies or products (Wang and Li, 2022).

[4] Here, the variables Incentive-based Environmental Regulation (CER_Incentive) and Green Investment (GreenInv) are constructed using the Word Embedding model.

designed environmental regulations can stimulate corporate innovation, especially green innovation (Porter and Linde, 1995). To comply with the regulatory requirements while building up sustained competitive advantages over the longer term, firms can be pressurised/incentivised to invest in green technologies and adjust their competitive strategies accordingly (Farooq et al., 2021). To ensure the appropriate functioning of the environmental regulation system, it should have the following characteristics: broad coverage: it should provide the largest potential space for corporate innovation; continuity: it should stimulate continuous innovation; flexibility: it should allow firms to implement the policies in stages with certain level of discretionary power; and enforceability: it should be able to control and enforce firm behaviours effectively with a well-designed appraisal mechanism and encourage government-firm collaboration (Porter and Linde, 1995).

Many studies have demonstrated the validity of PH (Zhao et al., 2015; Ouyang et al., 2020). For instance, firms can create new market opportunities by developing greener products (Ouyang et al., 2020), which can motivate firms to invest more in green innovation.[5] Over the longer term, investments in green technology may be fully compensated by the potential gain from reduced costs in pollution control, increased productivity, and positive publicity. This can be especially true when firms face greater environmental regulation intensity, which can accelerate green innovation processes and lead to the development of an environmentally friendly industry (Zhao et al., 2015). However, green investments also require substantial financial support. As such, the GFP can help in this respect by easing financing constraints, thereby complementing environmental regulations and promoting green innovation activities.

Recent research has started to leverage environmental policies as quasi-natural experiments to investigate the PH and mitigate potential endogeneity issues, such as the introduction of the carbon emissions trading system (Hu et al., 2020). For instance, Hu et al. (2020) discover that the carbon emissions trading market has had a significant positive impact on both the volume and quality of innovation amongst Chinese enterprises. As a significant tool in environmental regulation, the role of the GFP in environmental governance has received increased attention in recent years (Yao et al., 2021). Certain studies have found that the enactment of the GFP resulted in reductions in bank loans and the scale of investments in HPEs, leading ultimately to a decrease in these enterprises' operational performance and total factor productivity (Liu et al., 2019). Liu et al. (2019), using the announcement of the 2012 Green Credit Guideline as a quasi-natural experiment, demonstrate that the debt financing capacity of HPEs has decreased significantly. Moreover, the negative net effect of debt financing is more pronounced in state-owned enterprises and those located in regions with weaker financial ecosystems.

However, according to the PH, the effectiveness of an environmental regulation policy in influencing innovation serves as a crucial measure of a successful green transition (Pizer and Popp, 2008). It is evident that the primary goal of the GFP is to mitigate environmental pollution, not to undermine corporate competitiveness. Recently, Li et al. (2018) build a green loan theory using quantitative models to support the GFP's role in promoting clean production innovation. Nevertheless, the exact influence of China's GFP on green innovation remains ambiguous, especially regarding its impact on diverse enterprises in practical scenarios. These questions are significant in verifying the applicability of the PH in China. Furthermore, existing research exploring the synergistic effect of other environmental regulations in conjunction with the GFP is limited. Neglecting this facet may lead to an incomplete estimation of the PH's validity (Zefeng et al., 2018). Therefore, this study addresses this research gap and expands upon the PH by considering the synergistic effect of various environmental regulations.

2.2. Green finance policy and green innovation performance

Among various GFPs, the Green Credit Guideline (GCG) implemented in 2012 has generated profound impacts, leading to a significant increase in green credit balance in China over years (Fig. 1). According to the GCG, all commercial banks must strengthen the management of enterprise environmental performance and establish an information-sharing mechanism to develop green credit (Zhang et al., 2021a; Yao et al., 2021).[6] The credit is then used to promote green innovation performance via the development of technologies or approaches that contribute to energy savings, emissions reduction, and environmental protection, among others (Chen et al., 2006). Similar to other types of general innovation, green innovation can help the technological advancement of enterprises, empowering them to develop more innovative services and products (Aldieri et al., 2020). The green characteristics of such innovation also benefit the environment (Huang and Li, 2017). Therefore, green innovation may help achieve the dual targets of environmental protection and economic development simultaneously (Ganda, 2019; Shao et al., 2021). Thus, green innovation fits well within the scope of GFP.

Over the past decades, many HPEs have been keen to structurally transform themselves to continue to access and attract stable capital inflow from financial institutions. Therefore, achieving qualified environmental and sewage performance has become particularly important for these HPEs (Berrone et al., 2013). Despite extensive capital market reforms, loans remain the primary financing resource for Chinese firms, especially for HPEs (Xing et al., 2020). Due to the GFP, HPEs that want to

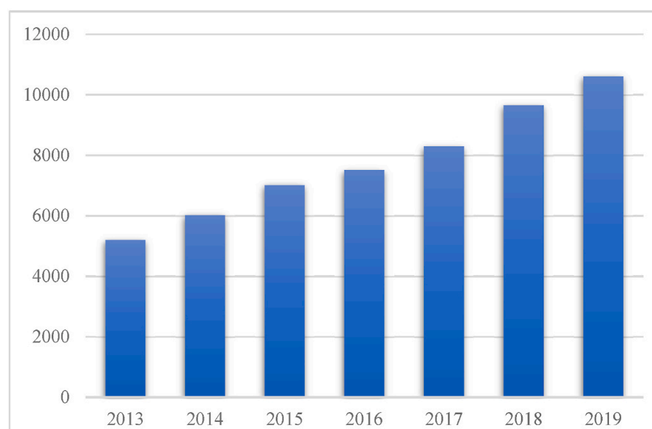

Fig. 1. The green credit balance of China, by year
Note: The green credit balance of China from 2013 to 2019. The volume (¥bn) of green credit is show on the left axis.
Data source: CSMAR.

[5] The innovation compensation effect of PH posits that during the dynamic process of economic development, environmental regulations can stimulate enterprises to innovate their production modes, improve economic efficiency, and offset the effect of circular cost (Ouyang et al., 2020).

[6] The main points of the 2012 GCG are as follows. First, a strict access mechanism requires credit-granting financial institutions to consider not only the economic performance and risks of enterprises but also their environmental performance and potential environmental risks. Credit to enterprises with poor environmental performance is curtailed. Second, information communication and dynamic tracking mechanisms must be established for enterprises that have obtained loans after thorough examination and approval, and their credit should be terminated if environmental problems occur. Third, stronger coordination and cooperation must be established with government and environmental protection departments. Information sharing must be improved to link environmental protection and financial credit (Yao et al., 2021; Zhang et al., 2021b).

secure financial support may be motivated to cut emissions, including via green innovation, as they must fulfil GFP requirements to access loans from financial institutions (Shi et al., 2022). This also helps HPEs build good relationships with the local government because they can demonstrate commitment to environmental sustainability (Hu et al., 2021b). Based on the above discussion, the first hypothesis is proposed as follows:

Hypothesis 1. GFP improves the green innovation performance of HPEs.

2.3. The moderating effect of environmental regulations

Environmental regulations may change the behaviour of firms through various channels, such as encouraging them to invest more in green activities or cultivating a green culture in the firm (Kesidou and Demirel, 2012; Dong et al., 2023). In general, apart from MER, ERs also consist of two categories: command-and-control (CER) and voluntary environmental regulations (VER). The former is mainly based on government command (Tang et al., 2020) and comprises environmental law enforcement, administrative penalties, and government subsidies (Carrión-Flores et al., 2013). VER refers to firms' voluntary environmental information disclosure (Jiang et al., 2020). These disclosures can effectively reduce information asymmetry between financial institutions and firms, increasing firms' accessibility to green finance.

2.3.1. Command-and-control environmental regulation

Due to its relatively strong enforcement power, CER, especially the penalty-based CER, remains an important environmental regulation in developing countries. Through the introduction of additional financial punishment and administrative detention penalties to firms, CER_Penalty has significantly elevated the cost of environmental violations for firms, forcing them to engage more in green innovation practices (Wang et al., 2022b). A similar picture emerged in China as firms with high energy consumption and low efficiency are driven out of the market due to the timely oversight and emissions control exerted by CER_Penalty policies (Zhu et al., 2021). However, CER_Penalty has also been criticised for its high costs, low operational efficiency, and deviation from the original targets of promoting technological innovation among enterprises (Joshi et al., 2001). Further, Hotte and Winer (2012) point out that as CER_Penalty often fails to consider the substantial cost differences among firms, it may actually impede the adoption rate of technology, especially among small firms. Since penalties can only be applied to specific measurable targets, regulations structured based on them may not prevent all types of pollution activities effectively (Shevchenko, 2021). When firms possess more information than the regulators, this situation can become even worse.

Therefore, the inherent limitations of CER_Penalty have made it a less efficient alternative than the incentive-based regulations in China (Lin and Xie, 2023). Instead of stimulating increased green innovation funded by favourable GFP, CER_Penalty may impose an additional financial burden on HPEs, worsening their financing situation while sending bad signals to the market (Requate and Unold, 2003). Consequently, green innovation efforts may have less funding. Moreover, the long-term financing capacity of firms may be further restrained. Based on this discussion, this study proposes the following hypothesis:

Hypothesis 2a. CER_Penalty does not positively moderate the relationship between GFP and green innovation performance among HPEs.

