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Modelling economic policy issues

Government's awareness of Environmental protection and corporate green innovation: A natural experiment from the new environmental protection law in China

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A B S T R A C T

Based on the impact of the new environmental protection law promulgated by the Chinese government in 2015, we employ the difference-in-differences (DID) approach to investigate the impact of government environmental regulation on corporate green innovation. The evidence shows that government environmental regulation can significantly increase the number of green patents of heavily polluting industries. This result holds after a series of robustness tests. The analysis of the economic mechanism indicates that the new environmental protection law brings supervision pressure to heavily polluting firms, prompting them to improve the quality of information disclosure, thus improving green innovation. In addition, the regional economic development level, government subsidies, and public supervision can significantly affect the positive impact of the new environmental protection law. Meanwhile, the effect is more prominent in non-state-owned enterprises and in firms with small scale, low profitability, and weak internal governance.

1. Introduction

Green innovation is a general term for technologies, processes, or products that can reduce environmental pollution as well as energy and raw material consumption (Braun and Wield, 1994). Prior studies have proven that green innovation is positively correlated with firm competitiveness and technological innovation (Tang et al., 2018; Xie et al., 2019) and can help firms mitigate the adverse impact of economic activity on the environment (Horbach, 2008; Song and Yu, 2018). Meanwhile, green innovation has become an important means for heavily polluting firms to achieve sustainable development (Ooba et al., 2015). However, the effect of government regulation policies on green innovation is still not clear. In this paper, the new environmental protection law launched in China is used as a natural experiment to explore whether and how the improvement of government environmental protection awareness affects the green innovation ability of listed firms in heavily polluting industries. This study has important theoretical value and practical significance

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for clarifying the relationship between government environmental regulation and green innovation and for promoting pollution control and environmental protection from the perspective of green innovation.

To prevent worsening environmental problems and achieve sustainable development, governments around the world have been strengthening environmental supervision and introducing environmental regulation policies to enhance regulatory effectiveness (Cai et al., 2016a,b; Kraus et al., 2020). Previous studies point out that government environmental regulation plays an increasingly critical role in the firms' development. Specifically, it can bring more international capital to firms, promote firms to improve energy efficiency, and encourage firms to carry out green investment (Elliott and Zhou, 2013; Bi et al., 2014; Liao, 2018).

In addition, some theoretical studies indicate that government environmental regulation may provide incentives for industrial technological innovation and production efficiency (Ambec et al., 2013; Rubashkina et al., 2015). However, empirical evidence on the impact of government environmental regulation on corporate green innovation behavior is still limited.

Two opposite arguments are generated from the literature regarding the impact of government environmental regulation and green innovation: the "crowding-out effect" and the "compensation effect". One view is that strict environmental regulation may inhibit the technological innovation of firms. To meet the new environmental standards, firms generally adopt the end-management strategy, that is, the upgrading of their production processes to reach the environmental protection threshold required by the government. Therefore, for the abovementioned upgrade processes, firms may pay higher costs, which may crowd out the R&D expenses of firms, thus resulting in a "crowding-out effect" (Frondel et al., 2008). This conclusion is supported by Gray (1987), Kemp and Pontoglio (2011), and Testa et al. (2011).

The other view, namely, the "compensation effect", suggests that strict and appropriate environmental regulation can provide potential incentives for the individual firm' technological innovation (Porter and Van der Linde, 1995; Cohen and Tubb, 2018); this view is known as the *Porter Hypothesis*. Specifically, after the government implements appropriate environmental regulation, firms may actively choose strategies that meet environmental regulation standards. In the operations process, firms may take the initiative to carry out green technology innovation to achieve the goal of reducing pollution emissions and optimizing the production process (Rubashkina et al., 2015). Therefore, the pressure of environmental regulations may generate an innovation impetus that is beneficial to environmental protection. These actions not only meet the requirements of relevant laws and regulations but also make the production process more efficient. Meanwhile, cost savings are sufficient to compensate for the compliance costs (Yuan and Xiang, 2018). This is an important reason why environmental regulation has been promoted as a win–win strategy that leads to better environmental quality and higher corporate production performance. Therefore, strict environmental regulation is likely to change the strategic decision of a given firm and further promote innovation behavior, thus affecting the green innovation level.

Based on the above analysis, we take the Chinese stock market as the research object to explore the impact of government environmental regulation on corporate green innovation. The reasons for choosing China's stock market are as follows. First, like most emerging economies, China has experienced a rapid economic growth that has been accompanied by severe environmental pollution and energy consumption (Peng et al., 2015). According to the Global Environmental Performance Index (EPI) jointly released by the World Economic Forum and other organizations in 2014, China ranked 118th out of 178 participating countries and regions with 43 points. In addition, China's GDP has become the second largest in the world, but the extensive development model has brought it into the dilemma of "environmental pollution vs. economic development". Du et al. (2019) indicate that green innovation may be a useful approach to alter the above development pattern. Therefore, the Chinese market can provide a good platform for the research on environmental pollution, environmental regulation, and green technology innovation.

Second, along with the improvement of public quality of life requirements, the Chinese government introduced *the Environmental Protection Law of the People's Republic of China* in 2015, known as "the strictest environmental protection law in Chinese history". The implementation of this exogenetic policy provides a good natural experiment for us to explore the consequences of the participation of government environmental regulation in listed firms. Specifically, the law sets up a new chapter on information disclosure and public participation, requiring firms to regularly disclose information about environmental protection and pollution emissions. Meanwhile, the law also clearly states that citizens, legal persons, and other organizations have the right to obtain environmental information and to participate in and supervise environmental protection in accordance with the law. In addition, public interest groups can file "public interest lawsuits" against the firms' polluting activities. This clause closely links environmental protection with corporate social image, which is regarded as an external driver for the effective implementation of the new law (Jiang et al., 2020). More importantly, provisions in the new law, such as the stipulation that "daily fines have no upper limit" and the ban on retroactively applying for environmental impact assessments, have raised the cost of breaking the law and greatly strengthened the deterrent effect of economic punishment on firms. Therefore, the revision and implementation of the new environmental protection law actually provides a natural experiment, which can be used to study government environmental awareness (environmental regulation level) and the green innovation level of listed firms.

Based on the impact of the new environmental protection law promulgated by the Chinese government in 2015, we use the difference-in-differences (DID) approach to investigate the relationship between government environmental regulation and the firms' green innovation. The evidence shows that government environmental regulation can significantly increase the number of green patents of heavily polluting industries, providing thereby empirical evidence from

China for the *Porter Hypothesis*. This result holds after a series of robustness tests. Second, our analysis of the economic mechanism indicates that the new environmental protection law brings supervision pressure to heavily polluting firms, prompting them to improve the quality of information disclosure, thus improving the level of green innovation. We also find that the regional economic development level, government subsidies, and public supervision effectively reinforce the positive impact of the new environmental protection law. Meanwhile, reflecting the supplementary role of government environmental regulation on the formal corporate governance system, the effect is more prominent in non-state-owned enterprises, small firms, low profitability firms, and firms with weak internal governance. Finally, the tests on the heterogeneity of green patent types show that the incentive effect mainly exists in green utility model patents but is not significant for green innovation patents.

This paper contributes to the extant literature in five ways. First, we provide empirical evidence of the positive impact of government environmental regulation. Previous studies hold two opposite views on the role of environmental regulation. On the one hand, some studies believe that environmental regulation restrains corporate innovation, reduces corporate profits, and crowds out corporate R&D spending (Feichtinger et al., 2005; Cohen and Tubb, 2018). On the other hand, others believe that based on the goal of long-term development, firms may take the initiative to change their business strategies to adapt to the high threshold of environmental regulation, which can encourage firms to improve green innovation (Zhang et al., 2019; Song et al., 2020). Based on a natural experiment, our results indicate that the new environmental protection law has significantly increased the number of green patents of heavily polluting industries, which supports the view that government environmental regulation is conducive to improving the green innovation ability of firms. Therefore, this paper not only complements the relevant literature on new environmental law but also expands the research on the economic consequences of government environmental regulation.

Second, we provide a reference to the underlying economic mechanism of government environmental regulation. On heavily polluting industries, the new environmental protection law imposes supervision pressure, which encourages firms to improve their information disclosure quality and to effectively reduce information asymmetry. The law causes firms to obtain more attention and support from stakeholders, thus improving the level of green innovation. This paper helps us understand the role of government environmental regulation policies and provides a theoretical basis for promoting the development of information disclosure systems and improving corporate governance.

