Technological Forecasting & Social Change 207 (2024) 123629

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Exploring the catalysts of eco-innovation: Employee ownership and sustainable practices

Wenjun Liu [a], Qian He [b], June Cao [c,*], Amina Kamar [d,e]

[a] College of Economics and Management, Fujian Agriculture and Forestry University, Fuzhou, China
[b] School of Accountancy, Central University of Finance and Economics, Beijing, China
[c] School of Accounting, Economics and Finance, Curtin University, Perth, Australia
[d] Laboratory of Economic Analysis and Forecasting (LAPE), University of Limoges, Limoges, France
[e] Centre for Digital Transformation, Imperial College Business School, Imperial College London, London, UK

ARTICLE INFO

JEL classification:
G32
Q20
O31

Keywords:
Employee stock ownership
Green innovation
Environmental performance

ABSTRACT

Climate change is a critical and urgent issue worldwide. Green innovation is a key means of abating carbon emissions. Our study investigates whether and how employee stock ownership plans (ESOPs) affect corporate green innovation. Using a powerful difference-in-differences approach, we provide causal evidence of the positive effect of ESOPs on corporate green innovation. Our baseline results are robust after addressing potential endogeneity issues using an entropy balancing technique, a Heckman two-stage model, and a placebo test, and after including an industry effect and different model specifications. Our channel analyses reveal that ESOPs mainly promote green innovation through increased risk-taking ability and employee productivity in green innovation. We find that the positive effects are more pronounced when firms are not state-owned, have less powerful CEOs, and are in heavily polluting industries. In addition, we find that companies with increased green innovation after adopting ESOPs have better environmental performance than other firms.

'Great things in business are never done by one person.'

————*Steve Jobs*

1. Introduction

'Net-zero' and 'carbon neutrality' have become global climate goals. As one of the largest carbon emitters, China accounted for approximately 25 % to 40 % of the world's total carbon emissions between 2019 and 2021 (Li et al., 2022). China has committed to peak carbon emissions by 2030 and achieving carbon neutrality in 2060 (International Energy Agency [IEA], 2021), and it needs to take urgent action to lessen its CO_2 emissions. It is well-documented that technological development and green innovation are the most effective ways to reduce emissions (Huang et al., 2021; Xu et al., 2021; Cao et al., 2022). If we ask the question 'who has innovative ideas?', the answer is 'employees' (The Wall Street Journal, 2010).[1] Around 82 % of employees have ideas that can generate new and improve existing products, services, processes, and experiences (The State of Employee Ideas, 2018). Anecdotal evidence indicates the innovation contributions made by employees of various firms. For example, Nestlé, which greatly values employees' ideas, used an integrated approach to increase employee engagement by over 90 %, collected over 4800 ideas, and achieved funding for 67 projects worldwide.[2] AstraZeneca intensively engaged its 64,000 employees to achieve the company's strategic goals by taking full advantage of the creativity of its employees across 120 countries.[3] In China, President Xi Jinping emphasises that technology is the primary productive force, talent is the primary resource, and innovation is the primary driving force to achieve China's strategies. However, a key question is: what can motivate employees to engage in green innovation? Our study investigates whether and how employee stock ownership plans (ESOPs) affect corporate green innovation.

ESOPs are being included by an increasing number of firms as a key component of employees' compensation for both executives and rank-

* Corresponding author.
E-mail addresses: wjliu@fafu.edu.cn (W. Liu), qhe@email.cufe.edu.cn (Q. He), june.cao@curtin.edu.au (J. Cao), amina.kamar@gmail.com (A. Kamar).

[1] For more detail, see https://www.wsj.com/articles/SB10001424052748704100604575146083310500518.
[2] For more detail, see https://www.sideways6.com/customers/nestle.
[3] For more detail, see https://www.sideways6.com/customers/astrazeneca#1.

https://doi.org/10.1016/j.techfore.2024.123629
Received 7 October 2023; Received in revised form 5 June 2024; Accepted 25 July 2024
Available online 9 August 2024

and-file employees (Oyer and Schaefer, 2005). However, studies indicate that ESOPs are a double-edged sword. Many studies show that ESOPs have a significant incentive effect due to the economic link between employees' income and firms' performance (Blasi et al., 1996). Specifically, the positive incentive effect is reflected in increased team effort and co-monitoring among employees (Blasi et al., 1996), enhanced firm performance (Fang et al., 2015), and increased productivity (Jones and Kato, 1995) and corporate innovation (Chang et al., 2015). Nonetheless, other studies indicate that group-based reward systems lead to a weak connection between individual effort and income, such that free-rider problems arise, which may adversely affect corporate performance and lead to employees' shirking (Blasi et al., 1996). The divergent findings of the literature indicate the need for a rigorous research design and an ideal setting to understand the role of ESOPs and provide evidence of causality regarding their effects.

As mentioned above, Chang et al. (2015) investigate how ESOPs affect corporate innovation. Our study extends literature by focusing on green innovation. In contrast to traditional innovation, which aims to bolster corporate competitiveness and operational efficiency, the ultimate goal of corporate green innovation is to diminish the adverse effects on the ecological environment during production and operational processes (Sun et al., 2024). Consequently, it is challenging to generate commercial value in the short term. Moreover, due to its dual externalities of knowledge and environmental spillovers, the social benefits of green innovation tend to surpass the economic benefits that enterprises can capture (Dong et al., 2024). This dual externality will lead to market failure and position enterprises at a suboptimal level of green innovation (G. Hu et al., 2021). The difference between conventional innovation and green innovation makes it worth further investigation, especially in a setting where green innovation is growing rapidly,[4] but significant developments remain required to reach carbon neutrality. Thus, it is of great importance to investigate the key methods to promote green innovation in China.

Second, it is well documented that green innovation is a key driver to achieving the sustainability of companies, nations, and society through innovative environmental technologies and advances and eco-design of products and services. It generates long-term value and positive externalities (Amore and Bennedsen, 2016). Rank-and-file employees are one of the most important stakeholders in relation to ESOPs, and they play a significant role in promoting corporate environmental engagement, as ESOPs tend to be broadly based and involve long-term plans (Kong and Wang, 2021). Examining whether and how ESOPs for rank-and-file employees affect green innovation is particularly salient given the long-term orientation and broad base of ESOPs.

Third, compared with conventional innovation, green innovation is characterised by high-risk and complex multi-stage processes (Holmstrom, 1989; Hall and Vredenburg, 2003). It, therefore, requires a complex set of competencies and skills. As one of the largest groups in a firm, employees collectively possess the diverse skills to deal with complex innovation activities together. As Steve Jobs states that one person never does great things in business, studies show that broad-based employee stock ownership is an effective factor that can enhance employees' collaboration, team effort, and productivity (Kim and Ouimet, 2014). Thus, we expect employees granted broad-based stock ownership to be motivated to engage in complex green innovation activities.