Among various types of CERs, government subsidy actually shares some incentive-based characteristics (CER_Incentive), despite some design deficiencies. As observed by Shleifer and Vishny (1994), government subsidies can be influenced by rent-seeking behaviours and mutual bribery between enterprises and local government officials. This in turn elevates the non-production costs of firms, eroding their competitiveness and disentangling the innovation stimulus effect of the subsidies. Further, some enterprise managements might pursue green subsidies with the aim of appeasing the government for short-term gains. This has again distorted the genuine purpose of green subsidies (Li et al., 2023). Nevertheless, given China's robust anti-corruption measures and the stringent review mechanisms of GFP, many studies posit that it is challenging for HPEs to rely solely on short-term rent-seeking to navigate the complexities of long-term environmental policies (Bai et al., 2019). This suggests that HPEs might predominantly view green subsidies as financial aids to bolster green innovation performance (Horbach et al., 2012).

As for CER_Incentive, it refers to the free transfer of funds from local governments to enterprises (Huang et al., 2019), while restraining the use of funds for certain purposes like green investments (Zhang, 2022). It acts as a direct substitute for debt financing, providing a viable alternative to HPEs for their innovative green transformations (Horbach et al., 2012). Furthermore, CER_Incentive also signifies the government's support for the company, enabling it to bypass the restrictions imposed by debt financing (Zhang, 2022). In other words, CER_Incentive can assist firms in diversifying the risks involved in green innovation to some extent, thereby increasing their willingness to invest in such activities (Bai et al., 2019). Moreover, to nurture a long-term relationship with the government, HPEs tend to be more strongly motivated to improve their environmental performance via green innovation. Therefore, this study proposes the following hypothesis:

Hypothesis 2b. CER_Incentive can positively moderate the relationship between GFP and the green innovation performance of HPEs.

2.3.2. Voluntary environmental regulation

Compared with CER and MER, VER is considered the 'third generation' of tools for controlling pollution (Tietenberg, 1998). The disclosure of pollutant emissions, such as the environmental information disclosure of listed companies in China, is a good example of this (Jiang et al., 2020). Nevertheless, it is argued that as the existing intensity of VER in China remains relatively low, and the cultivation of environmental awareness is a protracted endeavour, VER is unable to generate any material impacts on firms' GI improvement (Wang et al., 2022b). Conversely, to avoid environmental scrutiny by the public or media, enterprises might resort to short-term management strategies, like terminal governance. Such approaches not only waste the resources of firms but also divert funds from green R&D investments, impeding the firms' GI enhancement further (Wang et al., 2022b). However, as environmental information disclosure data becomes more readily accessible in China, a growing body of research highlights the advantages of VER (Lundqvist, 2001; Huang and Chen, 2015; Bu et al., 2020). By reducing costs and improving the time efficiency in providing, processing, and disseminating related information, VER reduces the information asymmetry between firms and financial institutions (Lundqvist, 2001; Bu et al., 2020). This can help establish a long-term trusted relationship between the two, which can help improve overall organisational performance (Huang and Chen, 2015). Therefore, considering the positive impact of VER on firm performance and its signalling effect, this study proposes the following hypothesis:

Hypothesis 3. VER can positively moderate the relationship between GFP and the green innovation performance of HPEs.

3. Methodology and variables

3.1. Data and sample selection

The sample includes data on China's A-share listed companies from 2007 to 2019.2007 is the sample's starting year because new accounting standards were implemented in China this year. Meanwhile, 2019 is set as the ending year to mitigate the impact of the COVID-19 pandemic.[7] HPEs are defined according to the '*Guidelines for the Industry Classification of Listed Companies*' revised by the China Securities Regulatory Commission in 2012 and '*Guidelines for Environmental Information Disclosure of Listed Firms (Draft for Soliciting Opinions)*' published by the China Environmental Protection Administration in 2010 (hereafter, Draft) (Shi et al., 2022). The sample is filtered as follows: (1) excluding financial and ST firms; (2) removing firms with missing key variables; (3) winsorising all continuous variables at the 1% and 99% levels to mitigate the effect of outliers; and (4) removing firms which change their status between heavily and non-heavily polluting industries over the sample period. All data are collected from the China Stock Market and Accounting Research (CSMAR) database, Chinese Research Data Services (CNRDS) database, annual reports, and corporate social responsibility (CSR) reports of respective listed companies.

3.2. Models

Following Zhang et al. (2021a) and Shi et al. (2022), this study constructs the difference-in-differences (DID) model to explore the effect of GFP on green innovation and mitigate the endogeneity issue.

$$LnGI_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \beta_2 X_{i,t} + u_p + \nu_t + \gamma_s + \lambda_q + \varepsilon_{i,t} \tag{1}$$

$$LnGI_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \beta_2 ERs_{i,t} + \beta_3 DID_{i,t} \times ERs_{i,t} + \beta_4 X_{i,t} + u_p + \nu_t + \gamma_s + +\lambda_q + \varepsilon_{i,t} \tag{2}$$

$LnGI_{i,t}$ measures corporate green innovation. $DID_{i,t}$ is the interaction between Treat × Post and it captures the DID effect. $ERs_{i,t}$ represent CER and VER. $X_{i,t}$ represents the set of control variables. u_p, ν_t, γ_s, and λ_q denote the firm, industry, year, and region fixed effects, respectively. The original rough time and treat variables are not included since the firm and year fixed effects are considered. This can effectively alleviate endogeneity problems, such as omitted variable bias, to a certain extent (Meyer, 1995; Shi et al., 2022).

3.3. Variables

3.3.1. Dependent variables

Following Hu et al. (2021b) and Yuan and Pan (2023), this study uses the natural logarithm of the sum of 1 and the number of overall green patent applications of firm i in year t to proxy green innovation (GI). The green patent data are collected from the CNRDS database.

3.3.2. Independent variables

The independent variables are the treated group (Treat) and policy implementation (Post). Treat is a dummy variable equalling one if the firm is an HPE and zero otherwise. Post is a dummy variable that equals one if the GFP has been implemented, or within the period of 2012–2019. According to the model construction, the interaction Treat × Post (DID) is the key variable and should be significant if the DID effect exists (Wang and Li, 2022).

3.3.3. Moderating variables

CER is mainly divided into two types: CER_Penalty and CER_Incentive. CER_Penalty refers to the penalties imposed by the government on listed firms with environmental issues (Ma et al., 2022). It is proxied by whether the company has had the environmental violation noted in the year. CER_Incentive is mainly related to the green subsidies granted by the government.[8] To capture various types of sponsorships initiated by the government, this study uses the Word Embedding model from machine learning to construct the green subsidy dictionary and then obtains the green subsidy data by examining the notes to the annual reports of companies using this dictionary.[9] After filtering, the logarithm of the sum of the amount of green subsidy items detected is used to construct the CER_Incentive indicator.

Traditional text analysis methods often rely on the manual identification of synonyms to expand the word set (Loughran and McDonald, 2011). However, this method entails high subjectivity and may introduce bias into the word set. Consequently, this study employs the Word Embedding model to construct the CER_Incentive indicator. The model utilises a neural network to deeply parse a substantial volume of financial texts, thereby building a word similarity model from which similar words are trained. The similarity dictionary, crafted by this model, enables a comprehensive and objective variable measurement, thus enhancing the accuracy of variable measurement and the robustness of empirical results (Li et al., 2021).

VER is measured by the pollutant emissions disclosure level of a company. In China, the disclosure of environmental liabilities is voluntary, and thus, its intensity can be reflected by the environmental regulation pressure faced by the company and its willingness to disclose environmental information voluntarily (Huang and Chen, 2015). Specifically, if a company chooses to disclose the pollutant emissions information, measured here by six indicators, voluntarily, that indicator is assigned a value of 1, and 0 otherwise. Then, the values of different indicators are aggregated to obtain the VER.[10]

3.3.4. Control variables

The following control variables are considered to control for the influence of firm-specific characteristics.

3.3.4.1. Profitability. Firm profitability is measured by the ratio of net profits to total assets, or the return on assets (ROA) (Zhang et al., 2022b). This should enhance firms' innovation capacity as a higher profit margin allows firms to accumulate more retained earnings for R&D investments (Hu et al., 2021b). While others argue that as innovation can be costly, managers of those companies with high ROA may be reluctant to invest financial resources in green innovation. This may have led to an inconsistent relationship between profitability and innovation (Zhang et al., 2022b).

3.3.4.2. Firm size (size). The natural logarithm of the company's total assets is used to measure firm size (Size) (Hu et al., 2021b; Ma et al., 2021; Xie et al., 2023; Zhang et al., 2022b). A firm's size has always been one of the most important factors affecting its technological innovation capabilities. A scale expansion, such as through merger and acquisition, may facilitate innovation resource sharing, and hence, enhance a firm's

[7] Firstly, the pandemic exerted a substantial shock to the global economy, including China. Including the post-2020 data might introduce biases into the empirical results due to these unprecedented external influences. Secondly, in response to the pandemic, China, along with many other countries, implemented restrictive lockdown measures and fiscal stimulus policies. These interventions substantially altered the economic behaviours of firms and individuals. Consequently, it becomes challenging to disentangle the actual effects attributable to the Green Finance Policy from those stemming from the pandemic's repercussions. Therefore, the study considers the selection of the year 2019 as the cut-off point for the sample period to be appropriate.