Third, the literature focuses on green innovation in industries, regions, or countries (Yuan and Xiang, 2018) and seldom pays attention to the micro-enterprise—the object of environmental regulation. Moreover, there is still a lack of research evidence to directly investigate the impact of government environmental regulation on the environmental protection behaviors of firms in emerging markets. Taking the new environmental law in the Chinese stock market as a natural experiment, this paper adopts green patent quantity to measure the green innovation ability of heavily polluting firms and explores the influence of government environmental regulation on micro-environmental innovation activities. The above analyses expand not only the research perspective of green innovation but also government environmental regulation and corporate behavior research in emerging markets.

Fourth, this paper fully discusses the important external factors, firm characteristics and heterogeneity of patent types in the process of policy implementation. Compared with those of the prior literature, the conclusions in our study are more comprehensive and should be of great significance in helping the government formulate differentiated environmental regulation systems according to local conditions and strengthen the binding force of the new environmental protection law. More importantly, our findings should also help firms to understand the new law and take advantage of it to turn passivity into initiative and carry out green innovation activities effectively. Overall, the conclusions of this paper shed light on the role of government environmental regulation in corporate governance and corporate decision-making.

Finally, previous studies on environmental regulation policies mostly focus on developed countries (Du et al., 2019). This study is carried out under the institutional background of China, an emerging economy. In the initial stages, emerging economies often achieve rapid development at the expense of the environment; therefore, the environmental problems of developing countries are more serious. In this context, it is more practical to examine the role of environmental regulation policies. This study not only provides theoretical and empirical support for testing the incentive effect of government environmental regulation policies but also provides a reference for researchers to study the practice in China.

The remainder of this study is organized as follows. Section 2 presents the research hypotheses. Section 3 describes the data and gives the DID approach used to examine the effect of government environmental regulation on green patents in China's stock market. Section 4 shows our empirical results. Section 5 concludes this paper.

2. Hypothesis development

Traditional economics believes that environmental regulation increases the firms' production costs, thus reducing corporate innovation and competitive advantage (Frondel et al., 2008). However, an increasing amount of academic research has verified the correctness of the *Porter Hypothesis*; that is, strict and appropriate environmental regulation can encourage corporate innovation (Porter and Van der Linde, 1995).

Zhang et al. (2019) indicate that according to environmental regulation, the government embeds environmental protection into the development of firms, and this internalization of external environmental costs directly affects corporate investment decisions. To meet the new threshold of environmental regulation and realize the goal of long-term profit maximization, firms may take the initiative to increase investment in technological innovation and improve green environmental protection technology. Compared with general corporate innovation, green innovation can not only increase economic benefits by improving production efficiency and optimizing production methods (Feichtinger et al., 2005) but also help firms save energy and reduce pollutant emissions to achieve win–win benefits for both the environment and the environment. Therefore, green innovation is an important way to mitigate the adverse impact of economic activities on the environment (Rubashkina et al., 2015; Yuan and Xiang, 2018). In addition, with the improvement of the legal system and patent protection, it is difficult for firms to occupy a place in a fiercely competitive market by only relying on copying or imitating advanced technologies (Tan et al., 2014). Thus, it is necessary for firms to achieve green technological innovation under strict environmental regulation. From a long-term perspective, environmental regulation is conducive to forcing firms to carry out green innovation.

The new environmental protection law is a binding and flexible policy tool. On the one hand, the new environmental protection law officially incorporates "information disclosure and public participation" into legal provisions, clearly stipulating that citizens, legal persons, and other organizations have the right to obtain environmental information and to participate in and supervise environmental protection in accordance with the law. Moreover, the new law further clarifies the responsibilities and powers of government functional departments in environmental supervision. The abovementioned "highlights" have greatly increased the coerciveness and deterrence of the new law. On the other hand, reducing green innovation costs and further enhancing the motivation of green technology innovation, the new environmental protection law also directly stipulates that firms with excellent environmental protection performance can obtain substantial rewards related to finance, taxes, and government procurement. Thus, the new environmental protection law brings pressure and motivation to firms and is an important driving force to carry out green technological innovation.

Amore and Bennedsen (2016) point out that green technology has become the key tool for heavily polluting firms to reduce pollution and make profits. Heavily polluting firms could disclose environmental protection information voluntarily and selectively disclose information that is beneficial to them before the new law came into effect. However, the new law explicitly requires that heavily polluting firms actively disclose environmental information, such as the pollutants' name, emission methods, and emission concentrations, and accept the supervision of the public. Therefore, the implementation of the new law has greater compulsion and deterrence for heavily polluting firms. In addition, compared with firms in other industries, heavily polluting firms, due to the particularity of their main business field, face greater environmental pressure. These heavily polluting firms have a strong motivation to seek long-term profit maximization by means of green innovation. Based on the above analysis, we propose the first hypothesis.

Hypothesis 1. Compared with non-heavily polluting firms, heavily polluting firms are significantly encouraged to carry out green innovation by the implementation of the new environmental protection law.

A series of regulations on information disclosure in the new environmental protection law increase the cost to whitewash pollution information and reduce the opportunistic behaviors by which heavily polluting firms hide bad news and evade environmental supervision, thus helping improve the level of information disclosure (Jiang et al., 2020; Zhang et al., 2020a,b). Information disclosure promotes the firms' green innovation in the following two ways. First, information disclosure is a basic communication method between a firm and its stakeholders. It can meet the information needs of stakeholders and at the same time encourage firms to establish intimate relationships with investors and consumers (Salama et al., 2011; El-Kassar and Singh, 2019). With environmental regulation policy becoming increasingly strict, a large number of investors, consumers, and other stakeholders take green factors into consideration when making decisions (Luo et al., 2019). To cater to the preferences of stakeholders, firms tend to become excellent environmental performers through positive environmental behavior (Clarkson et al., 2008). In addition, Stanko and Henard (2017) pointed out that green innovation activities are characterized by high risk, large investment, and long cycles, which require long-term financial support. Through high-quality information disclosure, firms can effectively alleviate the information asymmetry with stakeholders, enabling the firm to not only attract the attention of stakeholders and obtain more investment but also to cater to the current environmental protection needs of consumers and generate more sales revenue (Marzucchi and Montresor, 2017). Based on the above analysis, we propose the following hypothesis.

Hypothesis 2. Information disclosure quality offers a crucial linkage from the new environmental protection law to the increasing green innovation of heavily polluting firms.

In the process of marketization, there are obvious differences between eastern China and central and western China. Compared with the central and western regions, the eastern region enjoys a higher level of economic development, a relatively advanced industrial and energy structure (Su and Lian, 2018; Song et al., 2020). Therefore, when the new environmental protection law increases the pressure on firms to protect the environment, due to their inherent advantages, heavily polluting firms in the eastern region may have better environmental performance under the pressure and incentive of the new law.

Due to the high cost and high risk of green innovation, when facing the demand for green technology, firms usually prefer to wait and see rather than take the initiative (Lei et al., 2012). The firms' enthusiasm for green innovation is hard to stimulate under a market mechanism, while government R&D subsidies can solve the problem of market failure by sharing the cost of green innovation. In addition, government R&D subsidies can reduce the loss caused by environmental protection, thereby maintaining firms' enthusiasm for green innovation (Huang et al., 2019).

High-quality supervision has a positive impact on corporate governance (Xu and Tang, 2010). Under strict public supervision, firms may take the initiative to carry out environmental protection activities to meet public environmental requirements and win the favor of consumers and stakeholders (Luo et al., 2012; Matsumura et al., 2014). Therefore, the promotion effect of the new environmental protection law on the green innovation of heavily polluting firms may be stronger under the condition of strict public supervision. Based on the above theoretical analysis, we propose the following hypothesis.

Hypothesis 3. Regional economic development level, government R&D subsidies, and public supervision affect the relationship between the new environmental protection law and green innovation.

Prior literature suggests that firms with large size and high profitability have stronger incentives for innovation (Lin et al., 2011; Yuan and Wen, 2018). Small-cap and low-profit firms are generally regarded as having poor corporate governance, low market attention, and low incentives for green innovation (Jensen and Meckling, 1976; Feng and Johansson, 2018). However, after the promulgation of the new environmental protection law, the Chinese government implemented a number of measurements to adjust and upgrade the industrial structure and eliminate backward production capacity. Under pressure to survive, small and low-profitability firms may be forced to pay more attention to green innovation. With a large number of employees, state-owned enterprises (SOEs) usually need to balance economic efficiency and political stability. Thus, SOEs are likely to be conservative about green innovation activities that involve both risks and opportunities (Qi et al., 2018). However, non-SOEs are sensitive to price signals; they can grasp the policy direction more quickly and actively carry out green innovation activities. Therefore, non-SOEs may be more active in green technology innovation in the face of the new environmental protection law. According to the above analysis, we find that the incentive effect of the new environmental law on corporate green innovation shows heterogeneity among firms with different characteristics. We raise the fourth hypothesis.