Nevertheless, whether ESOPs promote corporate green innovation is an empirical question for the following reasons. First, as mentioned earlier, free-rider problems among individual employees in the case of ESOPs may lead to shirking and reduced productivity (Blasi et al., 1996). Kim and Ouimet (2014) document that the potentially beneficial effects of ESOPs for employees and shareholders are weakened when the number of employees is too large to mitigate free-riding problems. In addition, Meng et al. (2011) find that ESOPs have little impact on firm performance in China based on a historical ESOP policy experiment in 1992. However, this policy only applied to state-owned enterprises (SOEs) and was terminated two years after its initiation. The ESOP policy we focus on is quite different, particularly as it applies to both SOEs and non-SOEs. Given the significant difference between SOEs and non-SOEs in China (Wong, 2016), it may not be appropriate to generalise the findings of Meng et al. (2011), which are based on SOEs, to non-SOEs. Thus, an empirical test is required to evaluate the real impact of ESOPs and provide solid evidence for policymakers and regulators.

To examine the impact of ESOPs on corporate green innovation and environmental performance, we collect data from all Chinese listed firms during the fiscal years from 2010 to 2020. Taking firms' staggered adoption of ESOPs as a quasi-natural experiment, we use a powerful time-varying difference-in-differences (DiD) approach combined with propensity score matching (PSM) techniques. Using this approach, we find, in contrast with Meng et al. (2011), that ESOPs positively and significantly impact corporate green innovation. To check the robustness of our baseline results, we conduct a battery of tests to mitigate endogeneity concerns. First, we follow Bertrand and Mullainathan (2003) and Cao et al. (2022) and conduct a dynamic analysis to test the assumption underlying the causal inferences of the DiD model, i.e., that the trends in corporate green innovation in the period before the adoption of ESOPs are similar between the treatment and control groups. The results show that the increase in green innovation, especially in green invention, is only revealed after firms implement ESOPs.

Second, we conduct a placebo test by randomly selecting companies as the pseudo-treatment group to mitigate an endogeneity concern arising from spurious correlations and simultaneous confounding events. We repeat the random sampling 500 times and re-estimate our baseline model. We find that our baseline results are unlikely to be contaminated by spurious correlations or simultaneous confounding factors.

Third, we follow Beck et al. (2022) and Cazier et al. (2020) and use an entropy balancing technique to balance the covariate distributions of the treatment and control groups across the three moments, i.e., the mean, variance, and skewness. We re-estimate our baseline results using a matched sample and find they hold. Fourth, we modify the PSM techniques by using a one-to-one matching approach without replacement to match the two groups. Again, our baseline results remain the same.

Fifth, as firms may not randomly decide to adopt ESOPs, we mitigate self-selection concerns by constructing a Heckman two-stage model using two instrumental variables: the percentage of firms implementing ESOPs within an industry and the capital size of ESOPs within an industry in a city over that of an industry in the previous year. We incorporate the inverse Mills ratio (IMR) obtained from the first stage into the second-stage estimation to control the self-selection bias. Our results continue to hold.

Sixth, we consider both independent green patent applications and joint applications with other entities. We find that ESOPs can significantly increase both applications. In a further test, we use the number of green patents granted (rather than applications) as an alternative proxy for corporate green innovation. We find that ESOPs enhance both green patent applications and the number of green patents granted. Moreover, we provide evidence that ESOPs enhance the number of citations for granted green patents. Considering that more than half of the listed companies do not engage in green innovation, we re-estimate our results using the Tobit model. We find that our baseline results are not sensitive to the model specification.

We determine the underlying mechanisms through which ESOPs promote corporate green innovation, including enhanced risk-taking ability and increased employee green innovation productivity. Our cross-sectional tests show that our results are stronger (weaker) when firms are non-SOEs (SOEs), have less (more) powerful CEOs, are in

[4] In 2011, only 6005 green innovation patents were issued to Chinese listed firms. By 2018, however, the number had increased to 65,938 (Li et al., 2022).

heavily (lightly) polluting industries, and are (are not) managed by professional asset management institutions. Moreover, our tests provide evidence that the increased green innovation enabled by ESOPs can improve corporate environmental performance.

Our study advances the literature in the following ways. First, we answer the fundamental questions of who can and how to promote corporate green innovation to achieve net-zero or carbon neutrality. This is a particularly critical and urgent issue given that companies, nations, and the world are under increasing pressure to reduce carbon emissions. To the best of our knowledge, this study is the first to examine whether and how employees, as one of the largest stakeholders with innovative ideas, can be strongly motivated by stock ownership to promote corporate green innovation. In addition, we extend the literature (e.g., Chang et al., 2015) by focusing on green innovation rather than traditional innovation. Our study is of great importance to the strategic development of firms in the contemporary business landscape.

Second, our study contributes to the literature on the real impact of ESOPs. The issue of whether ESOPs can successfully motivate employees to enhance their productivity remains unresolved in the literature. We adopt the ideal setting of the staggered adoption of ESOPs by Chinese listed companies, which enables us to use a powerful DiD model to provide solid causal evidence of the impact of ESOPs. In addition, we determine the underlying mechanisms (enhanced risk-taking ability and increased employee productivity) through which ESOPs promote corporate green innovation. Through a series of additional tests, we provide in-depth insights into the variations in the real impact of ESOPs. Thus, our study has important implications for regulators and policymakers regarding managing and further promoting ESOPs.

The remainder of the paper is organised as follows. Section 2 presents the literature review and develops the hypothesis. Section 3 presents the research design. Section 4 discusses the empirical results. Then, Section 5 presents the mechanism tests, Section 6 discusses the cross-sectional tests and Section 7 examines additional tests. Finally, Section 8 concludes the study.

2. Literature review and hypothesis development

2.1. Corporate green innovation

The sustainable development of human society has become an increasingly prominent issue given the serious environmental pollution caused by economic development. Green technological innovation can alleviate the conflict between economic development and environmental protection (Cui et al., 2023). Such innovation has become an important concern for governments and enterprises, especially in China, where serious environmental problems are occurring in the face of rapid economic growth. However, innovation requires large resource inputs and carries a high risk of failure (Pang and Wang, 2020; Zhou et al., 2021b). Green innovation can generate environmental externalities (Xie and Teo, 2022), but the return may be invisible to companies because, in contrast to general innovation, they reap the benefits of innovation only in the long run (Zhao et al., 2023). Therefore, companies tend to lack the motivation to engage in green innovation, meaning that government funding and policy support (Sun et al., 2019), as well as regulatory and normative pressure (Berrone et al., 2013), are required to promote green innovation. The literature determines that government environmental legislation (Zhou et al., 2021a), environmental regulation (Zhang et al., 2020a), the establishment of environmental courts (Huang et al., 2022), anti-corruption measures (Zhou et al., 2022) and green credit and government subsidies (Li et al., 2018) can promote corporate green innovation. Several studies explore corporate green innovation from the perspective of the external environment. According to Sha et al. (2022), the opening up of capital markets improves firms' information transparency and their awareness of the environment, which facilitates corporate green innovation. Tang et al. (2021) argue that communication infrastructure generates network externalities, which can break the spatial barrier, reduce transaction costs, nurture innovation models, and improve corporate green innovation. Li et al. (2022) find that developing digital finance can alleviate financial constraints, facilitating corporate green innovation.