[8] To avoid potential bias caused by the decrease in total observations, this study also uses the logarithm of government subsidy (CER_Incentive1) to conduct a robustness test. The results are reported in Appendix 1.

[9] The model and data source of the Word Embedding model are from www.wingodata.com.

[10] The environmental liabilities database of CSMAR constructs an index of voluntary disclosure of corporate environmental pollutants, which include wastewater emissions, COD emissions, SO_2 emissions, CO_2 emissions, soot and dust emissions, and industrial solid waste emissions. The index can appropriately reflect the VER level of firms (Huang and Chen, 2015).

innovation capacity (Wang and Li, 2022). Larger firms also find it easier to get additional financial support from external sources, allowing them to invest more in R&D. Therefore, this study expects a positive relationship between firm size and green innovation.

3.3.4.3. Leverage. Leverage is measured by the ratio of liabilities to total assets (Zhang et al., 2022b; Wang and Li, 2022). A higher leverage may increase the financial risks for firms. In response, firms may cut R&D investments to reduce uncertainties and/or use the current resources more efficiently for more innovative outputs. Hence, the resulting impact is hard to predict and varies under different scenarios (Zhang et al., 2022b; Lu et al., 2022). Therefore, this study considers the effect of Leverage on green innovation to be uncertain.

3.3.4.4. Listing Years (age). The natural logarithm of the number of years the company has been listed plus one to measure enterprise maturity (Hu et al., 2021b).[11] As stock listing may allow firms to access a larger funding pool and enhance their public image, firms that have been listed for a longer period may be more innovative. However, others argue that stock listing is not a necessary condition for increased green innovation as firms may pursue other business objectives after listing (Zhang et al., 2022b). Therefore, this study considers the relationship between age and green innovation to be uncertain.

3.3.4.5. Corporate governance measures (INST and inden). This study considers two important corporate governance variables: the shareholding ratio of institutional investors (INST) and proportion of independent directors on the board (Inden) (Hu et al., 2021b; Zhang et al., 2022b; Wang and Li, 2022). As important board members, institutional investors may play a key role in influencing a firm's capital allocation.

However, due to weak public awareness and insufficient supervision towards environmental problems over the past decades, institutional investors may fail to capture green transition issues due to opportunistic and short-sighted behaviours (Wang and Li, 2022). Consequently, a negative relationship is expected between INST and green innovation. While independent directors play an important role in corporate governance, their ability to influence corporate decision-making remains doubtful (Zhang et al., 2022b). Thus, the relationship between Inden and green innovation is expected to be uncertain.

3.3.4.6. Corporate social responsibility. CSR is proxied by a dummy variable which equals one if enterprises disclose their CSR reports, and zero otherwise (Hu et al., 2021b). Firms that care about their social impact may take a more active attitude towards green technology innovation (Baker et al., 2021). Therefore, a positive relationship is assumed between disclosing CSR reports and green innovation.

After the variable construction, in the next section, this study first examines the effect of GFP on green innovation among HPEs using a DID model. Next, a series of tests, such as parallel trend analysis and propensity score matching-DID (PSM-DID), are conducted to ensure the robustness of the baseline results. The study then conducts the heterogeneity analysis, incorporating factors including types of green innovation, ownership structure of firms, and degree of external finance dependence, to explore the relationships under different scenarios. Further, to identify firms' responses to different types of environmental regulations, this study investigates the moderating effect of CERs and VERs on the relationship between GFP and green innovation in HPEs. Finally, to comprehensively understand the effects of GFP, this study explores the relationship between GFP and green innovation for green enterprises.

[11] Since the listed age is zero when a company goes public in its first year, taking the natural logarithm of 0 (Ln0) has no mathematical meaning.

4. Empirical results

4.1. Descriptive statistics and correlation analysis

Table 1 presents the descriptive statistics for all variables used in the baseline regression.[12] Among the 14,789 samples from 2007 to 2019, the minimum and maximum values of GI are 0 and 3.829, respectively, indicating substantial variations in green innovation levels among the sample firms. DID's mean value is 0.152, suggesting that approximately 15.2% of the sample firms are affected by the GFP. The results for other variables are consistent with the literature and fall within a reasonable range. Table 2 reports the correlation matrix between variables. The observed relationship between DID and GI demonstrates a significant positive correlation, with a coefficient of 0.097. This suggests that the implementation of China's GFP can significantly enhance the green innovation performance of HPEs. Further, the results of the correlation analysis provide preliminary evidence supporting the applicability of the Porter hypothesis in the context of China. Meanwhile, other variables have also been found to strongly correlate with green innovation performance, indicating the appropriateness of the chosen variable (Zhang et al., 2020).

4.2. Baseline results

First, based on Eq. (1), this study examines the effect of GFP on HPEs' green innovation. The results are listed in Table 3. Columns 1 and 2 show the results for all sampled firms, while columns 3–4 show the results when green enterprises are excluded (i.e. for HPEs) mainly due to concerns about estimation bias (Zhang et al., 2022b). Columns 1 and 3 only include the DID variable, while columns 2 and 4 also include additional control variables. The coefficients of DID are significantly positive regardless of the inclusion of other control variables and green enterprises. Such empirical results support hypothesis 1, that is, the GFP bolsters the green innovation of Chinese HPEs significantly. Drawing on the Porter hypothesis, well-formulated environmental policies can foster enterprises' innovation, achieving simultaneous pollution reduction and competitiveness enhancement. To secure more capital from financial

Table 1
Descriptive statistics.[a]

Variable	Obs.	Mean	Std. Dev.	Min	Max
GI	14,789	0.425	0.839	0.000	3.829
DID	14,789	0.152	0.359	0.000	1.000
ROA	14,789	0.044	0.050	−0.165	0.192
Size	14,789	22.230	1.308	19.890	26.069
Leverage	14,789	0.421	0.201	0.048	0.845
Age	14,789	2.145	0.785	0.000	3.258
INST	14,789	0.466	0.241	0.003	0.910
Inden	14,789	0.372	0.053	0.308	0.571
CSR	14,789	0.295	0.456	0.000	1.000

Notes: The full terms for variables' abbreviations: GI: Green Innovation; DID: Difference-in-Differences; ROA: Profitability; Size: Firm Size; Leverage: Leverage; Age: Listing Years; INST: Shareholding Ratio of Institutional Investors; Inden: Proportion of Independent Directors; CSR: Corporate Social Responsibility.

[a] One observation is dropped in the baseline regression, which leads to a minor difference in the total observations between the baseline model and descriptive statistics because this study controls firm-level fixed effect and uses the command 'reghdfe' in Stata to regress linear models. Maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Hence, the 'reghdfe' package now automatically drops singletons (Correia, 2015).

[12] The description of variables can be found in Table 11.

Table 2
Pearson correlation coefficients.

	GI	DID	ROA	Size	Leverage	Age	INST	Inden	CSR
GI	1								
DID	0.097***	1							
ROA	0.020**	−0.105***	1						
Size	0.270***	0.092***	−0.041***	1					
Leverage	0.107***	0.015*	−0.367***	0.533***	1				
Age	0.060***	0.084***	−0.176***	0.418***	0.388***	1			
INST	0.061***	−0.061***	0.146***	0.433***	0.247***	0.183***	1		
Inden	0.030***	−0.005	−0.047***	0.059***	−0.001	−0.016**	−0.065***	1	
CSR	0.203***	0.081***	0.061***	0.454***	0.150***	0.228***	0.218***	0.019**	1

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The full terms for variables' abbreviations: GI: Green Innovation; DID: Difference-in-Differences; ROA: Profitability; Size: Firm Size; Leverage: Leverage; Age: Listing Years; INST: Shareholding Ratio of Institutional Investors; Inden: Proportion of Independent Directors; CSR: Corporate Social Responsibility.

Table 3
Baseline regression.

Variables	(1)	(2)	(3)	(4)
	GI	GI	GI	GI
DID	0.090**	0.108***	0.107**	0.123***
	(2.08)	(3.22)	(2.42)	(3.58)
ROA		0.128		0.136
		(1.03)		(0.78)
Size		0.138***		0.140***
		(5.20)		(6.60)
Leverage		−0.060		−0.062
		(-1.03)		(-0.83)
Age		0.028		0.023
		(0.57)		(0.43)
INST		−0.181***		−0.215***
		(-3.20)		(-3.94)
Inden		−0.120		−0.082
		(-0.98)		(-0.95)
CSR		0.095**		0.093**
		(2.71)		(2.86)
Constant	0.461***	−2.555***	0.409***	−2.643***
	(79.66)	(-5.11)	(60.83)	(-6.44)
Firm F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Observations	16,814	16,814	14,788	14,788
R-squared	0.689	0.692	0.677	0.682

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI: Green Innovation; DID: Difference-in-Differences; ROA: Profitability; Size: Firm Size; Leverage: Leverage; Age: Listing Years; INST: Shareholding Ratio of Institutional Investors; Inden: Proportion of Independent Directors; CSR: Corporate Social Responsibility.

institutions and sustain their competitive edge, HPEs are motivated to maximise the green innovation outputs with funds available. Hu et al. (2021b) find a similar result for the effectiveness of the Porter hypothesis in China.