Hypothesis 4. The impact of the new environmental protection law on green innovation is more pronounced in small scale, low profitability and non-SOEs than in large size, high profitability, and SOEs.

3. Data and methodology

3.1. Sample selection and data sources

The sample used in this study initially comprises all firms listed on the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE). The new environmental protection law was officially implemented on January 1, 2015; thus, we set the sample interval as 2012–2018. Our sample excludes financial firms, ST firms and firms with incomplete financial data. In addition, the listed firms are complex businesses, and there may be cross-industry or firm transformation. Therefore, we screen the firms' main business composition and delete the firms whose main business changed and no longer applied to heavily polluting industries. All continuous variables are winterized by 1%. Finally, our full sample consists of 13,802 firm-year observations. The economic data are collected from the China Stock Market and Accounting Research (CSMAR) database and the RESSET database. The patent data are collected from the State Intellectual Property Office of China.

3.2. New policy and DID approach

3.2.1. Institutional background

The new environmental protection law has stronger supervision and legal constraints. First, a new chapter on information disclosure and public participation has been set up in the law. It stipulates that firms should regularly disclose information about environmental protection and pollution discharge and points out that citizens, legal persons, and other organizations have the right to obtain environmental information and to participate in and supervise environmental protection. Moreover, social public welfare organizations can pursue ''public welfare litigation'' for the firms' pollution behavior. This measure closely links environmental protection behavior with the corporate social image and is considered an exogenous driving force to promote the implementation of the new environmental protection law (Jiang et al., 2020). More importantly, the provisions of the new law, such as the stipulation that ''daily fines have no upper limit'' and the prohibition on the reissuance of the environmental impact assessment, have increased illegal costs and greatly enhanced the deterrent effect on illegal firms.

3.2.2. Difference-in-differences (DID) approach

Compared with firms in other industries, heavily polluting firms face more supervision and greater environmental protection pressure. Industry differences provide a good natural experiment for us to test the incentive effect of the new environmental protection law on the listed firms' green patents. We investigate this research question by using the difference-in-differences (DID) approach. In verifying the causal relationship between the new environmental protection law and green patents, the DID method helps reduce the influence of factors that do not change with time, are unobservable and are out of policy.

Designing the treatment group and control group is the key point in the DID approach; put differently, we need to identify those firms that are most affected by the new environmental protection law. According to the identification of heavily polluting firms in the Catalog of Classified Management of Environmental Protection Verification Industries of Listed Firms and the Guide to Environmental Information Disclosure of Listed Firms (Draft for Soliciting Opinions) and referring to the industry classification of Wang et al. (2020), firms in 16 industries, including thermal power, steel, cement, and electrolytic aluminum, are finally selected as heavily polluting firms. These heavily polluting firms would be more affected by the new environmental protection law. Therefore, we define heavily polluting firms as the treatment firms (Treat) and non-heavily polluting firms as the control firms (Control). Since the new environmental protection law came into effect on January 1, 2015, we took 2015 as the grouping sign of the time dummy variable $Post_t$; that is, $Post_t$ is equal to 1 for those years after 2015 and is equal to 0 otherwise.

3.3. Variable definitions

3.3.1. Measure of green innovation

The World Intellectual Property Organization (WIPO) launched the "Green List of International Patent Classification" in 2010. According to the United Nations Framework Convention on Climate Change, the list divides green patents into seven categories: waste management, energy conservation, nuclear energy regeneration, alternative energy, administrative regulation design, transportation, agriculture and forestry, and explains the classification number (IPC) of each category. Following Tan et al. (2014) and Qi et al. (2018), if the patent applied for is consistent with the IPC classification number, it will be judged as a green patent. According to the above criteria, we collect and count the number of the firms' green patents every year and define the green patent level ($EnvrPat_{t+1}$) equal to the natural logarithm of the number plus one.

We use the number of patent applications instead of the number of patent authorizations as the proxy for corporate green patents for the following reasons. First, resource input and use efficiency are finally reflected in the firms' technological innovation, while patent applications properly reflect the output of the innovation (Dosi et al., 2006; Hall and Harhoff, 2012). Therefore, the number of patent applications is more representative. Second, the patent grant needs to be tested, and an annual fee has to be paid, which makes patent authorization more uncertain, unstable, and vulnerable to bureaucratic factors (Tan et al., 2014). Patent technology is likely to have an impact on firm performance during the application process. Therefore, patent application data can be more stable, reliable, and timely than patent authorization data (Tong et al., 2014).

3.3.2. Control variables

To analyze the real impact of the new law on corporate green patents, according to previous literature (Ben-Amar et al., 2017; Li et al., 2018), we control the following variables in the empirical model: (1) $Size_t$, the natural logarithm of the total assets; (2) Age_t, the years of listing; (3) Lev_t, the asset–liability ratio of listed firms, i.e., the ratio of total liabilities to total assets; (4) Roa_t, the return on assets, i.e., the ratio of net profit to total assets; (5) $Tobin_t$, Tobin's Q, the ratio of total market value of equity to total book value of equity; (6) $Growth_t$, the annual sales growth rate, which is equal to the difference between the operating revenue of this year and that of last year divided by the operating revenue of last year; (7) $Risk_t$, business risk, which is equal to the three-year standard deviation of EBITDA by the industry average; (8) $R\&D_t$, the independent ratio of R&D investment to the operating revenue; (9) $Board_t$, the size of the board of directors, which is measured by the total number of directors; (10) $Indep_t$, the proportion of independent directors in the board.

3.4. Model specification

To examine the impact of the new law on corporate green patents, we use the DID approach as follows:

$$\begin{aligned} EnvrPat_{i,t+1} = {} & \beta_0 + \beta_1 Treat_i * Post_t + \beta_2 Treat_i + \beta_3 Post_t \\ & + \sum_k \gamma_k Control_{k,i,t} + + \sum Year + \sum Industry + \varepsilon_{it,} \end{aligned} \tag{1}$$

where $EnvrPat_{i,t+1}$ is the green patents of firm i in year $t+1$; $Treat_i$ is an indicator variable that equals one if firm i belongs to the treatment group; $Post_t$ is a binary variable that takes the value one for the year after the new environmental protection law (2016–2018) and takes the value of zero otherwise (2012–2015); $Control_{k,i,t}$ is the set of control variables defined in the above section; $\sum Year$ and $\sum Industry$ indicate that we also control the year fixed effect and the industry fixed effect.

The difference-in-differences estimator is β_1, which measures the pre-post difference in the green patents of heavily polluting firms relative to the pre-post difference in the green patents of non-heavily polluting firms. If Hypothesis 1 is tenable, the coefficient β_1 in Eq. (1) should be significantly positive, which means that the new environmental pollution law encourages corporate green innovation.

Table 1
Descriptive statistics and sample distribution. Panel A reports the descriptive statistics of the variables used in our empirical study. The sample includes 13,802 firms listed on the SHSE and the SZSE from 2012 to 2018. We report the mean, standard deviation, minimum, median and maximum of the selected variables. All continuous variables are winsorized at the 1% and 99% percentiles. The detailed descriptions of all variables are shown in Sections 3.3.1 and 3.3.2. Panel B represents the firm-year distribution of green patents for both the treatment and control groups. It also provides the number of firms in each group.