Although the studies mentioned above explore the factors that enhance corporate green innovation from the perspectives of macroeconomic policy, environmental regulation, and the external environment, firms at the micro level engage in green innovation. Thus, exploring the firm characteristics that motivate or constrain green innovation is particularly important. The literature examines the influence on corporate green innovation of organisational capabilities and social interactions (Huang and Li, 2017), analyst following (Fiorillo et al., 2022), and the multinational status of the firm (Kim et al., 2021). These studies find that dynamic capability, coordination capability, and social reciprocity (Huang and Li, 2017), the informative role of analysts (Fiorillo et al., 2022), and exposure to foreign markets with strict environmental regulations are important factors driving green innovation.

In the process of corporate innovation, human capital is an extremely important production factor (Kesting and Ulhøi, 2010). A company's human capital includes not only senior executives but also a large number of ordinary employees. However, because green innovation decisions are generally made by CEOs, a lot of literature revolves around CEO characteristics to study corporate green innovation, including from the perspectives of CEO's hubris (Arena et al., 2018), education (Amore et al., 2019), gender (Javed et al., 2023), and experience (He et al., 2021; Quan et al., 2023; He et al., 2024; Wang and Li, 2024). Although CEOs have a significant impact on the process of corporate green innovation, the role of employees should not be overlooked, as they are an important part of the company's human capital and also the executors of green innovation decisions. Therefore, it is very important to motivate employees to actively participate in the company's green innovation. ESOP is an important way to improve employee enthusiasm; however, no studies have revealed the role of employees in green innovation, leading us to focus on this issue in this study.

2.2. Employee stock ownership

Employees are frontline personnel who are engaged in their firm's production, but they often lack motivation and tend to be slack rather than hardworking. In addition, although employees are familiar with corporate production and operations, firms with large numbers of employees, particularly when these employees are mobile (Klein, 1987), find that employees often lack loyalty to the company and are unwilling to participate in corporate governance (Kim and Ouimet, 2014). Thus, employees must be treated well to increase their loyalty and satisfaction with their firm. Studies find that better treatment of employees can enhance corporate performance in innovation (Chen et al., 2016; Wei et al., 2020), competitiveness in the product market (Chang and Jo, 2019) and firm value (Fauver et al., 2018), as well as reducing the risk of being acquired (Macias and Pirinsky, 2015). To improve employees' productive motivations and enhance their willingness to participate in corporate governance, it is essential to align their personal interests with those of the company.

ESOPs are an important tool to achieve this goal and are widely used in national capital markets (Hennig et al., 2023). Some studies find that ESOPs can improve firm performance and generate positive governance effects. For example, Jones and Kato (1995) find that the introduction of ESOPs in Japan increases firm productivity. Fang et al. (2015) determine that the adoption of ESOPs by China's listed companies improves firm performance. Chen et al. (2020) even argue that employee shareholding can reduce the interest rates applied to corporate loans because it improves corporate governance, discourages management risk-taking, reduces information asymmetry and increases employee retention. In addition, Bova et al. (2015) argue that ESOPs mitigate the motivation for opaqueness in corporate disclosure and increase voluntary corporate disclosure. Zhang et al. (2020b) argue that employee stock ownership can optimise the internal environment and reduce internal control weaknesses within the firm. Chang et al. (2015) examine the impact of non-executives' employee stock ownership on the corporate innovation of US companies and suggest that it can reduce free-riding and increase corporate innovation.

However, there is no literature exploring the impact of employee shareholding on corporate green innovation. The risks and returns of green innovation are significantly different from those of general innovation, and the lack of incentives for firms to engage in green innovation makes it necessary to explore whether and how employee shareholdings affect corporate green innovation. Furthermore, we find that employee shareholdings facilitate corporate green innovation primarily through two paths: facilitating corporate risk-taking and improving employee productivity. Conversely, Chang et al. (2015) argue that the impact of employee shareholdings on corporate innovation is mainly due to employees' increased risk-taking rather than their performance motivation based on stock options. This suggests that the mechanisms of the effects of employee shareholdings on general and green innovation are not identical.

2.3. Hypothesis

Governments and the public are increasingly concerned about protecting the environment, making environmental pollution caused by corporate activities increasingly unacceptable. As a result, green innovation by corporations is important to strengthen organisational legitimacy and implement sustainable corporate development (Zhou et al., 2021a). However, the principal-agent problem means that managers avoid risky activities and focus on the 'quiet life' of their organisations to maintain their interests and reputations (Bertrand and Mullainathan, 2003). Corporate innovation is exploratory and complex, involves large amounts of capital and significant risks, and requires considerable managerial effort and organisational change (Pang and Wang, 2020; Zhou et al., 2021b). Moreover, its benefits, which tend to be long-term, are reaped largely by shareholders and stakeholders rather than managers. Consequently, managers are motivated by opportunism to seek short-term gains and lack incentives to engage in innovation.

Green innovation, in particular, is characterised by its long-term nature, high risks, and double externalities (Malen and Marcus, 2019; Xie and Teo, 2022). During the innovation process, managers engaging in green technological innovation must make extra efforts to reduce pollutant emissions, such as wastewater and flue gases. This involves redesigning internal production processes, which can enhance corporate green competitiveness (Kock et al., 2012). However, as corporate production involves negative environmental externalities, companies profit from polluting items and shift the polluting costs to others. Consequently, the benefits of green innovation and competitiveness are costly to the corporation but do not necessarily bring private corporate benefits.

Moreover, green innovation requires corporations to incur all costs yet make profits, and the positive externalities of innovation mean that other companies benefit from their processes. As a result, companies lack incentives to reduce pollution through green technological innovation or improve environmental externalities (Jaffe et al., 2005). Therefore, the insufficient motivation to take on the risks of green innovation combined with inadequate supervision of managers will reduce green innovation by corporations (Amore and Bennedsen, 2016). Employees are important beneficiaries of the company's green innovation because green innovation can improve the working and production environment for employees, which is conducive to the health of employees and the sustainable development of the company. Therefore, employees pay particular attention to the company's green innovation, but they are not shareholders of the company and do not have the ability to supervise managers to actively engage in green innovation.