Regarding control variables, only Size, INST, and CSR significantly impact green innovation, in line with prior studies (Hu et al., 2021b; Wang and Li, 2022). Compared with smaller firms, only large firms may have sufficient financial capital and experience in R&D activities. This translates into increased green innovation outputs. Meanwhile, to maintain their leadership in their respective industries, large firms are also under pressure to achieve continuous technological advancements (Wang and Li, 2022). Next, the shareholding ratio of institutional investors has a significant negative relationship with firms' green innovation outputs, which is consistent with expectations. Institutional investors tend to be relatively risk-averse. However, as R&D investments are highly risky, firms with more institutional investors may find it hard to gain the board's approval/support for such investments (Wang and Li, 2022). Lastly, firms disclosing CSR reports may care more about their social perception and are more likely to engage actively in green innovation.

Among other control variables with insignificant results, having higher profitability and a longer listing period does not necessarily guarantee more green innovation outputs as firms' R&D decisions may be affected by a series of complicated factors. Further, although firms with higher leverage levels may be subject to stricter lending restrictions and increased financial risks, this does not necessarily restrain their green innovation. (Zhang et al., 2022b). Finally, independent directors' influence on corporate decision-making may be limited.

4.3. Robustness tests

An important assumption of the DID model is that the trends of the treated and controlled groups are similar before policy implementation.[13] This study uses an event study method to test this assumption (Zhang et al., 2021a). Following Lu et al. (2022), year dummies are constructed to track the effect of GFP in 2012. Post_-4 to Post_-1 are dummy variables that equal one if the observation year is 2008–2011, respectively, and zero otherwise. Post_0 to Post_7 are dummy variables that equal one if the observation year is 2012–2019, respectively, and 0 otherwise. Post_-4 to Post_7 are respectively multiplied with Treat to obtain 12 dummy variables (DID_-4 to DID_7). Then, Eq. (1) is re-estimated with DID_-4 to DID_7 to examine the parallel trends assumption. The coefficients of DID_-4 to DID_7 are presented in Fig. 2, corresponding to points −4 to 7. All coefficients are insignificant (all confidence intervals include zero), suggesting that all interactions before 2012 are insignificant. Therefore, the parallel trend assumption is supported and the DID model can be used.

To reduce the potential endogeneity problems caused by self-selection bias, this study employs the PSM method to match the treatment and control groups, and reports the results in Table 4. Following Cui et al. (2022), this study selects the control variables ROA, Size, Leverage, Age, INST, Inden, and CSR as the covariates to run a logit regression to obtain the propensity score of enterprises in the treatment group and then matches enterprises in the control groups with similar characteristics using the neighbour match method. This method can effectively solve the initial difference between the treatment and control groups, thus making the estimation results more accurate (Zhang and Jiang, 2022). After performing the PSM, the unmatched observations are deleted and the estimations are repeated. The results shown in column 1 are consistent with the main findings of the baseline model.

The Chinese government has initiated a series of environmental protection policies over the past two decades. As the inclusion of a long

[13] If a significant difference is observed in the green innovation between HPEs and other enterprises before the implementation of the GFP, then the results may not be caused by GFP (Yao et al., 2021).

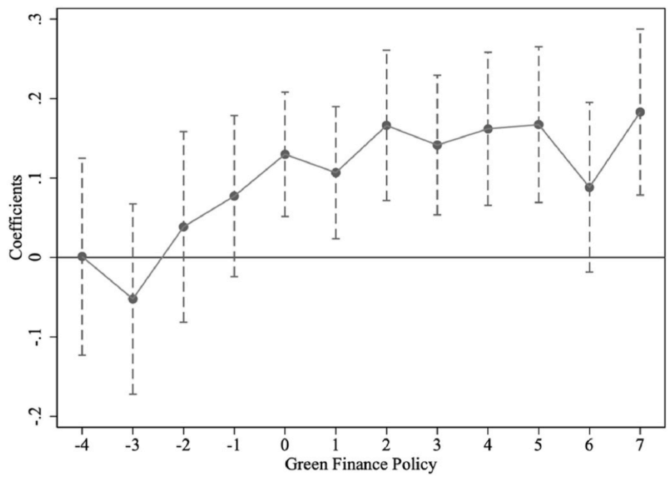

Fig. 2. Parallel trend analysis.

Table 4
Other tests for the baseline model.

Variables	(1)	(2)	(3)	(4)
	PSM-DID	2008–2015	Delete2008&2009	Delete Provinces
DID	0.123***	0.101***	0.101***	0.132**
	(3.56)	(3.10)	(3.17)	(2.66)
Constant	−2.650***	−2.974***	−2.392***	−2.924***
	(-6.47)	(-5.66)	(-6.08)	(-6.49)
Control Variables	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Observations	14,778	9010	13,182	12,385
R-squared	0.682	0.728	0.700	0.660

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: DID: Difference-in-Differences.

sample period after the implementation of GFP may lead to biased estimations, the sample period is shortened to 2008–2015 (Wang et al., 2022a).[14] The coefficient of DID remains significantly positive in column 2. However, other events during the sample period, such as the Great Financial Crisis (2008–2009) and the Beijing Olympics (2008), may also affect the estimation results as these events may have disrupted normal business activities (Zhang et al., 2022b). To remove the potential effects of the great financial crisis, this study drops the observations during 2008 and 2009, and reruns the regression. The results in column 3 are consistent with the baseline results. As for the impact of the Beijing Olympics, a few new initiatives were introduced during this period, including the 'Green Olympics' concept, and the "blue-sky and green-water projects" in Beijing and surrounding regions. In addition, in 2015, with the introduction of the Outline of the Plan for the Coordinated Development of Beijing-Tianjin-Hebei, issues related to environmental protection escalated to a historically high level. Therefore, following Tang et al. (2020), this study drops the data of related regions in China and reruns the baseline model. The findings in column 4 remain robust.[15] The study also employs the placebo test by randomly generating a selection of HPEs and repeating the sampling process 500 times. The results remain robust (see Appendix 4).

Thus, the DID model employed here is a good fit for the sample, and for both heavily polluting and green enterprises. Overall, GFP emerges as an important factor which affects firms' innovation outputs. In the following heterogeneity analysis, although the inclusion of green enterprises did not affect the estimated results in the baseline model, only HPEs are included to minimise the estimation bias.

4.4. Heterogeneity analysis

4.4.1. Heterogeneity analysis by the types of green innovation

It is suggested that regulations may stimulate different types of green innovation differently due to the investments needed, risks involved, and regulatory intensity (Jaffe and Palmer, 1997). To comprehensively investigate GFP's impact on different types of green innovation, this study divides green innovation into green innovation quality performance (*GI_qua*), and green innovation increment performance (*GI_inc*). As Wang and Li (2022) note, *GI_qua* is more related to newly created inventions, while *GI_inc* tends to build on existing technologies or products. Consequently, compared with *GI_inc*, *GI_qua* requires more resource inputs and faces higher uncertainties. Hence, it should be affected more by the GFP.

GI_qua is measured by the natural logarithm of one plus the number of green invent patent applications of firm *i* in year *t* (Zhang et al., 2023). *GI_inc* is measured by the natural logarithm of one plus the number of green utility patent applications of firm i in year t (Wang and Li, 2022). Meanwhile, diversified ownership categories of enterprises indicate that green patents are not only an internal research activity but an inter-firm cooperative activity (Liu and Wang, 2023). Patent applications can be divided into independent and joint green innovation.[16] Considering the variation of the dependent variable GI, this study also considers different green patent indicators. Therefore, considering that both *GI_qua* and *GI_inc* comprise independent and joint green innovation, we have *GI_qua_ind*, *GI_qua_joi*, *GI_inc_ind*, and *GI_inc_joi* (Liu and Wang, 2023).[17] The results are reported in Table 5.

The interaction item, DID, significantly stimulates all types of green innovation, regardless of the variables used. Notably, the coefficient of GI_inc is more significant than that of GI_qua (GI_qua: 0.069, significant at 5% level and GI_inc: 0.124, significant at 1% in Table 5), in line with expectations and prior research (Wang and Li, 2022). To attract external funding, HPEs are keen to advance their green innovation performance to meet the loan requirements under the Chinese GFP framework. Increasing the number of patents is easier than improving their quality (Zhang et al., 2022b). This may be particularly true for firms with limited green innovation experiences and operating in heavily polluting industries. Similar conclusions hold for either independent or joint green innovation, as shown in columns 3–6. These results indicate that GFP not only motivates HPEs to improve their own green innovation capabilities, but also enables them to value cooperation with other companies.

4.4.2. Heterogeneity analysis by ownership structure of firms

Next, this study explores the influence of the ownership structure of firms on the relationship between GFP and HPEs' green innovation performance by dividing the sample into state-owned enterprises (SOEs) and non-SOEs (Yao et al., 2021). The results are presented in Table 6.

The coefficients of DID in columns 1–3 are significantly positive and

[14] For example, the regression results may be influenced by other policies (Wang et al., 2022a).