Panel A: Descriptive statistics

Variable	N	Mean	Std. dev	Min	Median	Max
$EnvrPat_{t+1}$	13,802	0.348	0.762	0	0	3.638
$Treat_i * Post_t$	13,802	0.184	0.388	0	0	1
$Treat_i$	13,802	0.528	0.499	0	1	1
$Post_t$	13,802	0.358	0.479	0	0	1
$Size_t$	13,802	22.07	1.280	19.01	21.87	28.52
Age_t	13,802	9.567	6.830	1	8	29
Lev_t	13,802	0.395	0.202	0.008	0.381	2.861
Roa_t	13,802	0.041	0.074	−2.555	0.040	0.494
$Tobin_t$	13,802	2.084	1.223	0.896	1.691	7.764
$Growth_t$	13,802	0.125	0.259	−0.582	0.103	1.159
$Risk_t$	13,802	0.026	0.031	0	0.018	0.960
$R\&D_t$	13,802	0.048	0.059	0	0.036	2.516
$Board_t$	13,802	8.548	1.674	3	9	18
$Indep_t$	13,802	0.375	0.056	0	0.333	0.800

Panel B: Sample composition

Year	Total average green patents	Average green patents of treatment group (1)	Average green patents of control group (2)	Differences (1)–(2)	Number of firms	Number of firms in treatment group	Number of firms in control group
2012	0.330	0.256	0.373	−0.117	1558	574	984
2013	0.316	0.248	0.357	−0.109	1567	580	987
2014	0.333	0.267	0.372	−0.105	1624	599	1025
2015	0.361	0.299	0.397	−0.098	1766	643	1123
2016	0.383	0.337	0.409	−0.072	2000	712	1288
2017	0.391	0.364	0.406	−0.042	2499	871	1628
2018	0.402	0.398	0.404	−0.006	2788	958	1830

4. Empirical results

4.1. Descriptive statistics

Panel A in Table 1 reports the descriptive statistics of the main variables. As shown in Panel A, the maximum value of $EnvrPat_i$ is 3.638, the minimum value is 0, the average value is 0.348, the median is 0, and the standard deviation is 0.762. This indicates that there is a great difference in the level of green patents among the sample, and most firms have not carried out environmental innovation. This is consistent with the uneven quality of green innovation in Chinese firms. The mean values of $Treat_i$ and $Post_t$ are 0.528 and 0.358, respectively, showing that the sample in the treatment group accounts for 52.8% of the total sample, and the sample after the implementation of the new environmental protection law makes up 35.8% of the total sample. At the same time, the statistical results of other control variables are in the normal range.

Panel B of Table 1 shows the sample distribution of green innovation in the treatment group (heavily polluting firms) and the control group (non-heavily polluting firms) in each year. Before 2015, when the new environmental law was not enacted, the level of green innovation of heavy polluters was much lower than that of the controlled firms. Green innovation is an activity that costs considerable money and has a low success rate. In the absence of adequate supervision, heavily polluting firms tend to escape rather than take the initiative to undertake green innovation. From the variation tendency of the mean of the green innovation proxy variable $EnvrPat_{t+1}$, in the short term, it can be seen that the implementation of the new environmental protection law promotes the enthusiasm for green innovation in the listed firms, and the number of green patents increases accordingly. In the long run, as time passes, the gap between the green innovation level of heavy polluters and non-heavy polluters decreases (from a maximum of 0.117 to a minimum of 0.006). The new environmental protection law severely impacts pollution behaviors and has strict requirements for environmental information disclosure, which promotes the green enthusiasm of some heavily polluting firms. This preliminarily proves that the new environmental protection law has a greater incentive effect on the green innovation of heavily polluting firms. In addition, Panel B also indicates that the number of companies allocated in the two groups is within the normal range and that the gap is reasonable, which is suitable for the following empirical analysis.

4.2. Baseline results

Before regression, we test the variance inflation factor, and mean VIF = 1.55, which is far less than 10, indicating that there is no multicollinearity between the variables. Table 2 reports the regression results of the impact of the new

Table 2
The impact of government environmental regulation on corporate green innovation. This table reports the regression estimates for the relation between the new environmental protection law and green innovation. To control for year and industry heterogeneity, a two-way fixed effect model is applied. Industry and year fixed effects are controlled for, and the standard errors are corrected by using the double-clustering (firm and year) method, as suggested by Petersen (2009). The *t*-statistics are given in parentheses.

Variable	(1)	(2)
$Treat_i * Post_t$	0.052**	0.037**
	(2.071)	(2.043)
$Treat_i$	−0.276***	−0.256***
	(−14.336)	(−9.986)
$Post_t$	−0.322***	−0.289***
	(−13.141)	(−15.207)
$Size_t$	0.181***	0.130***
	(25.970)	(14.344)
Age_t	−0.013***	−0.009***
	(−11.809)	(−5.553)
Lev_t	0.239***	0.134***
	(5.870)	(3.051)
Roa_t	0.404***	0.185**
	(4.402)	(2.483)
$Tobin_t$	0.006	0.000
	(1.156)	(0.009)
$Growth_t$	−0.001*	−0.000
	(−1.849)	(−1.012)
$Risk_t$	−0.048	0.065
	(−0.236)	(0.389)
$R\&D_t$	0.897***	0.278***
	(7.885)	(2.583)
$Board_t$	0.014***	0.006
	(3.060)	(1.188)
$Indep_t$	0.056	−0.041
	(0.444)	(−0.309)
Constant	−3.967***	−2.714***
	(−25.482)	(−12.827)
Year FE	No	Yes
Industry FE	No	Yes
Observations	13,802	13,802
Adjust-R^2	0.150	0.073

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

environmental protection law on corporate green patents. Column (1) is the pooled regression model, and Column (2) is the fixed-effect model. To control for year and industry heterogeneity, a two-way fixed effect model is applied to estimate the regressions. We also estimate the regressions based on the standard errors corrected by double clustering at the firm and year levels (Petersen, 2009).

The results show that the coefficients of $Treat_i * Post_t$ are 0.052 (t value = 2.071) and 0.037 (t value = 2.043), respectively, which are significant at the 5% statistical level. This illustrates that compared with ordinary firms, heavily polluting firms experienced a significant increase in their green patents after the implementation of the new environmental protection law. On average, each standard deviation of heavily polluting firms affected by the new environmental protection law (the standard deviation of $Treat_i * Post_t$ is 0.388) makes the next year of green innovation - $EnvrPat_{t+1}$ increase equivalent to 1.884% (=0.037 ∗ 0.388/0.762) of the sample standard deviation. Therefore, the results of the DID regression support Hypothesis 1, indicating that the new environmental protection law significantly promotes the green innovation of heavily polluting firms.

In addition, the coefficients of the control variables are basically consistent with previous studies (Ben-Amar et al., 2017; Li et al., 2018). For example, the larger a company is, the better its profitability and the higher its asset–liability ratio; the greater a company's R&D investment is, the more green patents it has. At the same time, young firms are related to a higher level of green innovation.

4.3. Robustness checks

To test whether the regression results are stable and exclude the influence of endogeneity, on the basis of the above regression, we test the robustness of the DID results in six methods: controlling firm fixed effects, excluding the influence of other policies in the same period, replacing the proxy variable, using the PSM-DID approach, considering parallel trend and dynamic effect, and adding some omitted variables.

4.3.1. Firm fixed effects model

To exclude the potential impact of unobservable individual factors on the firms' green patents and to solve the problem of missing variables that may vary with individuals in the model, this paper uses the individual (firm) fixed effect model for regression to consider the variation in the explained variable in the same firm (Cai et al., 2016a,b). The results in Column (1) of Table 3 show that the coefficients of $Treat_i * Post_t$ is still significantly positive at the 5% statistical level after controlling the firm fixed effect. This also gives strong support to Hypothesis 1.

4.3.2. Excluding the influence of other policies in the same period

In 2011, the National Development and Reform Commission announced the expansion of the pilot work on carbon emissions trading in Beijing, Tianjin, Shanghai, Chongqing, Shenzhen, Guangdong and Hubei. According to the requirements of "gradually establishing carbon emission trading market" in the Chinese "12th Five-Year Plan", the carbon emission trading pilot project of "two provinces and five cities" was fully launched in 2013. To promote the construction of the carbon market, the authority department formulated the Interim Procedures for the Carbon Emission Trading Management 2014. With the introduction of institutional documents in various regions, the carbon emission trading market gradually developed. Studies have shown that this policy also promotes corporate innovation (Li et al., 2018; Zhang et al., 2020a,b). Therefore, to exclude the impact of carbon emission trading, Column (2) of Table 3 uses the sample eliminating the pilot provinces or cities for regression. The regression coefficient of $Treat_i * Post_t$ is 0.045, which is significantly positive at the 5% statistical level. This is the same as the above conclusion of the DID regression.

4.3.3. Alternative measure of green innovation

To exclude the impact of the deviation of indicator selection, referring to Qi et al. (2018), the number of green patents is closely related to the firms' overall innovation ability. Therefore, this paper uses the proportion of green patent applications to the total number of patent applications ($EnvrPatRatio_{t+1}$) as another indicator of green patents. Patents sorted by application date are good indicators of R&D activity (Griliches, 1998), and the comparison of proportion provides a measure of diffusion of the innovation (Popp, 2002, 2006). In addition, compared with the simple number of green patents, the proportion can effectively eliminate other unobserving factors, excluding pilot policies, that promote the firms' innovation (Qi et al., 2018). As shown in Column (3) of Table 3, the coefficient of $Treat_i * Post_t$ is still significantly positive, and thus, the results are robust.