By implementing ESOPs, employees become their company's shareholders, which links corporate development to the employees' personal interests. This enhances the employees' enthusiasm and motivation for participation in corporate governance. As employees are on the frontlines of production and operations, their capacity to obtain accurate information about their company gives them an advantage over outsiders in monitoring managers (European Commission, 2014; Feng et al., 2022b). The literature confirms that employee shareholding has positive corporate governance effects (Bova et al., 2015; Zhang et al., 2020b) and influences employees' incentives regarding risk-taking (Chang et al., 2015). Based on the management practices associated with the ESOPs implemented by listed companies in China, the management committee selected by shareholders to exercise shareholder rights, vote and monitor the material matters of the company allows for participation in corporate governance in practice.[5] Green innovation matters for long-term corporate development and employee shareholding because it strengthens the supervision of managers and encourages managers to consider the company's long-term interests, which reduces their personal opportunistic motives when making strategic decisions for the company, thereby increasing green innovation.

Second, ESOPs align the interests of shareholders and employees and reduce the free-riding problem within the workforce (Chang et al., 2015), thus enhancing the company's engagement in green innovation. Although decisions on green innovation are not made directly by employees, green innovation often arises from employees and is implemented by them (Kesting and Ulhøi, 2010). Therefore, strongly binding the interests of employees with those of shareholders is essential to secure the active involvement of employees in green innovation practices and ensure that they perform the work tasks optimally assigned for green innovation activities. ESOPs increase the likelihood of employees taking the initiative to identify problems in production and operations that cause environmental pollution and to suggest improvements, thus promoting green innovation. Implementing ESOPs can bind employees' interests together, reducing the problem of free-riding (Chang et al., 2015) and enhancing teamwork (Hochberg and Lindsey, 2010). Teamwork and alignment of benefits lead employees to exchange experiences and ideas, complement each other's strengths at work, and enable them to monitor each other, which enhances their productivity in implementing green innovation in the company. We propose research hypothesis 1 (H1) based on the above analysis.

Hypothesis 1. *Corporate green innovation increases after the implementation of an ESOP.*

Two factors may prevent ESOPs from influencing corporate green innovation. First, managers and not employees make corporate green innovation decisions (Kesting and Ulhøi, 2010), as noted previously, which can make it difficult for employees to influence green innovation. Second, if most employees are engaged in low-tech jobs, they will have little impact on the output of corporate green innovation (Leiponen, 2005). Thus, whether ESOPs can improve corporate green innovation requires empirical testing.

3. Research design

3.1. Initial sample

ESOPs were implemented as early as the 1980s among companies in

[5] For more details, see http://www.gov.cn/gongbao/content/2014/content_2775520.htm.

China, but their implementation in listed companies was terminated by the China Securities Regulatory Commission (CSRC) on December 25, 1998, because of issues relating to the immature capital market at that time. It was not until June 20, 2014, that ESOPs recommenced when the CSRC issued the Guidelines on the Pilot Implementation of Employee Stock Ownership Plans in Listed Companies. We use a DiD model to clarify the causal effects of ESOPs on corporate green innovation. To improve the efficiency of the DiD model, we need to ensure a sufficient number of observations of companies implementing ESOPs in the pre-implementation (pre-2014) period. Therefore, our initial sample includes all companies listed on the Shanghai and Shenzhen stock exchanges in China from 2010 to 2020, which totals 34,906 firm-year observations. We apply a one-period lag such that the dependent variables are related to the 2011–2021 period and the independent and control variables to the 2010–2020 period. After excluding B-share listed companies (1130 firm-year observations), financial companies (733), and observations with missing data for the continuous control variables (7845), we obtain 25,198 valid firm-year observations.

All standard deviations of the regressions are clustered at the firm level. The data are collected from the WIND database for ESOPs, the Chinese Research Data Services (CNRDS) database for corporate green patents, and the Internal Control and Risk Management (DIB) database for the internal control index. All other data are from the China Stock Market and Accounting Research (CSMAR) database.

3.2. Propensity score matching

Companies that adopt an ESOP (ESOP adopter) may exhibit systematic differences in their characteristics compared to those that do not (ESOP non-adopter). This could potentially confuse the research findings. We employ the PSM technique to match the treatment group with a similar control group based on a logit model, explained below, to mitigate this issue.

Following Kyung et al. (2019), Bao et al. (2018) and Erkens et al. (2018), we first select a range of financial characteristics and governance characteristics as covariates. Firms implementing an ESOP during the sample period form the treatment group ($ESOP_i = 1$), and firms that do not implement an ESOP during this period form the control group ($ESOP_i = 0$).

We estimate the following logistic regression separately for each pre-implementation year:

$$\begin{aligned} ESOP_i = {} & \alpha_0 + \alpha_1 SIZE_{i,t-1} + \alpha_2 LEV_{i,t-1} + \alpha_3 ROA_{i,t-1} + \alpha_4 GROWTH_{i,t-1} \\ & + \alpha_5 SALESPP_{i,t-1} + \alpha_6 FIXEDPP_{i,t-1} + \alpha_7 RND_{i,t-1} + \alpha_8 LOSS_{i,t-1} \\ & + \alpha_9 AGE_{i,t-1} + \alpha_{10} FIRMAGE_{i,t-1} + \alpha_{11} SOE_{i,t-1} \\ & + \alpha_{12} CEO\_SHR_{i,t-1} + \alpha_{13} EXC\_SHR_{i,t-1} + \alpha_{14} INS_{i,t-1} \\ & + \alpha_{15} BOARD_{i,t-1} + \alpha_{16} INDE_{i,t-1} + \alpha_{17} SHAREBALANCE_{i,t-1} \\ & + \alpha_{18} WAGE_{i,t-1} + \alpha_{19} INTCOV_{i,t-1} + \varepsilon \end{aligned} \tag{1}$$

The probability of a company implementing an ESOP in the current year is estimated using the covariates in the prior year. The companies in the treatment group in the first year of implementing the ESOP are matched to the three control group companies with the closest propensity scores in the same year.[6] In particular, all observations that do not satisfy the common support hypothesis are excluded, and we use a nearest-neighbour matching method of one-to-three with a threshold of 0.005. We adopt one-to-three matching because there are more observations in the control group than in the treatment group. We use a putback matching approach, which allows the same control group company to be matched with different treatment group companies in different years to maximise the matching of treatment group companies to the closest control group company. To alleviate concerns about errors in matching methods, we conduct one-to-one PSM without replacement in Section 4.4.