[15] Regions include Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, and Liaoning.

[16] Joint green innovation refers to an application with green invention and/or green utility patents by two or more legal entities, whereas there is only one entity for independent green innovation.

[17] These are independent green innovation quality performance (GI_qua_ind), joint green innovation quality performance (GI_qua_joi), independent green innovation increment performance (GI_inc_ind), and joint green innovation increment performance (GI_inc_joi).

Table 5
Heterogeneity analysis for green innovation.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GI_qua	GI_inc	GI_qua_ind	GI_inc_ind	GI_qua_joi	GI_inc_joi
DID	0.069**	0.124***	0.048*	0.096***	0.032*	0.029**
	(2.25)	(5.08)	(2.09)	(5.71)	(2.04)	(2.23)
Constant	−2.408***	−1.379***	−2.005***	−1.185***	−0.736**	−0.415
	(-6.14)	(-3.83)	(-5.12)	(-4.50)	(-2.97)	(-1.69)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,788	14,788	14,788	14,788	14,788	14,788
R-squared	0.656	0.637	0.624	0.619	0.525	0.503

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; GI_qua_ind: Independent Green Innovation Quality; GI_inc_ind: Independent Green Innovation Increment; GI_qua_joi: Joint Green Innovation Quality; GI_inc_joi: Joint Green innovation Increment; DID: Difference-in-Differences.

greater than those in columns 4–6. GFP promotes both the quality and quantity of green innovation for SOEs (GI_qua: 0.117, significant at 10% level and GI_inc: 0.161, significant at 1% in Table 5), but only the quantity for non-SOEs. This is unsurprising as compared with non-SOEs, SOEs tend to be favoured by bank credit, enabling them to participate in high-quality green innovation (Ouyang et al., 2020). In turn, the close connection between the SOEs and the Chinese government has also exposed the former to increased pressure in complying with state-mandated emissions reduction targets (Wang et al., 2022a). Nevertheless, for both SOEs and non-SOEs, incremental green innovation remains the key focus mainly because the sample is comprised of heavy polluters only. For instance, any adjustments/minor amendments to existing green technologies may help them achieve significant emissions reductions. However, they are neither capable nor incentivised enough to engage in more high-quality green innovation.

4.4.3. Heterogeneity analysis by external finance dependence

The essence of GFP's design is linking the availability of bank credit with the environmental performance of firms. Therefore, firms that rely heavily on external financing are more likely to be affected by the GFP (Sun et al., 2019). To measure the extent of firms' reliance on external capital, following Rajan and Zingales (1998) and Sun et al. (2019), this study constructs an external finance dependence (EFD) index and then classifies firms into two categories high-EFD and low-EFD according to their reliance.[18] The results are reported in Table 7.

The results for both high- and low-EFD firms in columns 1–6 are consistent with earlier findings. However, as shown in columns 1–3, GFP has a larger effect on the green innovation performance of high-EFD HPEs, which is consistent with prior studies (Sun et al., 2019). When the Chinese government advocates green development, it may also adjust credit policies to restrict the inflow of bank loans to heavily polluting activities accordingly (Wang and Li, 2022). This forces the HPEs with high-EFD to enhance their green innovation performance, signifying their determination to achieve sustainable growth to secure banking credit. Notably, GFP significantly improves both the quality and quantity of green innovation in the high-EFD group, but only the quantity in the low-EFD group. This could be attributed to the fact that high-EFD firms are more inclined to boost advanced green innovation performance to ensure future green credit availability from banks. However, as they rely less on external finance, low-EFD firms might be reluctant to assume higher risks associated with advanced green innovation. In contrast, low-EFD firms tend to enhance their GI_inc primarily to comply with the environmental protection mandates of relevant regulations.

4.5. Moderation effects analysis

The CERs and VERs play a key role in the green transformation process of Chinese environmental regulations, leading to the development of a synergistic effect in green innovation promotion. Here, additional tests are conducted to investigate the moderating effect of other environmental regulations on the relationship between the GFP and green innovation among HPEs. In the analysis, the study uses the environmental violation imposed by the government to measure the impact of the penalty-based environmental regulation, the green subsidies granted by the government to proxy for the incentive-based environmental regulation and the pollutant emissions disclosure for influence exerted by voluntary environmental regulation. The study conducts the moderating analysis separately for these three types of environmental regulations. The results are reported in Table 8.

As a commend-based regulatory instrument, *CER_Penalty* has a negative relationship with GI and GI_qua (Columns 1–3). This is unsurprising as CER_Penalty implemented by the Chinese government represents additional environmental costs to the HPEs, reducing the capital available for their R&D activities. In some extreme cases, firms could be suspended for rectification due to environmental violations (Ma et al., 2022). In terms of the moderation effect, CER_Penalty has no significant impact on the relationship between GFP and green innovation. Thus, hypothesis 2a is supported. This may be because GFP is more of a market mechanism but CER_Penalty is more of a policy instrument. They tend to function on firms' innovation behaviours differently. Notably, as only 47 firms, or 0.5% of observations, are fined over the sample period. Thus, the *CER_Penalty* is used more like a demonstrating mechanism to showcase the government's intention.

CER_Incentive has a significantly positive moderation effect (e.g. the coefficient of DID in column 4 of Table 8 (0.031) is significant at 5% level), in support of hypothesis 2b. However, it is unable to significantly affect firms' green innovation on its own. Consistent with Huang et al. (2019), if the HPE can access state subsidies, it can favourably position itself to secure additional green credit from banks. With sufficient funding, high-quality green innovation is more likely to be delivered. Meanwhile, to continuously attract future government funding, instead of relying on short-term rent-seeking, firms are also motivated to fulfil the requirements of the Chinese government and financial institutions with the highest possible quality. This may enhance their green innovation efficiency. This may be why the moderation effect of CER_Incentive is more significant in the case of green innovation quality

[18] EFD = (Capital expenditures − Cash flow from operations)/Capital expenditures. Firms are classified as high-EFD if the index value is above the median (0.216), and low-EFD otherwise.

Table 6
Heterogeneity analysis for the property rights structure.

Variables	SOE			Non-SOE		
	(1)	(2)	(3)	(4)	(5)	(6)
	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.181**	0.117*	0.161***	0.037*	−0.008	0.074***
	(2.96)	(2.00)	(5.20)	(1.88)	(-0.41)	(5.26)
Constant	−2.337***	−2.142***	−1.055***	−3.027***	−2.658***	−1.842***
	(-5.00)	(-3.69)	(-5.12)	(-6.30)	(-6.18)	(-3.81)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6674	6674	6674	7870	7870	7870
R-squared	0.734	0.710	0.684	0.630	0.598	0.586

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI: Green Innovation; GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; DID: Difference-in-Differences; SOE: State-owned Enterprise.

Table 7
Heterogeneity analysis for external finance dependence.

Variables	High-EFD			Low-EFD		
	(1)	(2)	(3)	(4)	(5)	(6)
	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.127***	0.080**	0.122***	0.111**	0.049	0.114***
	(3.76)	(2.86)	(6.38)	(2.69)	(0.96)	(8.04)
Constant	−2.808***	−2.317***	−1.817***	−3.026***	−2.448***	−2.121***
	(-4.57)	(-3.68)	(-4.31)	(-4.24)	(-4.82)	(-3.28)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4748	4748	4748	4723	4723	4723
R-squared	0.716	0.682	0.682	0.769	0.750	0.738

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI: Green Innovation; GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; DID: Difference-in-Differences; EFD: External Finance Dependence.

rather than the simpler incremental green innovation.

The moderation effect of VER is significantly positive for all types of green innovation measures (Columns 7–9) (e.g. the coefficient of DID in column 7 of Table 8 (0.023) is significant at 1% level). Thus, hypothesis 3 is supported. The maturing environmental information disclosure in the Chinese market has reduced information asymmetry. The higher VER intensity signifies the green transition determination of HPEs and their motivation to engage more in green innovation activities in China (Huang and Chen, 2015). Furthermore, this positive impact is more prominent for green innovation quality than increment (Columns 8–9). To achieve a more thorough green transformation, HPEs try to produce high-quality green innovation (Bu et al., 2020). However, due to the lack of core green technologies and green capital, HPEs also invest part of their financial resources in green innovation increment to meet the compliance requirements of financial institutions and the government.

Thus, CER_Incentive and VER can positively moderate the relationship between GFP and green innovation performance in most cases, indicating the continued enhancement of China's environment regulation system and the applicability of the Porter hypothesis in the Chinese market. However, *CER_Penalty* tends to be ineffective. Meanwhile, green quality innovation is more significantly promoted by the CER_Incentive and VER than incremental innovation, as firms are more motivated to build long-term competitive advantages in their green transition. The finding is further illustrated with the moderation effect plots in Appendix 5.

4.6. *Channel analysis for corporate green investments*

This study explores how GFP influences firms' green innovation performance. Specifically, this study focuses on the efficiency of green capital utilisation (GreenInv) in HPEs. The data of GreenInv is collected manually from the notes of 'projects under construction' in the annual report of enterprises (Lu, 2021). Specifically, this study uses the Word Embedding model to construct a green investment dictionary and then extracts the GreenInv data based on this dictionary. After data cleaning, the amount of different green investment items is aggregated to create the GreenInv variable. The results are reported in Table 9.