4.3.4. PSM-DID

To overcome the systematic differences in the change trend of green patents between heavily polluting firms and other listed firms and reduce the bias of the DID estimation, we also use the PSM-DID method to study the impact of the new law on the corporate green innovation of heavily polluting firms. The PSM-DID method originates from the matching estimation. The basic idea is to find a certain firm j in the control group of non-heavily polluting industry such that it is as similar as possible to the observation of firm i in the treatment group of the heavily polluting industry; that is, $Xi \approx Xj$. The matching estimation contributes to solving the problem that the treatment group and the control group cannot meet the common trend assumption before being affected by the new law.

In this paper, we use kernel matching to determine weights. The test results in Table 4 show that after propensity score matching, the mean values of the covariate variables are not significantly different between the treatment group and the control group. The absolute values of all matching variables' standard deviations are within 5%, which shows that the matching results are reasonable and reliable. Thus, the distribution of each variable between the treatment group and the control group becomes balanced, which indicates that the PSM-DID method is suitable. We use the matched sample with 1:2 matching, and 13,798 samples are obtained for the DID estimation, including 4936 from the treatment group and 8862 from the control group. The results are shown in Column (4) of Table 3. The regression coefficient of $Treat_i * Post_t$ is 0.037, which is still significantly positive at the 5% statistical level, and the results are consistent with Hypothesis 1.

4.3.5. Parallel trend and dynamic effect

Following Jacobson et al. (1993), we test the parallel trend hypothesis. We set the year dummy variable of the sample period and put its interaction term with the treatment group variable into the model, namely, *DID_ 2013*, *DID_ 2014*, *DID_ 2015*, *DID_ 2016*, *DID_ 2017*, and *DID_2018*. Considering multicollinearity, we delete the interaction between the annual dummy variable and treat in 2012. First, the results in Table 5 show that *DID_ 2013*, *DID_ 2014*, *DID_ 2015* are not significant, indicating that there is no significant difference between the treatment group and the control group before the implementation of the pilot policy, which meets the parallel trend hypothesis; that is, without policy intervention, the development trends of the outcome variables in the treatment group and the control group are consistent. The above conclusion shows the rationality of the selection of the treatment group and the control group.

Then, we examine the dynamic effect of the new environmental protection law. After the implementation of the law, the estimated coefficients of the interaction term are significantly positive from the second year (2016) and gradually increase. As green innovation is characterized as requiring a large investment and as having a long R&D cycle, the effect of the new environmental protection law on green innovation lags behind. One year after the implementation of the new environmental protection law, the green innovation level of heavily polluting firms improved significantly. The above results show that a difference exists between the treatment group and the control group after the implement of the new law. In addition, the variation trend of the dynamic effect under the 95% confidence interval in Fig. 1 also supports the above conclusion.

Table 3
Robustness checks. This table shows the robustness test results. Column (1) shows the results obtained by using the firm fixed effect model. Column (2) shows the results excluding the influence of other policies. Column (3) shows the results with another alternative measure of green innovation. Column (4) shows the results under the PSM-DID method. Industry and year fixed effects are controlled, except in Column (1). The t-statistics are given in parentheses.

Variable	FE (1)	Excluding the influence of other policies (2)	$EnvrPatRatio_{t+1}$ (3)	PSM (4)
$Treat_i * Post_t$	0.030**	0.045**	0.002*	0.037**
	(2.081)	(2.073)	(1.721)	(2.066)
$Treat_i$		−0.220***	−0.002**	−0.254***
		(−7.310)	(−1.994)	(−9.872)
$Post_t$		−0.270***	−0.007***	−0.291***
		(−11.373)	(−7.272)	(−15.284)
$Size_t$	0.015	0.131***	0.000	0.130***
	(1.239)	(11.145)	(1.194)	(14.346)
Age_t	−0.035***	−0.007***	−0.000***	−0.009***
	(−11.886)	(−3.590)	(−3.957)	(−5.470)
Lev_t	0.054	0.145***	0.005***	0.139***
	(1.289)	(2.716)	(2.664)	(3.161)
Roa_t	0.081	0.109	0.008**	0.186**
	(1.319)	(1.199)	(2.068)	(2.494)
$Tobin_t$	−0.007*	0.005	−0.000	−0.000
	(−1.894)	(0.771)	(−0.692)	(−0.053)
$Growth_t$	−0.000	−0.000	−0.000	−0.000
	(−0.359)	(−0.639)	(−0.451)	(−1.013)
$Risk_t$	−0.011	−0.057	0.011	0.060
	(−0.081)	(−0.290)	(1.289)	(0.344)
$R\&D_t$	0.084	0.315**	0.006	0.438***
	(0.903)	(1.975)	(1.080)	(3.208)
$Board_t$	0.002	0.005	0.000*	0.006
	(0.391)	(0.697)	(1.691)	(1.178)
$Indep_t$	0.034	−0.066	−0.006	−0.039
	(0.281)	(−0.382)	(−1.029)	(−0.298)
Constant	0.038	−2.756***	−0.009	−2.719***
	(0.153)	(−10.346)	(−1.032)	(−12.853)
Firm FE	Yes	No	No	No
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
Observations	13,802	8528	13,802	13,798
Adjust-R^2	0.070	0.064	0.018	0.073

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

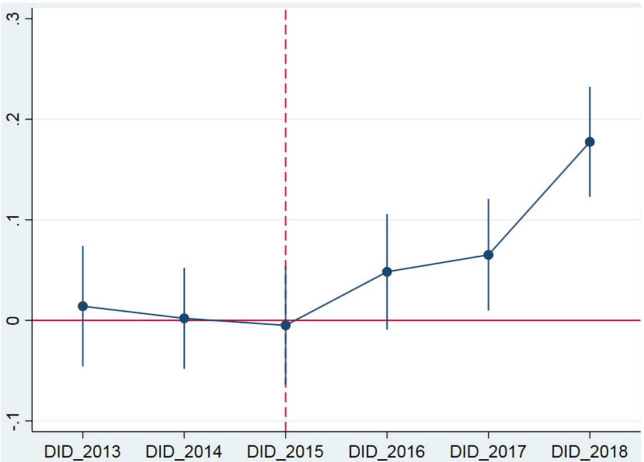

Fig. 1. Dynamic effect in DID method. The figure mainly represents the dynamic effect. DID_2013, DID_2014, DID_2015, DID_2016, DID_2017, and DID_2018 are interactions of dummy variables of each year multiplied by *Treat*.

Table 4
Balance test. This table shows the results of the balance test before PSM. The variables in the balance test include firm total assets ($Size_t$), the years of listing (Age_t), the asset–liability ratio of listed companies (Lev_t), the return on assets (Roa_t), the ratio of total market value of equity to total book value of equity ($Tobin_t$), the annual sales growth rate ($Growth_t$), business risk ($Risk_t$), the ratio of R&D investment to operating revenue ($R\&D_t$), the size of the board of directors ($Board_t$), and the proportion of independent directors on the board of directors ($Indep_t$).

Variable	Unmatched	Mean			%reduct	t-test
	matched	Treated	Control	%bias	|bias|	t
$Size_t$	U	22.225	21.979	19.3		10.86
	M	22.225	22.211	1.2	94.0	0.56
Age_t	U	10.606	8.984	23.9		13.46
	M	10.606	10.593	0.2	99.2	0.09
Lev_t	U	0.397	0.394	1.2		0.67
	M	0.397	0.399	−1.2	−0.9	−0.60
Roa_t	U	0.046	0.038	10.5		5.93
	M	0.046	0.045	0.9	91.1	0.51
$Tobin_t$	U	2.010	2.168	−11.3		−6.20
	M	2.010	2.004	0.5	95.6	0.27
$Growth_t$	U	0.347	0.587	−1.5		−0.76
	M	0.347	0.406	−0.4	75.3	−0.33
$Risk_t$	U	0.027	0.025	5.5		3.15
	M	0.027	0.027	0.8	86.2	0.35
$R\&D_t$	U	0.032	0.056	−47.3		−24.9
	M	0.032	0.033	−0.2	99.6	−0.15
$Board_t$	U	8.755	8.433	19.2		10.86
	M	8.755	8.745	0.6	96.8	0.30
$Indep_t$	U	0.370	0.380	−13.7		−7.62
	M	0.370	0.370	0.6	95.3	0.33

4.3.6. The inclusion of some omitted variables

In addition, the empirical results in this paper may still be influenced by omitted variables. Following Dougal et al. (2015), we also introduce the lagged-one and lagged-two terms of the dependent variable into the panel regression model to control the influence of some omitted variables and unobserved factors. As shown in Table 6, the coefficients of $Treat_i * Post_t$ are still significantly positive after controlling for the potential impact of lagged corporate green innovation. The above results indicate that the current green innovation of listed firms is affected by past green innovation achievements in the short term (two years). After considering the impact of past factors, our regression results are still robust.