Referring to the literature (Chang et al., 2015; Shen et al., 2018), the following are selected as covariates: firm size (*SIZE*), leverage (*LEV*), return on assets (*ROA*), sales growth (*GROWTH*), sales per person (*SALESPP*), fixed assets per person (*FIXEDPP*), whether the firm is loss-making (*LOSS*), investment in R&D (*RND*), years since the listing date of the firm (*AGE*), firm age (*FIRMAGE*), the nature of property rights, i.e., whether the firm is state-owned (*SOE*), CEO shareholding (*CEO_SHR*), executive shareholding (*EXE_SHR*), institutional shareholding (*INS*), board size (*BOARD*), proportion of independent directors (*INDE*), equity restriction (*SHAREBALANCE*), employee compensation (*WAGE*) and level of internal control (*INTCON*).[7] All variables are defined in Panel A of Appendix A. Based on this approach, we match the treatment group companies with ESOPs for the 2014–2020 period with the control group companies with the nearest propensity score in the same year, year by year. This yields a matched sample of 546 treatment group companies and 1626 control group companies. Among them, 706 companies in the control group are matched with different treatment group companies in different years. Hence, the matched sample contains 546 companies in the treatment group and 920 companies in the control group.

Finally, for each matched control group, we allocate an artificial implementation date and artificial ESOP duration using the treatment group's implementation date and ESOP duration with which the company is matched.[8] Taking observations of matched companies over the sample period as the research subject, we obtain 21,458 firm-year observations, representing 1466 companies.[9]

Table 1 shows the differences in the mean values of the covariates before and after matching. Columns (1)–(3) relate to the observations in the ESOP implementation year for the treatment group (553) and for all control groups (17,224). Columns (4)–(6) relate to the observations in the ESOP implementation for the treatment group (546) and the matched control group in that year (1626). The mean values of most covariates differ significantly between the treatment and control groups before matching, except for a few variables. However, the differences in all covariates between the treatment and control groups are not significant after matching. This indicates that our PSM approach is effective.

3.3. Division of the ESOP period

Before constructing the model, we characterise the period relating to the ESOP implemented by each company into three phases: pre-implementation, duration, and end period. As shown in Fig. 1, the

[6] For example, companies in the treatment group that started their ESOPs in 2014 are matched with three control group companies with the closest covariate characteristics based on their covariate characteristics in 2013.

[7] The continuous variables in the covariates are winsorised at the 1st and 99th percentiles for each matching year.

[8] If a control group company is matched with different treatment group companies in different years, the observation of that company is replicated, and its artificial ESOP implementation date and ESOP duration are set to the values of the corresponding experimental group companies in turn. If a control group is matched with three treatment group companies in 2014, 2017 and 2019, the observations of that control group are replicated three times in each year, and the artificial ESOP implementation date and ESOP duration are set as the corresponding values of the treatment group companies matched in 2014, 2017 and 2019, respectively.

[9] The observations with missing continuous variables are excluded before matching, and the continuous dependent variables $Green\_P_{i,t+1}$ and $Green\_Inv_{i,t+1}$ are lagged by one period. Hence, all companies in our study have more than one observation after implementing their ESOP. Moreover, all companies must have more than one observation before implementing the ESOP because of PSM in the pre-implementation year. Therefore, no company is excluded from the sample when we exclude companies with less than one observation before or after the implementation of ESOPs.

Table 1
Differences in covariates before and after matching.

Variables	Before matching			After matching		
	Treatment (N = 553)	Control (N = 17,224)	Diff. T-value	Treatment (N = 546)	Control (N = 1626)	Diff. T-value
$SIZE_{i,t-1}$	22.16	22.18	−0.274	22.14	22.15	−0.242
$LEV_{i,t-1}$	0.394	0.464	−4.946***	0.393	0.392	0.149
$ROA_{i,t-1}$	0.047	0.030	2.610***	0.047	0.045	0.599
$GROWTH_{i,t-1}$	0.336	8.279	−0.182	0.281	0.261	0.686
$SALESPP_{i,t-1}$	13.74	13.76	−0.459	13.72	13.74	−0.364
$FIXEDPP_{i,t-1}$	12.36	12.58	−4.246***	12.37	12.37	−0.017
$LOSS_{i,t-1}$	0.047	0.109	−4.615***	0.048	0.047	0.025
$RND_{i,t-1}$	0.045	0.032	3.968***	0.045	0.044	0.671
$AGE_{i,t-1}$	1.963	2.245	−8.664***	1.966	1.971	−0.151
$FIRMAGE_{i,t-1}$	2.805	2.850	−3.083***	2.803	2.803	−0.048
$SOE_{i,t-1}$	0.107	0.465	−16.797***	0.108	0.114	−0.405
$CEO\_SHR_{i,t-1}$	0.082	0.039	9.589***	0.080	0.079	0.111
$EXC\_SHR_{i,t-1}$	0.113	0.056	10.338***	0.112	0.110	0.203
$INS_{i,t-1}$	0.383	0.461	−7.593***	0.382	0.386	−0.295
$BOARD_{i,t-1}$	2.223	2.258	−4.510***	2.222	2.223	−0.059
$INDE_{i,t-1}$	0.378	0.374	1.599	0.377	0.379	−0.604
$SHAREBALANCE_{i,t-1}$	0.780	0.665	4.468***	0.773	0.786	−0.419
$WAGE_{i,t-1}$	9.240	9.259	−0.389	9.245	9.239	0.118
$INTCON_{i,t-1}$	6.538	6.307	3.313***	6.532	6.553	−0.451

Notes: The table shows the differences in covariates before and after propensity score matching. Columns (1)–(3) show the differences in covariates between the treatment and control groups before matching, and columns (4)–(6) show the differences in covariates between the treatment and control groups after matching. All variables are defined in Panel A of Appendix A. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively.

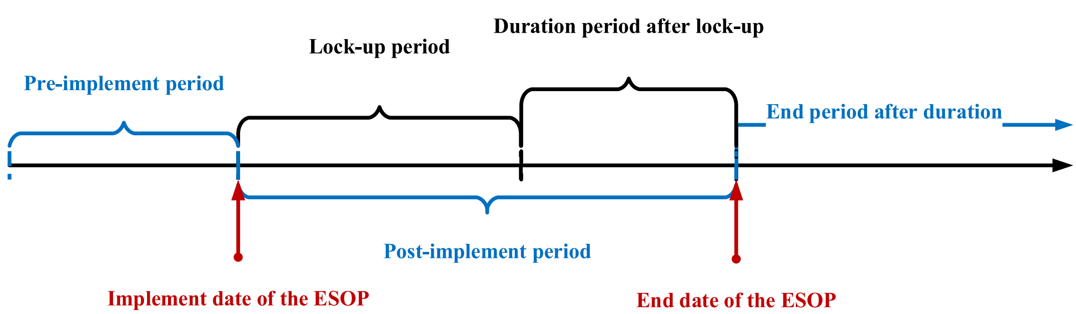

Fig. 1. Each period of the ESOP.
Notes: The figure shows each period of ESOPs implemented by companies. The sample period is divided into the period before the company implements the ESOP, the duration of the first implemented ESOP, and the period after the ESOP ends. The duration of the ESOP is divided into the lock-up period and the duration after the lock-up period, taking into account the lock-up period for employee shareholdings.

pre-implementation period is from the beginning of the sample period to the first time that the company implements an ESOP. The duration period is when the first ESOP implemented by the company remains valid, which determines the latest time of employee ownership. The duration (middle) phase is further divided into the lock-up and post-lock-up periods. During the lock-up period, employees are initially barred from selling their shares to prevent arbitrage. The end period, as the name implies, concerns the end of the ESOP, and it is excluded from the test to exclude other omitted factors and policies that may influence the findings after the ESOP ends (1652).