GFP and GreenInv have an insignificant relationship, while GreenInv and green innovation are significantly related. Thus, while GFP does not affect the green investment made by HPEs (Column 1), it can significantly enhance their green innovation performance (Column 3). Similar results are found for green innovation quality and increment (Columns 5 and 7). This may be because the implementation of GFP may further constrain the capital inflow to HPEs, they may be motivated to improve their innovation efficiency given the limited funding. This may be the only viable way for such cash-strapped firms to transform themselves for long-term sustained development. Yan et al. (2022) find similar results in their study of green finance and corporate investment efficiency in the Chinese market. Consequently, GFP imposes added compliance obligations and elevates social reputational pressure on HPEs, compelling these firms to augment their green innovation outputs. Given the rising awareness of environmental protection in China, GFP also captures

Table 8
Moderation effect analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.112***	0.067**	0.110***	0.129*	0.083	0.095***	0.085**	0.038	0.101***
	(3.39)	(2.25)	(5.57)	(2.06)	(1.43)	(3.58)	(2.91)	(1.52)	(5.31)
CER_Penalty × DID	0.050	0.079	0.084						
	(0.25)	(0.89)	(0.40)						
CER_Penalty	−0.121***	−0.193***	0.018						
	(-3.14)	(-3.22)	(0.66)						
CER_Incentive × DID				0.031**	0.022***	0.027*			
				(2.74)	(9.87)	(2.12)			
CER_Incentive				−0.001	−0.002	−0.001			
				(-0.36)	(-0.80)	(-0.41)			
VER × DID							0.023***	0.026***	0.008**
							(4.72)	(8.86)	(2.19)
VER							0.005	−0.000	0.005*
							(1.28)	(-0.01)	(1.95)
Constant	−2.500***	−2.337***	−1.280***	−3.109***	−2.931***	−1.954***	−2.573***	−2.417***	−1.299***
	(-6.01)	(-5.66)	(-4.23)	(-8.75)	(-10.21)	(-13.31)	(-6.16)	(-5.87)	(-4.33)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,064	14,064	14,064	4779	4779	4779	14,064	14,064	14,064
R-squared	0.693	0.670	0.650	0.696	0.666	0.669	0.694	0.670	0.651

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI: Green Innovation; GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; DID: Difference-in-Differences; CER_Penalty: Penalty-based Environmental Regulation; CER_Incentive: Incentive-based Environmental Regulation; VER: Voluntary Environmental Regulation.

Table 9
Channel analysis of corporate green investment.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenInv	GI	GI	GI_qua	GI_qua	GI_inc	GI_inc
GreenInv			0.010***		0.005***		0.007**
			(4.22)		(3.59)		(2.78)
DID	0.080	0.160***	0.160***	0.102***	0.102***	0.174***	0.173***
	(0.62)	(7.17)	(6.92)	(8.49)	(8.30)	(22.14)	(21.64)
Constant	−2.443	−1.063***	−1.039***	−1.167***	−1.154***	−0.312	−0.294
	(-0.89)	(-3.50)	(-3.27)	(-6.38)	(-6.41)	(-1.20)	(-1.25)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3045	3045	3045	3045	3045	3045	3045
R-squared	0.651	0.729	0.729	0.719	0.719	0.702	0.702

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI: Green Innovation; GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; DID: Difference-in-Differences; GreenInv: Green Investment.

societal concern, pressing firms to boost their innovation efficiency to secure future green capital or to prevent it from being left behind.

4.7. The impact of GFP on green enterprises

Since the GFP affects both highly polluting and green enterprises simultaneously, a comparative study is conducted here to test the robustness of the findings. According to Al-Tuwaijri et al. (2004) and Wang et al. (2020), green enterprises refer to firms whose main business involves environmental-friendly products. Based on annual reports and the industry classification of the listed companies developed by Tonghuashun Finance and Economic, this study manually analyses the main business of every firm to determine whether it can be classified as a green enterprise.[19] Furthermore, this study checks the selection results of green enterprises with the Hexun, one of the most famous financial and economic platforms, to ensure the accuracy of the results.[20] Then, we replace the treated group with green enterprises.[21] Specifically, Treat is a dummy variable equalling one if the firm is a green enterprise. Post is another dummy variable that equals one if the GFP has been implemented, or the samples are within the 2012–2019 period. The interaction Treat × Post (DID) should be significant if the DID effect exists (Wang and Li, 2022). The results are reported in Table 10.

[19] https://www.10jqka.com.cn/.

[20] https://www.hexun.com/?from=rongshuxia; Specifically, this study uses Python to crawl the main business content of listed companies from Tonghuashun Finance and Economic, and Hexun, and then manually judges related information.

[21] Furthermore, this study drops HPEs from the regression sample to avoid potential research bias.

Similar to HPEs, GFP can significantly promote green innovation among green enterprises (Column 1).[22] To maintain market competitiveness, green enterprises are also under pressure to enhance their innovation capacity to deliver better green products and services (Xu and Li, 2020). Further, GFP promotes the green innovation quality and increment of green enterprises (Columns 2–7). Notably, the promotional effect of GFP on green innovation quality is greater for green enterprises than that in HPEs.[23] This is expected as green enterprises tend to have a better foundation in green innovation.[24] Therefore, they are more likely to concentrate more on high-quality green innovation to build their long-term competitive advantages in the Chinese market.

This study then applies similar tests to capture the impact of ownership structure, external finance dependence, and the moderating effect of government regulations among green enterprises. The results are available upon request. In general, the conclusions for HPEs hold. The GFP has a greater effect on green innovation among SOEs, especially for the green innovation quality performance. However, GFP has no effect on non-SOE green enterprises. This finding is different from that for non-SOE HPEs. Hu et al. (2021b) reach similar conclusions. Unlike HPEs, green enterprises are not that cash-strapped. Further, the non-SOE green enterprises are not largely influenced by government policies but are more likely to follow their own green development pace. In addition, green enterprises that depend heavily on external finance are more willing to improve green innovation performance to secure future funding, whereas those with low-EFD tend to care little about continuous green innovation outputs. This is in line with Sun et al. (2019). Compared with HPEs, green enterprises tend to already have a sound level of green innovation. Therefore, they may not experience serious difficulties in accessing funding directly from banks and other financial institutions (Peng et al., 2022).

Regarding the moderating effect of other environmental regulations, CER_Penalty still fails to positively moderate the effect of the GFP on green innovation for green enterprises. This is unsurprising as green enterprises tend to have better environmental performance and fewer environmental violations than the HPEs in the Chinese market.[25] Regarding CER_Incentive, the significant moderating effect is only present in the case of green innovation quality performance. Given green enterprises tend to possess stronger green innovation capabilities, additional financial support from the Chinese government may encourage them to pursue more advanced innovation, driving the overall industrial structural upgrading. Finally, VER only significantly promotes the positive relationship between GFP and GI or GI-qua. This is consistent with earlier findings. Adhering to VER often demands a substantial allocation of resources, including time and finances. Consequently, GEs might opt to channel these resources into advanced green innovation instead of dispersing them across multiple projects (Huang and Chen, 2015).

Lastly, the channel analysis results for green enterprises are consistent with those for HPEs. Overall, the GFP is playing a more active role in stimulating green innovation efficiency among listed green enterprises in China (Xu and Li, 2020).

[22] The parallel trend analysis also shows that the adoption of the DID model is rational. The results of this analysis are available upon request.

[23] The coefficient of DID on GI_qua is 0.098 for green enterprises at the 1% level, whereas it is 0.069 for HPEs at the 5% level.

[24] The average green innovation performance of green enterprises is higher than that of HPE, see Appendix 2.

[25] The mean value of environmental violation for HPEs is 0.0079, which is nearly twice higher than that for green enterprises at 0.0041.

5. Conclusion and policy implications

5.1. Conclusion

China's 12th Five-Year-Plan (2011–15) reported for the first time that the country was facing severe environmental degradation, showing the government's interest in considering these issues. Indeed, various policy initiatives, including the GFP, were initiated to rebalance the economy for environmental protection and sustained development. The GFP can be regarded as a valuable market-based environmental regulatory instrument designed to mitigate environmental pollution and provide more funding for green activities (Lu et al., 2022). This study empirically investigates the influence of GFP on green innovation using panel data on Chinese listed companies from 2007 to 2019. A DID model is employed for the baseline test, and then a series of tests, such as the parallel trend analysis and PSM-DID, are conducted to ensure the robustness of the results. Next, this study explores the heterogeneous impacts of various factors, including types of green innovation (green quality innovation and green incremental innovation), the ownership structure of firms (SOEs and non-SOEs), and the degree of external finance dependence.