4.4. Economic channel

High-quality information disclosure plays an important role in the development of listed firms (Cheng et al., 2020; Huang et al., 2020) and is also the key factor in promoting green innovation (Stanko and Henard, 2017). The new environmental protection law regulates the information disclosure system of heavily polluting firms. To meet strict standards, firms may actively increase information disclosure (Clarkson et al., 2008). Therefore, the new environmental protection law may improve the quality of the firm's information disclosure, enable firms to obtain more financial support for firms, and improve the firm's level of green innovation. To confirm this potential transmission path, this paper takes the total absolute values of discretionary accruals (*AbsDA*) as the proxy for information disclosure quality and then uses a two-step regression approach to test the mediating effect.

First, regarding Cohen and Zarowin (2010), to measure the information disclosure quality, we use, as calculated from the Jones Model, the total absolute values of the discretionary accruals (*AbsDA*) over the past three years. The larger the *AbsDA* is, the worse the information quality. The first step is to use the following equation to calculate a firm's annual return by industry:

$$\frac{TA_{\mathrm{it}}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{\Delta SALES_{it}}{Assets_{i,t-1}} + k_3 \frac{PPE_{it}}{Assets_{i,t-1}} + \varepsilon_{it}, \tag{2}$$

where $TA_{i,t}$ is the total accrual of firm i in year t; we define $TA_{i,t} = EBXI_{i,t}\text{-}CFO_{i,t}$, where $EBXI_{i,t}$ is operating profit and $CFO_{i,t}$ is the net cash flow from operating activities in the statement of cash flows; $Assets_{i,t-1}$ represents the total assets with a lag of one year, $\Delta SALES_{it}$ represents the increment in operating income, and $PPE_{i,t}$ is the net fixed assets/total assets.

In the second step, the estimated regression coefficient is substituted into the following equation, and then the discretionary accruals are estimated: $DA_{i,t} =$ (2)–(3)

$$NA_{\mathrm{it}} = \hat{k}_1 \frac{1}{Assets_{i,t-1}} + \hat{k}_2 \frac{\Delta SALES_{it}}{Assets_{i,t-1}} + \hat{k}_3 \frac{PPE_{it}}{Assets_{i,t-1}} \tag{3}$$

Table 5
The results of parallel trend and dynamic effect. The table mainly reports the results of parallel trends and dynamic effects. *DID_2013*, *DID_2014*, *DID_2015*, *DID_2016*, *DID_2017*, and *DID_2018* are interactions of dummy variables of each year multiplied by *Treat*. The standard errors are corrected by using the double-clustering (firm and year) method, as suggested by Petersen (2009). Industry and year fixed effects are controlled. t-statistics are given in parentheses.

Variable	(1)
$Treat_i$	−0.244***
	(−8.842)
$Post_t$	0.386***
	(4.453)
DID_2013	0.014
	(0.461)
DID_2014	0.002
	(0.080)
DID_2015	−0.005
	(−0.164)
DID_2016	0.048*
	(1.649)
DID_2017	0.065**
	(2.301)
DID_2018	0.178***
	(6.354)
$Size_t$	0.122***
	(5.831)
Age_t	−0.007***
	(−5.537)
Lev_t	0.076**
	(1.974)
Roa_t	0.114*
	(1.692)
$Tobin_t$	0.005
	(1.244)
$Growth_t$	−0.000
	(−1.434)
$Risk_t$	0.059
	(0.388)
$R\&D_t$	0.258***
	(2.687)
$Board_t$	0.004
	(0.815)
$Indep_t$	−0.074
	(−0.634)
Constant	−2.424***
	(−3.553)
Year FE	Yes
Industry FE	Yes
Observations	13,802
Adjust-R^2	0.078

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

Third, the information disclosure quality (*AbsDA*) is equal to the sum of the absolute values of the discretionary accruals over the past 3 years:

$$AbsDA = Abs\left(DA_{t-1}\right) + Abs\left(DA_{t-2}\right) + Abs\left(DA_{t-3}\right) \tag{4}$$

Then, referring to Kim et al. (2016), we use a two-step regression approach to analyze the mediating effect of information disclosure quality in the process of the new environmental protection law affecting a firm's green innovation: first, this paper examines the relationship between the new environmental protection law and information disclosure quality; second, this paper examines the role of information disclosure quality in the firms' green innovation. The regression equation is as follows:

$$Opaque_{i,t} = \alpha_0 + \alpha_1 Treat_i * Post_t + \alpha_2 Treat_i + \alpha_3 Post_t + \sum_k \gamma_k Control_{k,i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{5}$$

Table 6
Endogeneity concern: controlling for the impact of lagged green innovation. This table reports the regression results after controlling for lagged green innovation. $EnvrPat_{i,t}$ and $EnvrPat_{i,t-1}$ are the lagged one-period and lagged two-period terms of the dependent variable. To control for year and industry heterogeneity, a two-way fixed effect model is applied. Industry and year fixed effects are controlled for, and the standard errors are corrected by using the double-clustering (firm and year) method, as suggested by Petersen (2009). t-statistics are given in parentheses.

Variable	(1)	(2)	(3)
$Treat_i * Post_t$	0.036**	0.035*	0.037*
	(2.052)	(1.678)	(1.718)
$Treat_i$	−0.112***	−0.072***	−0.102***
	(−8.390)	(−4.842)	(−6.197)
$Post_t$	−0.226***	−0.224***	−0.230***
	(−12.929)	(−10.546)	(−10.352)
$Size_t$	0.048***	0.050***	0.036***
	(9.537)	(8.571)	(5.715)
Age_t	−0.005***	−0.007***	−0.005***
	(−7.058)	(−7.377)	(−5.367)
Lev_t	0.074***	0.126***	0.091**
	(2.580)	(3.757)	(2.547)
Roa_t	0.133**	0.039	0.021
	(2.116)	(0.484)	(0.258)
$Tobin_t$	−0.007*	−0.004	−0.004
	(−1.882)	(−1.049)	(−0.928)
$Growth_t$	−0.000	−0.000	−0.000
	(−0.600)	(−0.705)	(−0.394)
$Risk_t$	0.027	−0.053	−0.133
	(0.187)	(−0.298)	(−0.730)
$R\&D_t$	−0.050	−0.176**	−0.144
	(−0.645)	(−2.008)	(−1.580)
$Board_t$	0.000	−0.000	−0.005
	(0.017)	(−0.125)	(−1.359)
$Indep_t$	−0.006	0.015	−0.081
	(−0.070)	(0.141)	(−0.742)
$EnvrPat_{i,t}$	0.302***		0.216***
	(5.106)		(3.099)
$EnvrPat_{i,t-1}$		0.377***	0.190***
		(6.015)	(6.727)
Constant	−1.001***	−0.951***	−0.697***
	(−8.964)	(−7.736)	(−5.012)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	10,944	8324	8324
Adjust-R^2	0.283	0.265	0.329

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

$$EnvrPat_{i,t+1} = \beta_0 + \beta_1 Opaque_{i,t} + \sum_k \gamma_k Control_{k,i,t} + \sum Year + \sum Industry + \varepsilon_{i,t}, \tag{6}$$

where $Opaque_{i,t}$ is the mediating variable, that is, the total absolute values of the discretionary accruals (*AbsDA*). Considering the policy's lag, the mediating variable should be synchronized with the core explanatory variable $Treat_i * Post_t$; therefore, it lags for one period in model (6) with $EnvrPat_{t+1}$.

As shown in Table 7, the regression coefficient of $Treat_i * Post_t$ in Column (1) is −0.011, which is significant at the 5% level, indicating that the new environmental protection law can reduce corporate earnings management and apparently improve information disclosure quality. Moreover, the regression coefficient of $Opague_t$ in Column (2) is also negative, which proves that the better the information disclosure quality is, the more green innovation patents there are. Therefore, the firms impacted by the new environmental protection law have better information disclosure quality and a higher level of green innovation. The empirical results strongly support Hypothesis 2.

4.5. Additional analyses

According to the existing literature, the implementation effect of government environmental regulation is affected by many external factors, and the performance is not the same among firms with different characteristics (Lin et al., 2011; Lei et al., 2012; Song et al., 2020). At the same time, there is also heterogeneity in the type of green patents (Tan et al., 2014). Therefore, to further understand the incentive effect of the new law on green innovation for heavily polluting firms, this

Table 7
Mediating variable estimation results: information disclosure quality. This table reports the mediating effect results. Columns (1) and (2) show the results with *AbsDA* as a proxy for the mediating variable (referring to Cohen and Zarowin, 2010). The standard errors are corrected by using the double-clustering (firm and year) method, as suggested by Petersen (2009). Industry and year fixed effects are controlled. t-statistics are given in parentheses.