We have 4373 firm-year observations in the treatment group and 12,938 artificial firm-year ESOP observations in the control group. We winsorise all continuous variables at the 1 % and 99 % percentiles to exclude the effect of outliers. All regressions are estimated based on weights calculated using propensity scores.[10] The process of sample selection is shown in Panel B of Appendix A.

Panels A and B in Table 2 show the distribution of ESOPs and green patents across industries and years, respectively. The proportion of the sample implementing ESOPs is around 25 % for both the majority of industries and years, but this may be related to our one-to-three matching. However, in terms of absolute value, the manufacturing industry has the largest number of implemented ESOPs. In contrast, the education and resident services, repair, and other services industries have the smallest number. This is broadly consistent with the industry distribution of listed companies in China. In addition, the mean value of the number of green patents issued by listed companies in the following year is <10 in terms of both industry and year. We use Tobit models in the robustness tests to mitigate this issue. Some industries issued zero green patents in the following year. In a robustness test, we restrict the sample to manufacturing.

3.4. Models

Referring to the method of Bertrand and Mullainathan (2003), Kyung et al. (2019), and Du et al. (2022), we construct the following DiD model:

[10] Compared with one-to-one matching without putback, the one-to-three putback PSM method can reduce sampling variance and enhance the stability of matching. However, it requires weighting the regresses to reflect the effect of the times at which matching occurs.

Table 2
Sample distribution.

Panel A: The distribution of ESOPS and green patents across industries

	$ESOP_i$				$Green\ Patents_{i,t+1}$			
	$ESOP_i = 1$	$ESOP_i = 0$	N	Ratio	Mean	P50	P75	Max
Agriculture, Forestry, Animal Husbandry, and Fishery	89	80	169	52.66 %	0.142	0	0	2
Mining	47	193	240	19.58 %	23.71	0	2	442
Manufacturing	3129	9182	12,311	25.42 %	2.367	0	1	526
Production and Supply of Electricity, Gas and Water	22	199	221	9.95 %	0.421	0	0	41
Construction	160	230	390	41.03 %	3.172	0	2	92
Wholesale and Retail trade	176	524	700	25.14 %	0.016	0	0	3
Transportation, Warehousing and Postal Service	68	206	274	24.82 %	0.077	0	0	5
Accommodation and Catering	11	27	38	28.95 %	0	0	0	0
Information Transmission, Computer Services and Software Industry	337	1068	1405	23.99 %	1.118	0	1	21
Estate	139	600	739	18.81 %	0.028	0	0	4
Leasing and Business Services	37	157	194	19.07 %	0.103	0	0	8
Scientific Research, Technical Services and Geological Exploration	40	90	130	30.77 %	1.454	0	2	17
Water Conservancy, Environment and Public Facilities Management Industry	54	102	156	34.62 %	6.827	3	8	76
Resident Services, Repair and Other Services	2	2	4	50.00 %	0	0	0	0
Education	2	1	3	66.67 %	0	0	0	0
Health and Social Work	26	46	72	36.11 %	0.083	0	0	2
Culture, Sports and Entertainment	24	91	115	20.87 %	0.009	0	0	1
Comprehensive	10	140	150	6.67 %	0.027	0	0	2
Total	4373	12,938	17,311	25.26 %	2.258	0	0	526

Panel B: The distribution of ESOPs and green patents across years

	$ESOP_i$				$Green\ Patents_{i,t+1}$			
	$ESOP_i = 1$	$ESOP_i = 0$	N	Ratio	Mean	P50	P75	Max
2010	186	589	775	24.00 %	2.071	0	0	161
2011	274	864	1138	24.08 %	1.920	0	0	232
2012	370	1100	1470	25.17 %	1.823	0	0	269
2013	422	1236	1658	25.45 %	2.111	0	1	227
2014	446	1286	1732	25.75 %	2.198	0	0	304
2015	476	1388	1864	25.54 %	2.798	0	1	366
2016	497	1492	1989	24.99 %	3.038	0	1	503
2017	500	1475	1975	25.32 %	3.174	0	1	526
2018	468	1389	1857	25.20 %	2.038	0	0	412
2019	407	1188	1595	25.52 %	1.900	0	1	132
2020	327	931	1258	25.99 %	0.778	0	0	73
Total	4373	12,938	17,311	25.26 %	2.258	0	0	526

Notes: The table shows the distribution of ESOP implementation and green patent applications across industries and years for the regression sample in this paper. Panel A shows the sample distribution across industries, while Panel B shows the sample distribution across years. Industries are classified according to the CSRC Industry Classification in 2012.

$$Green\_P_{i,t+1} \,|\, Green\_Inv_{i,t+1} = \alpha_0 + \alpha_1 ESOP_i \times POST\_Imply_{i,t} + \alpha_2 POST\_Imply_{i,t} + \sum_{k=1}^{19} \beta_k CONTROL_{i,t,k} + FIRM + YEAR + \varepsilon \tag{2}$$

The dependent variables, $Green\_P_{i,t+1}$ and $Green\_Inv_{i,t+1}$, refer to the logarithm of one plus the number of green patents and green invention patents, respectively, independently applied by listed companies in the next year. The number of green patents refers to the sum of green invention and utility patents independently applied by listed companies. The independent variable $ESOP_i$ equals one if the company has implemented an ESOP during the sample period and zero otherwise. The dummy variable $POST\_Imply_{i,t}$ equals one if the firm-year falls in the year in which the ESOP is implemented and subsequent years, and zero otherwise. As noted previously, we artificially assign values to the ESOP implementation date and duration for the companies in the control group during the PSM process, using the values of the corresponding treatment group. Hence, the value of $POST\_Imply_{i,t}$ for the control group companies is the same as that for their corresponding companies in the treatment group. Following the literature (Shen et al., 2018; Zheng et al., 2021), if companies implement ESOPs multiple times during the sample period, we exclude the failed and discontinued ESOPs and focus on the first ESOP implemented.