Overall, the results show that GFP can enhance the green innovation performance of both heavily polluting (e.g. the coefficient of DID in column 4 of Table 3 (0.123) is significant at 1% level) and green enterprises (e.g. the coefficient of DID in column 1 of Table 10 (0.104) is significant at 1% level). Compared with green enterprises, heavy polluters tend to pay more attention to the green innovation increment due to their limited green innovation experiences and financial resources (GI_qua: 0.069, significant at 5% level and GI_inc: 0.124, significant at 1% in Table 5). Incremental green innovation is easier and more feasible for them to meet government regulatory requirements while achieving a certain degree of green transformation. Meanwhile, compared to HPEs, with the support of GFP, green enterprises have a stronger capability to deliver green quality innovation and this may help them build up long-term competitive advantages. SOEs are also better motivated by the GFP to deliver high-quality green innovation, given their closer relationship with the government. Compared with non-SOEs, SOEs tend to be favoured by banking credit but are also under more pressure to meet state-mandated emissions reduction requirements (Wang et al., 2022a). Lastly, firms that need more external financial support are more likely to be affected by the GFP as they are forced to deliver superior performance to meet the borrowing conditions.

Given the close connection between other environmental regulations, the GFP, and firm innovation, this study further investigates the moderation effects of different types of environmental regulations, including CERs and VERs. The penalty-based regulation, CER_Penalty, has no significant moderation effect, while the incentive-based regulation (CER_Incentive) can promote the relationship between the GFP and green innovation for HPEs significantly (e.g. the coefficient of DID in column 4 of Table 8 (0.031) is significant at 5% level). A similar conclusion is also reached for the VER (e.g. the coefficient of DID in column 7 of Table 8 (0.023) is significant at 1% level). Moreover, the CER_Incentive and VER have more significant positive moderation effects for higher-quality green innovation, especially for green enterprises. A higher intensity of VER signifies the green transition determination of firms, signifying their motivation to engage more in high-quality green innovation activities (Huang and Chen, 2015). Lastly, the channel analysis shows that the GFP can enhance green innovation performance by improving the efficiency of green investment use.

5.2. Policy implications

First, more targeted GFPs can be implemented to encourage greater bank lending to HPEs for increased green innovation. This can help accelerate overall industrial transformation. Next, stimulated by GFP, although HPEs are willing to innovate, they tend to focus more on

Table 10
Results of green innovation for green enterprises.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GI	GI_qua	GI_inc	GI_qua_ind	GI_inc_ind	GI_qua_joi	GI_inc_joi
DID	0.104***	0.098***	0.107***	0.045*	0.040**	0.077***	0.080***
	(3.25)	(4.19)	(4.84)	(1.81)	(2.43)	(13.60)	(5.09)
Constant	−2.626***	−2.247***	−1.529**	−1.863***	−1.198**	−0.782*	−0.579*
	(-4.47)	(-4.45)	(-2.74)	(-4.31)	(-2.77)	(-2.12)	(-2.03)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,496	13,496	13,496	13,496	13,496	13,496	13,496
R-squared	0.698	0.672	0.648	0.654	0.637	0.481	0.480

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI: Green Innovation; GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; GI_qua_ind: Independent Green Innovation Quality; GI_inc_ind: Independent Green Innovation Increment; GI_qua_joi: Joint Green Innovation Quality; GI_inc_joi: Joint Green innovation Increment; DID: Difference-in-Differences.

Table 11
Description of variables.

Type	Abbreviated Variable	Variable Name	Variable Definitions	Data Source
Dependent Variable	GI	Green innovation	Natural logarithm of the sum of 1 and the number of green patent applications.	CNRDS
	GI_inc	Green Innovation Increment	Natural logarithm of the sum of 1 and the number of green utility patent applications.	CNRDS
	GI_inc_ind	Independent Green Innovation Increment	Natural logarithm of the sum of 1 and the number of independent green utility patent applications.	CNRDS
	GI_inc_joi	Joint Green innovation Increment	Natural logarithm of the sum of 1 and the number of joint green utility patent applications.	CNRDS
	GI_qua	Green Innovation Quality	Natural logarithm of the sum of 1 and the number of green invention patent applications.	CNRDS
	GI_qua_ind	Independent Green Innovation Quality	Natural logarithm of the sum of 1 and the number of independent green invention patent applications.	CNRDS
	GI_qua_joi	Joint Green Innovation Quality	Natural logarithm of the sum of 1 and the number of joint green invention patent applications.	CNRDS
Independent Variable	DID	The interaction term of Treat × Post	Treat equals to 1 for HPEs, and 0 otherwise; Post equals to 1 for 2012–2019, and 0 for 2007–2011.	Draft
Moderation Variables	CER_Penalty	Penalty-based Environmental Regulation	It is proxied by whether the company has had the environmental violation noted in the year.	CNRDS
	CER_Incentive	Incentive-based Environmental Regulation	Natural logarithm of the sum of the amount of green subsidy items received for a firm in a year.	CSMAR
	VER	Voluntary Environmental Regulation	The disclosure of six pollutant emissions information, it ranges from 0 to 6.	CSMAR
Mediation Variable	GreenInv	Green investment	Natural logarithm of the sum of the amount of green investment for a firm in a year.	CSMAR
Control Variables	ROA	Profitability	The ratio of net profits to total assets.	CSMAR
	Size	Firm size	Natural logarithm of the company's total assets.	CSMAR
	Leverage	Leverage	The ratio of liabilities to total assets.	CSMAR
	Age	Listing years	Natural logarithm of numbers of years the company has been listed plus one.	CSMAR
	INST	Shareholding ratio of institutional investors	The proportion of shares held by institutional investors.	CSMAR
	Inden	The proportion of independent directors	Number of independent directors/Number of directors.	CSMAR
	CSR	Corporate social responsibility	A dummy variable which equals to 1 if enterprises disclose their CSR reports, and 0 otherwise.	CSR reports

incremental innovation due to their lack of experience and resources. Therefore, policy efforts should encourage information/knowledge sharing among firms in the same industry. This can help improve resource use efficiency. Meanwhile, effective performance measures should be designed to evaluate the long-term green performance of HPEs. This may encourage their management to commit valuable financial resources towards higher quality green innovation, which requires more investments and a longer development cycle. Lastly, the Chinese government should use different environmental policy tools to leverage their synergistic effects effectively. Firms should be both pressured and motivated to engage more in high-quality green innovation. This requires the further improvement of the current green finance system. As a key player, banks need to take a more proactive role in this process. They should establish comprehensive procedures to encourage promising green innovation at an early stage. Banks should also provide sufficient supervision throughout the process to encourage firms, especially the heavy polluters, to participate in more green innovation and socially responsible behaviours.

5.3. Limitations and future research directions

The study demonstrates that the implementation of GFP effectively bolsters the firms' green innovation performance. Nonetheless, it is essential to highlight that an important objective of both green finance policies and green innovation is the reduction of firms' CO_2 emissions. Investigating this issue is of significant research value as insights obtained can be used to verify whether firms are genuinely dedicated to the green transition, alleviating the potential greenwashing concerns. However, due to data availability (sporadic and non-uniform reporting), the current research is unable to obtain adequate firm-level CO_2 emissions data in the Chinese market for more in-depth analysis at the firm level. Along with the further evolution of the information reporting system and the regulatory control framework, further studies could be conducted to explore the nexus among green finance policies, firms' emissions reduction and green innovation strategies. The findings obtained could be used to deepen China's green reform and provide valuable guidance to other developing economies in their green transition process.

CRediT authorship contribution statement

Kaiwen Chang: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Dan Luo:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Yizhe Dong:** Writing – review & editing, Resources. **Chu Xiong:** Software, Resources.

Declaration of competing interest

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The remaining authors declare that they have no conflicts of interest to declare.

Data availability

Data will be made available on request.

Appendix

Appendix 1
Regression results of CER_Incentive1[a]

Variables	HPEs			Green enterprises		
	(1)	(2)	(3)	(4)	(5)	(6)
	GI	GI_qua	GI_inc	GI	GI_qua	GI_inc
DID	0.084**	0.033	0.100***	0.065*	0.061**	0.083***
	(2.71)	(1.34)	(4.40)	(1.90)	(2.67)	(3.24)
CER_Incentive1 × DID	0.045***	0.047***	0.032***	0.067***	0.060***	0.048**
	(4.72)	(9.45)	(7.94)	(3.56)	(6.27)	(2.70)
CER_Incentive1	0.019***	0.013***	0.016***	0.017***	0.013***	0.012***
	(5.86)	(4.81)	(5.46)	(4.27)	(3.76)	(4.35)
Constant	−2.679***	−2.487***	−1.366***	−2.656***	−2.292***	−1.547**
	(-6.71)	(-6.52)	(-4.63)	(-4.56)	(-4.46)	(-2.72)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,169	14,169	14,169	12,893	12,893	12,893
R-squared	0.681	0.655	0.637	0.700	0.674	0.650

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions are robustly clustered to industries. Robust t-statistics are enclosed in parentheses. The full terms for variables' abbreviations: GI: Green Innovation; GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; DID: Difference-in-Differences; CER_Incentive1: Government Subsidy; HPEs: Heavily Polluting Enterprises.

[a] Columns 1–3 and 4–6 for HPEs and green enterprises, respectively.