Variable	$Opaque_t$ (1)		$EnvrPat_{t+1}$ (2)
$Treat_i * Post_t$	-0.011^{**}	$Opaque_t$	-0.002^{**}
	(−2.527)		(−2.088)
$Treat_i$	0.004	$Size_t$	-0.001^{***}
	(1.318)		(−4.813)
$Post_t$	0.003	Lev_t	0.003^{***}
	(0.656)		(2.784)
$Size_t$	0.001	Roa_t	0.004^{*}
	(1.383)		(1.663)
Age_t	0.003^{***}	$Tobin_t$	-0.001^{***}
	(16.844)		(−3.044)
$Tobin_t$	0.003^{***}	$Growth_t$	0.001^{**}
	(2.994)		(2.126)
$Growth_t$	0.001^{***}	$Risk_t$	0.002
	(18.176)		(0.461)
$Risk_t$	0.332^{***}	$R\&D_t$	0.003
	(9.718)		(1.169)
$R\&D_t$	-0.043^{**}	$Board_t$	−0.001
	(−2.234)		(−1.571)
$Board_t$	-0.002^{**}	$Indep_t$	−0.002
	(−2.338)		(−0.536)
$Indep_t$	−0.020		
	(−0.940)		
Constant	−0.004	Constant	0.025^{***}
	(−0.140)		(6.244)
Year FE	Yes	Year FE	Yes
Industry FE	Yes	Industry FE	Yes
Observations	13,802	Observations	13,802
Adjust-R^2	0.033	Adjust-R^2	0.013

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

section analyzes some factors affecting the relationship from the perspectives of external factors, firm characteristics, and the types of green patents.

4.5.1. Considering the influence of external factors

To further understand the role of external factors in the implementation of the new environmental protection law, following Bai et al. (2019), we mainly conduct an additional analysis from three perspectives: region (the western, central, and eastern regions), government subsidies and public supervision.

First, we divide the sample into eastern, central and western regions according to the province in which the firms were registered. The regression results in Columns (1) to (3) of Table 8 show that compared with firms in other regions, the firms in the eastern provinces experienced a significantly positive impact from the new environmental protection law, and the significance of $Treat_i * Post_t$ shows an increasing trend from the western region (economically backward areas) to the eastern region (economically developed regions). This is because in areas with higher economic levels, more advanced industrial and energy structure, and higher technological level. Thus, in the eastern region, the new law can play a better role in encouraging firms to carry out green innovation. Then, to verify the role of government subsidies, this paper conducts a subgroup test according to the level of government subsidies (i.e., whether it is higher than the median value in the same year and industry). The results in Columns (4) and (5) of Table 8 show that the regression coefficient of $Treat_i * Post_t$ is significant in the high-subsidy group but insignificant in the low-subsidy group. These results show that appropriate government subsidies can strengthen the role of environmental regulation and then promote green technology innovation. Finally, following Xu and Tang (2010), this paper uses the analyst attention provided by the CSMAR database, that is, how many analysts (or teams) have conducted tracking analysis on the firm in a year, as the proxy for public supervision. Then, a subgroup regression was conducted in accordance with the median value of analyst attention. As shown in Columns (6) and (7) of Table 8, it can be seen that the regression coefficient of $Treat_i * Post_t$ is significantly positive at the 5% level in firms with high attention, while it is not significant in the low-attention group. This shows that the "forced" effect of the new law on corporate green innovation is stronger under strict public supervision. In addition, the coefficients of the control variables in the models in Table 8 are consistent with those in the previous paper. In summary, the empirical results provide solid empirical evidence to support Hypothesis 3.

Table 8
The impact of external factors. We divide the full sample into the following subgroups: western/central/eastern region firms, low/high subsidy firms, and low/high attention firms. We then re-estimate Eq. (1) by using the subsample with the period from 2012 to 2018. The standard errors are corrected by using the double-clustering (firm and year) method, as suggested by Petersen (2009). Industry and year fixed effects are controlled. The t-statistics are given in parentheses.

Variable	Western region (1)	Central region (2)	Eastern region (3)	Low-subsidy (4)	High-subsidy (5)	Low-attention (6)	High-attention (7)
$Treat_i * Post_t$	0.027	0.041	0.040*	0.024	0.087**	0.019	0.051**
	(0.710)	(0.897)	(1.749)	(1.215)	(2.190)	(0.653)	(2.031)
$Treat_i$	−0.148**	−0.208***	−0.291***	−0.278***	−0.217***	−0.229***	−0.261***
	(−2.555)	(−2.915)	(−9.174)	(−9.367)	(−6.846)	(−7.121)	(−8.752)
$Post_t$	−0.243***	−0.392***	−0.278***	−0.394***	−0.332***	−0.239***	−0.321***
	(−5.487)	(−7.446)	(−12.033)	(−5.769)	(−13.297)	(−7.762)	(−12.913)
$Size_t$	0.128***	0.153***	0.125***	0.138***	0.151***	0.105***	0.149***
	(6.324)	(5.520)	(11.418)	(12.895)	(12.355)	(7.615)	(13.948)
Age_t	−0.011***	−0.009*	−0.008***	−0.010***	−0.007***	−0.009***	−0.011***
	(−3.290)	(−1.889)	(−3.807)	(−5.231)	(−3.871)	(−4.219)	(−5.862)
Lev_t	0.108	0.267**	0.126**	0.164***	−0.022	0.180***	0.168***
	(1.174)	(2.060)	(2.342)	(3.182)	(−0.321)	(2.804)	(2.957)
Roa_t	0.130	0.432	0.183**	0.240***	−0.022	0.298**	0.114
	(0.789)	(1.622)	(2.082)	(2.762)	(−0.149)	(2.178)	(1.168)
Tobint	0.001	0.004	−0.002	0.003	0.026*	−0.007	0.006
	(0.039)	(0.286)	(−0.302)	(0.678)	(1.688)	(−1.107)	(0.885)
Growtht	−0.002	−0.000	−0.000	−0.000	−0.001	−0.000	−0.001
	(−1.028)	(−0.233)	(−0.882)	(−0.780)	(−0.940)	(−0.735)	(−0.638)
$Risk_t$	−0.240	−0.127	0.173	0.093	−0.317	−0.021	0.007
	(−0.666)	(−0.221)	(0.862)	(0.443)	(−1.056)	(−0.079)	(0.032)
$R\&D_t$	0.256	0.265	0.282**	0.280**	0.525**	0.128	0.828***
	(1.197)	(0.668)	(2.185)	(2.332)	(2.471)	(1.034)	(4.401)
$Board_t$	−0.005	−0.001	0.010	0.012*	−0.001	0.003	0.008
	(−0.394)	(−0.043)	(1.547)	(1.895)	(−0.099)	(0.344)	(1.243)
$Indep_t$	−0.289	0.050	0.009	−0.010	0.026	0.156	−0.178
	(−1.028)	(0.140)	(0.054)	(−0.067)	(0.118)	(0.772)	(−1.048)
Constant	−2.515***	−2.866***	−2.768***	−2.882***	−3.063***	−2.315***	−3.082***
	(−5.629)	(−4.645)	(−10.289)	(−11.172)	(−11.069)	(−7.476)	(−12.525)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes.	Yes.	Yes	Yes.	Yes
Observations	2229	1995	9578	10,867	2934	5264	8538
Adjust-R^2	0.049	0.092	0.078	0.051	0.112	0.058	0.085

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

4.5.2. Conditional on firm characteristics

To explore the effect of the new law on corporate green innovation activities under different firm characteristics, this paper divides the sample into the following two subgroups: SOEs and non-SOEs; large firms and small firms; and high-ROA firms and low-ROA firms(we take the median of the same industry in the same year as the Grouping criteria). Then, we estimate the regression results by group. As shown in Table 9, the coefficients of $Treat_i * Post_t$ in non-SOEs, small firms and in low-ROA firms are positive at significance levels of 5%, 10% and 5%, respectively. In contrast, the coefficients of $Treat_i * Post_t$ in the remaining groups are insignificant. It can be seen that the new environmental protection law plays a key role in non-SOEs, small firms, and low-ROA firms. In these firms, the governance effect of the new environmental protection law is more obvious, and the effect of improving corporate green innovation ability is more remarkable. The above analysis provides strong support for Hypothesis 4.