With reference to the literature (Quan et al., 2023; Du et al., 2022; Hao and He, 2022; Liu and Li, 2022), we control for a range of financial characteristics of firms in model (2), including (as defined previously) $SIZE_{i,t}$, $LEV_{i,t}$, $ROA_{i,t}$, $GROWTH_{i,t}$, $SALESPP_{i,t}$, $FIXEDPP_{i,t}$, $LOSS_{i,t}$, $RND_{i,t}$, $AGE_{i,t}$, $FIRMAGE_{i,t}$, and $SOE_{i,t}$. Considering the impact of corporate governance on green innovation, we control for the governance indicators $CEO\_SHR_{i,t}$, $EXE\_SHR_{i,t}$, $INS_{i,t}$, $BOARD_{i,t}$, $INDE_{i,t}$, $SHAREBALANCE_{i,t}$, $WAGE_{i,t}$ and $INTCON_{i,t}$. We control for firm and year-fixed effects in the model (2). The definitions of all variables in the model (2) are provided in Panel A of Appendix A.

Table 3
Descriptive statistics.

Panel A: Descriptive statistic of full sample

Variable	N	Mean	Min	P25	P50	P75	Max	SD
$Green\ P_{i,t+1}$	17,311	0.377	0	0	0	0	3.714	0.786
$Green\ Inv_{i,t+1}$	17,311	0.250	0	0	0	0	3.258	0.619
$ESOP_i$	17,311	0.253	0	0	0	1	1	0.435
$POST\_Imple_{i,t}$	17,311	0.421	0	0	0	1	1	0.494
$ESOP_i \times POST\_Imple_{i,t}$	17,311	0.107	0	0	0	0	1	0.309
$SIZE_{i,t}$	17,311	22.21	19.95	21.36	22.08	22.88	25.91	1.205
$LEV_{i,t}$	17,311	0.412	0.053	0.247	0.402	0.560	0.877	0.203
$ROA_{i,t}$	17,311	0.039	−0.302	0.017	0.040	0.067	0.200	0.064
$GROWTH_{i,t}$	17,311	0.211	−0.498	−0.003	0.129	0.306	2.808	0.441
$SALESPP_{i,t}$	17,311	13.75	11.99	13.16	13.64	14.19	16.55	0.865
$FIXEDPP_{i,t}$	17,311	12.39	9.258	11.78	12.42	13.03	15.06	1.069
$LOSS_{i,t}$	17,311	0.081	0	0	0	0	1	0.273
$RND_{i,t}$	17,311	0.041	0	0.007	0.033	0.052	0.262	0.047
$AGE_{i,t}$	17,311	2.065	0.693	1.609	2.079	2.639	3.258	0.699
$FIRMAGE_{i,t}$	17,311	2.789	1.609	2.565	2.833	3.045	3.434	0.362
$SOE_{i,t}$	17,311	0.147	0	0	0	0	1	0.355
$CEO\_SHR_{i,t}$	17,311	0.069	0	0	0.001	0.070	0.541	0.127
$EXC\_SHR_{i,t}$	17,311	0.097	0	0	0.008	0.135	0.630	0.156
$INS_{i,t}$	17,311	0.397	0.003	0.171	0.400	0.605	0.890	0.249
$BOARD_{i,t}$	17,311	2.233	1.792	2.079	2.303	2.303	2.708	0.172
$INDE_{i,t}$	17,311	0.377	0.333	0.333	0.357	0.429	0.571	0.054
$SHAREBALANCE_{i,t}$	17,311	0.758	0.034	0.300	0.611	1.081	2.800	0.592
$WAGE_{i,t}$	17,311	9.236	5.951	8.661	9.318	9.902	11.76	1.054
$INTCON_{i,t}$	17,311	6.466	0	6.238	6.721	7.064	9.954	1.309

Panel B: Descriptive statistic of treatment and control groups

Variable	Treatment (N = 4373)			Control (N = 12,938)		
	Mean	Median	SD	Mean	Median	SD
$Green\ P_{i,t+1}$	0.446	0	0.856	0.353	0	0.759
$Green\_Inv_{i,t+1}$	0.308	0	0.682	0.231	0	0.595
$POST\_Imple_{i,t}$	0.424	0	0.494	0.420	0	0.494
$SIZE_{i,t}$	22.19	22.06	1.137	22.22	22.08	1.227
$LEV_{i,t}$	0.407	0.395	0.200	0.413	0.403	0.203
$ROA_{i,t}$	0.041	0.042	0.063	0.039	0.039	0.065
$GROWTH_{i,t}$	0.222	0.148	0.415	0.208	0.122	0.450
$SALESPP_{i,t}$	13.73	13.62	0.840	13.76	13.65	0.873
$FIXEDPP_{i,t}$	12.34	12.38	1.010	12.40	12.44	1.088
$LOSS_{i,t}$	0.077	0	0.267	0.082	0	0.275
$RND_{i,t}$	0.043	0.034	0.044	0.041	0.032	0.047
$AGE_{i,t}$	2.046	2.079	0.682	2.071	2.079	0.705
$FIRMAGE_{i,t}$	2.788	2.833	0.361	2.790	2.833	0.362
$SOE_{i,t}$	0.139	0	0.346	0.150	0	0.357
$CEO\_SHR_{i,t}$	0.071	0.002	0.129	0.068	0.001	0.127
$EXC\_SHR_{i,t}$	0.100	0.013	0.156	0.095	0.007	0.157
$INS_{i,t}$	0.393	0.401	0.245	0.399	0.400	0.251
$BOARD_{i,t}$	2.230	2.303	0.159	2.234	2.303	0.177
$INDE_{i,t}$	0.376	0.333	0.054	0.377	0.357	0.054
$SHAREBALANCE_{i,t}$	0.770	0.629	0.584	0.755	0.606	0.594
$WAGE_{i,t}$	9.232	9.284	1.025	9.237	9.332	1.063
$INTCON_{i,t}$	6.455	6.714	1.311	6.470	6.724	1.308

Notes: The table shows the descriptive statistics of the main variables in model (2) within the full sample, treatment, and control groups. The definitions of all variables can be found in Panel A of Appendix A.

3.5. Descriptive statistics

The descriptive statistics for all variables in the model (2) are presented in Table 3. In Panel A of Table 3, the mean values of $Green\_P_{i,t+1}$, and $Green\_Inv_{i,t+1}$ are 0.377 and 0.250, respectively, values that are similar to recent studies (Feng et al., 2022a; Cui et al., 2023). In total, 25.3 % of the firms with an ESOP in place during the sample period are classified as the treatment group, and the remaining observations are included in the control group. We find that 42.1 % of the sample relates to the current and subsequent years of the (artificial) ESOP implementation date. The descriptive statistics for other variables are similar to those found by recent studies in the Chinese context (Zhou et al., 2019; Quan et al., 2023). Panel B shows the descriptive statistics of the main variables for the treatment and control groups.