Appendix 2
The comparison of green innovation performance for HPEs and green enterprises

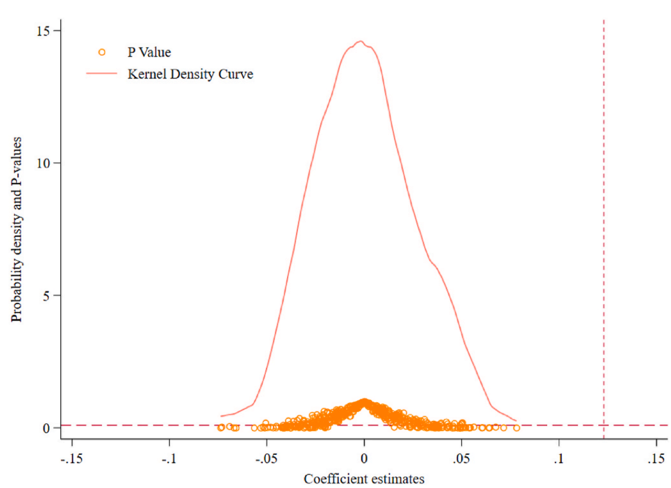
Variable	Obs.	Mean	Std. Dev.	Min	Max
HPEs					
GI	3316	0.544	0.899	0.000	3.829
GI_qua	3316	0.343	0.699	0.000	3.367
GI_inc	3316	0.364	0.699	0.000	3.045
Green enterprises					
GI	2026	0.822	1.127	0.000	3.829
GI_qua	2026	0.565	0.913	0.000	3.367
GI_inc	2026	0.548	0.851	0.000	3.045

Notes: The full terms for variables' abbreviations: GI: Green Innovation; GI_qua: Green Innovation Quality; GI_inc: Green Innovation Increment; HPEs: Heavily Polluting Enterprises.

Appendix 3
Acronyms

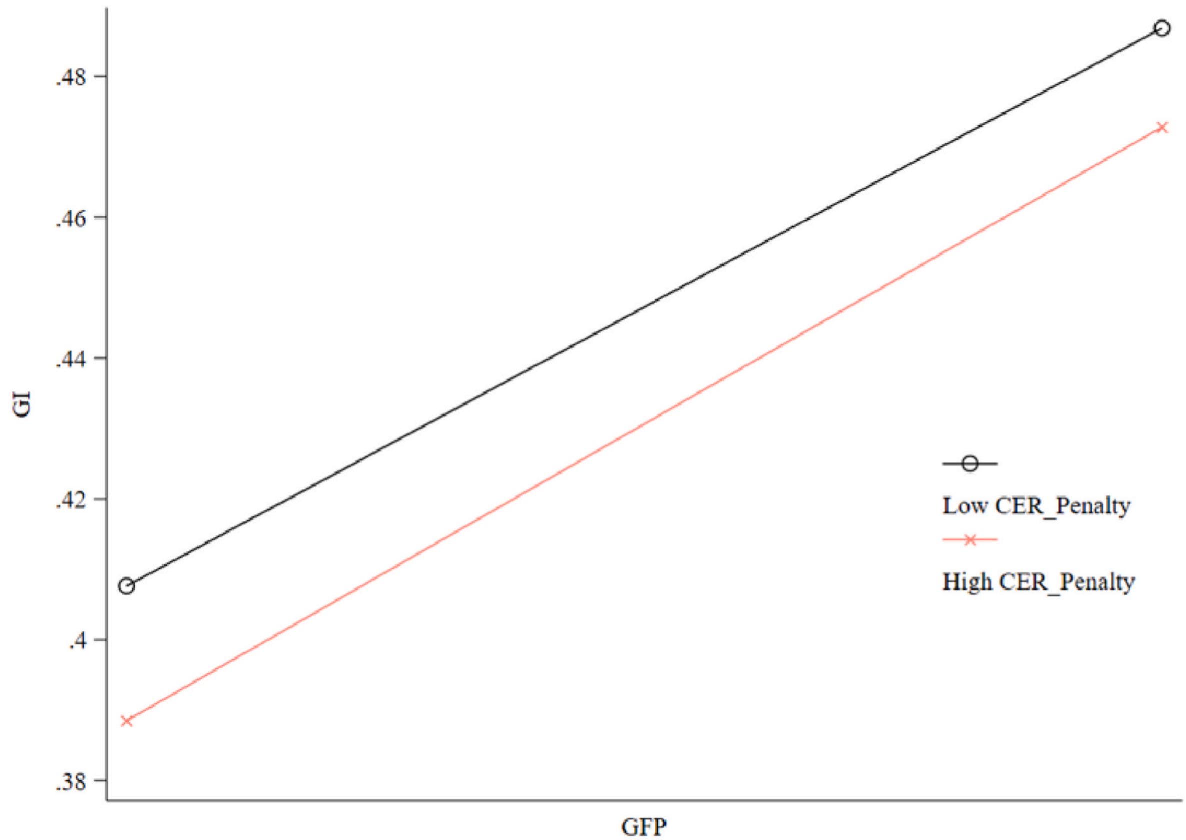
Acronym	Full name
Age	Listing Years
CER	Command-and-control Environmental Regulation
CER_Incentive	Incentive-based Environmental Regulation
CER_Incentive1	Government Subsidy
CER_Penalty	Penalty-based Environmental Regulation
CNRDS	Chinese Research Data Services
CSMAR	China Stock Market and Accounting Research
CSR	Corporate Social Responsibility
DID	Difference-in-Differences
EFD	External Finance Dependence
HPEs	Heavily Polluting Enterprises
Inden	Proportion of Independent Directors
INST	Shareholding Ratio of Institutional Investors
GCG	Green Credit Guideline 2012
GFP	Green Finance Policy
GI	Green Innovation
GI_inc	Green Innovation Increment
GI_inc_ind	Independent Green Innovation Increment
GI_inc_joi	Joint Green innovation Increment
GI_qua	Green Innovation Quality
GI_qua_ind	Independent Green Innovation Quality
GI_qua_joi	Joint Green Innovation Quality
GreenInv	Green Investment
Leverage	Leverage
MER	Market-based Environmental Regulation
PH	Porter Hypothesis
Post	Policy Implementation
ROA	Profitability
Size	Firm Size
SOEs	State-owned Enterprises
Treat	Treated Group
VER	Voluntary Environmental Regulation

Appendix 4 Placebo tests[26]

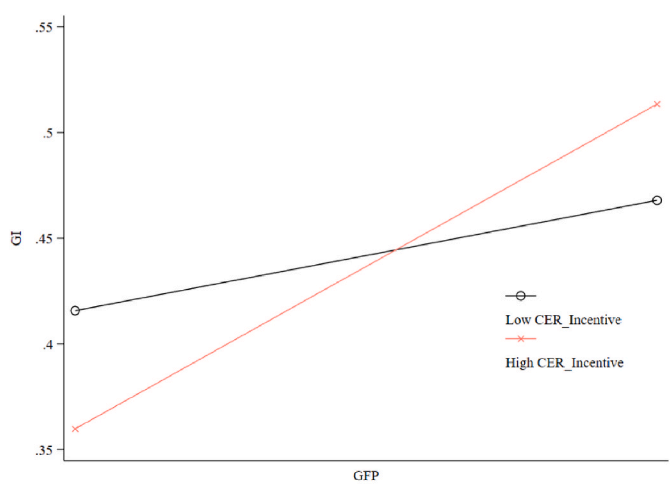


[26] According to Tan et al. (2022), the study randomly generates a selection of HPEs. Then the DID model is applied to Equation (1) and the sampling process is repeated 500 times for the placebo test, ensuring the robustness of the regression results. The coefficients from the DID term post-randomisation largely cluster around 0, with most p-values exceeding 0.1. Notably, the baseline estimation result (0.123) is located at the edge of the whole distribution. Such an observation indicates a significant dilution of the policy effect post-randomisation, both in terms of significance and magnitude. This indirectly affirms the robustness of the findings in the study, suggesting that the enhancement in enterprises' green innovation performance is genuinely attributable to the GFP, rather than being randomly instigated or influenced by other policies

Appendix 5 Moderation effect plot[27]

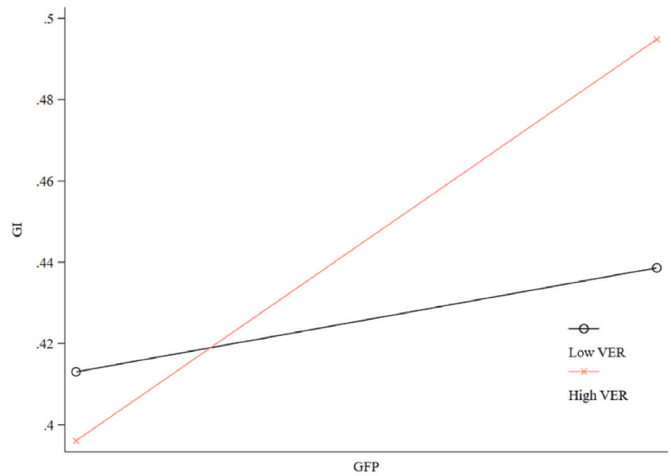


Moderation effect plot for CER_Penalty



Moderation effect plot for CER_Incentive

[27] These plots show that the impact of GFP on GI performance strengthens with increased intensity of CER_Incentive and VER. However, a rise in CER_Penalty does not produce a comparable shift. Thus, while CER_Incentive and VER both play a significant and positive role in moderating the relationship between GFP and green innovation performance, CER_Penalty does not exhibit a pronounced moderation effect



Moderation effect plot for VER

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