4.5.3. Conditional on types of green patents

To examine the impact of the new environmental protection law on different kinds of green patents, we estimate the results of the classification regression. Following Bai et al. (2019) and Zhang et al. (2019), we divide green patent applications into green invention patent applications and green practical new-type patent applications. Then, we define $InvtEnvrPat_{t+1}$ as the natural logarithm of the number of green invention patent applications plus one and $UtyEnvrPat_{t+1}$ as the natural logarithm of the number of green practical new-type patent applications plus one. As shown in Table 10, when the dependent variable is green invention patent application ($InvtEnvrPat_{t+1}$), the coefficient of $Treat_i * Post_t$ is insignificant. However, when the dependent variable is the green practical new-type patent application ($UtyEnvrPat_{t+1}$), the coefficient of $Treat_i * Post_t$ is positive at the significance level of 1%. Green practical new-type patents have a low cost, short development cycle, strong practicability, and great practical value (Tan et al., 2014; Tong et al., 2014). Thus, green practical new-type patents show greater advantages during the investigation period from 2012 to 2018. The new environmental protection law can significantly encourage firms to apply for green practical new-type patents.

Table 9
The impact of firm characteristics. We divide the full sample into the following subgroups: SOEs/non-SOEs, large/small firms, and high/low ROA firms. We then re-estimate Eq. (1) by using the subsample with the period from 2012 to 2018. The standard errors are corrected by using the double-clustering (firm and year) method, as suggested by Petersen (2009). Industry and year fixed effects are controlled. The t-statistics are given in parentheses.

Variable	SOEs (1)	Non-SOEs (2)	Large-size (3)	Small-size (4)	High-ROA (5)	Low-ROA (6)
$Treat_i * Post_t$	0.019	0.051**	0.035	0.043*	0.031	0.051**
	(0.607)	(2.310)	(1.266)	(1.805)	(1.090)	(1.973)
$Treat_i$	−0.214***	−0.278***	−0.334***	−0.201***	−0.300***	−0.199***
	(−3.872)	(−9.773)	(−8.198)	(−7.421)	(−8.907)	(−6.106)
$Post_t$	−0.343***	−0.250***	−0.363***	−0.222***	−0.321***	−0.310***
	(−9.220)	(−10.775)	(−9.890)	(−10.399)	(−11.226)	(−11.631)
$Size_t$	0.154***	0.114***	0.183***	0.068***	0.160***	0.126***
	(9.267)	(9.924)	(11.442)	(4.224)	(11.991)	(10.960)
Age_t	−0.010***	−0.012***	−0.011***	−0.008***	−0.011***	−0.007***
	(−2.925)	(−5.670)	(−4.748)	(−4.119)	(−5.100)	(−3.731)
Lev_t	0.022	0.193***	0.228***	0.092*	0.408***	0.045
	(0.256)	(3.761)	(2.984)	(1.813)	(5.702)	(0.794)
Roa_t	0.403**	0.190**	0.529***	0.092	0.566**	0.046
	(2.166)	(2.334)	(3.255)	(1.162)	(2.327)	(0.492)
$Tobin_t$	−0.004	0.000	0.004	−0.001	−0.003	−0.002
	(−0.375)	(0.094)	(0.527)	(−0.157)	(−0.402)	(−0.379)
$Growth_t$	−0.000	−0.000	−0.000	0.001	−0.002	−0.000
	(−0.492)	(−0.796)	(−0.839)	(0.193)	(−1.028)	(−1.029)
$Risk_t$	−0.118	0.099	−0.314	0.017	−0.343	0.261
	(−0.349)	(0.508)	(−0.928)	(0.091)	(−1.273)	(1.058)
$R\&D_t$	0.117	0.491***	0.542***	0.223*	0.789***	0.265**
	(0.728)	(3.455)	(2.695)	(1.943)	(3.565)	(2.204)
$Board_t$	0.004	0.001	0.007	−0.001	−0.003	0.018***
	(0.517)	(0.111)	(0.987)	(−0.142)	(−0.430)	(2.753)
$Indep_t$	−0.274	0.030	−0.243	−0.068	−0.252	0.318*
	(−1.231)	(0.177)	(−1.197)	(−0.391)	(−1.260)	(1.827)
Constant	−3.087***	−2.338***	−3.990***	−1.203***	−3.222***	−2.846***
	(−7.840)	(−8.667)	(−10.497)	(−3.335)	(−10.386)	(−10.968)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes.	Yes	Yes.	Yes
Observations	4297	9505	6815	6987	6901	6901
Adjust-R^2	0.083	0.070	0.093	0.066	0.079	0.072

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

5. Conclusion

Green innovation is a powerful tool to alleviate the contradiction between economic development and environmental pressure. However, due to the high cost and uncertainty, green innovation has natural shortcomings under the market economy system, which determines the important role of government policies in promoting corporate green innovation. The new environmental protection law revised by the Chinese government in 2015 strengthens the supervision of listed firms and the punishment for illegal acts. This measure encourages firms to voluntarily carry out green innovation activities. Based on the new environmental protection law in China, using the green patent application data of listed firms in heavily polluting industries, this paper explores the impact of government environmental regulation on corporate green innovation. First, we find that the "Porter Effect" exists in China. The perfection of environmental protection laws makes listed firms in heavily polluting industries actively carry out green innovation. Second, the channel test results show that the new environmental protection law encourages heavily polluting firms to improve their information disclosure quality and to effectively reduce information asymmetry. High-quality information disclosure causes firms to receive more attention and financial support from stakeholders, thus injecting constant energy into green innovation. Third, we also note that the regional economic development level, government subsidies, and public supervision affect the implementation effect of the new environmental protection law. In addition, the impact of the new environmental protection law effect is more pronounced in non-state-owned enterprises and in firms with small scale and low profitability. In addition, evidence reveals that the new environmental protection law can significantly accelerate corporate green practical new-type patent applications.

Our paper has crucial policy implications. First, as a government environmental regulation policy, the new environmental protection law in China helps firms enhance green innovation. This paper provides theoretical and empirical support for the incentive effect of a government environmental policy. The government and regulatory authorities should strengthen the enforcement of the new environmental protection law and ensure that it plays a full role in promoting the firms'

Table 10
The heterogeneous effects of government environmental regulation on different kinds of green patents. This table reports the results that divide green patent applications into green invention patent applications and green practical new-type patent applications (Bai et al., 2019; Zhang et al., 2019). The standard errors are corrected by using the double-clustering (firm and year) method, as suggested by Petersen (2009). Industry and year fixed effects are controlled. The t-statistics are given in parentheses.

Variable	$InvtEnvrPat_{t+1}$ (1)	$UtyEnvrPat_{t+1}$ (2)
$Treat_i * Post_t$	0.017	0.045***
	(1.163)	(3.197)
$Treat_i$	−0.186***	−0.177***
	(−8.769)	(−10.782)
$Post_t$	−0.175***	−0.231***
	(−11.250)	(−16.298)
$Size_t$	−0.006***	−0.007***
	(−4.553)	(−6.728)
Age_t	0.088**	0.097***
	(2.437)	(3.094)
Lev_t	0.161***	0.108*
	(2.650)	(1.903)
Roa_t	0.002	−0.004
	(0.610)	(−1.284)
$Tobin_t$	−0.000	−0.000
	(−0.908)	(−0.986)
$Growth_t$	0.084	−0.020
	(0.616)	(−0.156)
$Risk_t$	0.241***	0.142*
	(2.741)	(1.787)
$R\&D_t$	0.004	0.005
	(0.830)	(1.501)
$Board_t$	−0.067	0.072
	(−0.623)	(0.756)
$Indep_t$	0.017	0.045***
	(1.163)	(3.197)
Constant	−2.271***	−1.680***
	(−13.057)	(−12.124)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	13,802	13,802
Adjusted R^2	0.043	0.067

*Indicate statistical significance at the 10% level.
**Indicate statistical significance at the 5% level.
***Indicate statistical significance at the 1% level.

green transformation. Second, the *Porter Hypothesis* requires strict and flexible environmental regulation. In the process of law enforcement, relevant departments should grant more tax relief and financial subsidies to firms with outstanding environmental protection performance. This measure can compensate for the cost of environmental governance and improve the initiative of green innovation. Third, the effectiveness of the new environmental protection law on the firms' green innovation is influenced by many factors, such as the level of regional economic development, government subsidies, and public supervision. The incentive effect of the law also shows heterogeneity among firms with different characteristics. Therefore, to achieve better inspiration, regulatory authorities should consider the firms' institutional background and realistic conditions and adopt diversified and differentiated regulations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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