Table 4
Correlation matrix.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
$Green\ P_{i,t+1}$	1	0.867^{a}	0.049^{a}	−0.004	0.042^{a}	0.074^{a}	0.021^{a}	0.061^{a}	0.045^{a}	−0.029^{a}	−0.013^{c}	−0.042^{a}	0.210^{a}	−0.083^{a}	−0.089^{a}	0.019^{b}	0.036^{a}	0.060^{a}	0.015^{b}	0.049^{a}	−0.023^{a}	0.012	0.054^{a}	0.053^{a}
$Green\ Inv_{i,t+1}$	0.923^{a}	1	0.056^{a}	0.005	0.042^{a}	0.093^{a}	0.039^{a}	0.048^{a}	0.041^{a}	−0.013^{c}	−0.027^{a}	−0.034^{a}	0.201^{a}	−0.048^{a}	−0.067^{a}	0.036^{a}	0.037^{a}	0.058^{a}	0.016^{b}	0.051^{a}	−0.005	0.016^{b}	0.087^{a}	0.045^{a}
$ESOP_{i}$	0.051^{a}	0.054^{a}	1	0.004	0.596^{a}	−0.005	−0.011	0.029^{a}	0.042^{a}	−0.012	−0.031^{a}	−0.008	0.043^{a}	−0.017^{b}	−0.004	−0.015^{c}	0.037^{a}	0.043^{a}	−0.009	−0.006	−0.008	0.020^{a}	−0.012	−0.006
$POST\_Imple_{i,t}$	−0.002	0.004	0.004	1	0.406^{a}	0.208^{a}	0.036^{a}	−0.073^{a}	−0.063^{a}	0.138^{a}	0.072^{a}	0.098^{a}	0.141^{a}	0.250^{a}	0.300^{a}	−0.058^{a}	0.054^{a}	0.077^{a}	−0.070^{a}	−0.090^{a}	0.033^{a}	0.097^{a}	0.249^{a}	−0.182^{a}
$ESOP_{i} \times POST\_Imple_{i,t}$	0.045^{a}	0.045^{a}	0.596^{a}	0.406^{a}	1	0.102^{a}	0.013^{c}	−0.017^{b}	−0.002	0.052^{a}	0.020^{a}	0.033^{a}	0.076^{a}	0.101^{a}	0.122^{a}	−0.030^{a}	0.030^{a}	0.044^{a}	−0.033^{a}	−0.030^{a}	0.008	0.054^{a}	0.107^{a}	−0.070^{a}
$SIZE_{i,t}$	0.163^{a}	0.184^{a}	−0.012	0.186^{a}	0.086^{a}	1	0.523^{a}	−0.056^{a}	0.031^{a}	0.442^{a}	0.223^{a}	−0.054^{a}	−0.287^{a}	0.507^{a}	0.280^{a}	0.280^{a}	−0.285^{a}	−0.310^{a}	0.392^{a}	0.213^{a}	−0.058^{a}	−0.079^{a}	0.285^{a}	0.145^{a}
$LEV_{i,t}$	0.056^{a}	0.066^{a}	−0.013^{c}	0.032^{a}	0.010	0.515^{a}	1	−0.402^{a}	0.018^{b}	0.344^{a}	0.139^{a}	0.165^{a}	−0.398^{a}	0.431^{a}	0.237^{a}	0.248^{a}	−0.278^{a}	−0.319^{a}	0.223^{a}	0.107^{a}	−0.002	−0.122^{a}	0.115^{a}	−0.014^{c}
$ROA_{i,t}$	0.058^{a}	0.046^{a}	0.018^{b}	−0.106^{a}	−0.036^{a}	0.011	−0.336^{a}	1	0.292^{a}	−0.008	−0.172^{a}	−0.473^{a}	0.105^{a}	−0.204^{a}	−0.140^{a}	−0.113^{a}	0.151^{a}	0.165^{a}	0.082^{a}	0.038^{a}	−0.048^{a}	0.061^{a}	0.114^{a}	0.410^{a}
$GROWTH_{i,t}$	0.011	0.006	0.014^{c}	−0.058^{a}	−0.016^{b}	0.042^{a}	0.055^{a}	0.205^{a}	1	0.080^{a}	−0.097^{a}	−0.251^{a}	−0.005	−0.145^{a}	−0.127^{a}	−0.077^{a}	0.109^{a}	0.115^{a}	0.025^{a}	−0.009	−0.015^{b}	0.080^{a}	0.039^{a}	0.305^{a}
$SALESPP_{i,t}$	−0.011	0.003	−0.017^{b}	0.120^{a}	0.043^{a}	0.434^{a}	0.363^{a}	0.020^{a}	0.118^{a}	1	0.367^{a}	−0.069^{a}	−0.350^{a}	0.266^{a}	0.208^{a}	0.138^{a}	−0.161^{a}	−0.189^{a}	0.186^{a}	0.072^{a}	−0.015^{c}	−0.043^{a}	0.334^{a}	0.102^{a}
$FIXEDPP_{i,t}$	0.011	−0.003	−0.027^{a}	0.063^{a}	0.018^{b}	0.245^{a}	0.126^{a}	−0.070^{a}	−0.077^{a}	0.310^{a}	1	0.035^{a}	−0.135^{a}	0.166^{a}	0.120^{a}	0.150^{a}	−0.169^{a}	−0.194^{a}	0.097^{a}	0.090^{a}	−0.038^{a}	−0.081^{a}	0.049^{a}	−0.077^{a}
$LOSS_{i,t}$	−0.037^{a}	−0.029^{a}	−0.008	0.098^{a}	0.033^{a}	−0.057^{a}	0.181^{a}	−0.675^{a}	−0.174^{a}	−0.064^{a}	0.020^{a}	1	0.017^{b}	0.096^{a}	0.059^{a}	0.019^{b}	−0.055^{a}	−0.049^{a}	−0.074^{a}	−0.061^{a}	0.045^{a}	−0.007	0.013^{c}	−0.346^{a}
$RND_{i,t}$	0.125^{a}	0.141^{a}	0.019^{b}	0.095^{a}	0.048^{a}	−0.251^{a}	−0.341^{a}	−0.026^{a}	−0.054^{a}	−0.333^{a}	−0.208^{a}	0.065^{a}	1	−0.285^{a}	−0.148^{a}	−0.271^{a}	0.335^{a}	0.384^{a}	−0.280^{a}	−0.123^{a}	0.057^{a}	0.169^{a}	0.040^{a}	−0.109^{a}
$AGE_{i,t}$	−0.041^{a}	−0.002	−0.016^{b}	0.267^{a}	0.107^{a}	0.492^{a}	0.430^{a}	−0.158^{a}	−0.056^{a}	0.267^{a}	0.177^{a}	0.097^{a}	−0.199^{a}	1	0.598^{a}	0.319^{a}	−0.422^{a}	−0.487^{a}	0.241^{a}	0.135^{a}	−0.008	−0.153^{a}	0.248^{a}	−0.072^{a}
$FIRMAGE_{i,t}$	−0.052^{a}	−0.026^{a}	−0.002	0.309^{a}	0.127^{a}	0.260^{a}	0.240^{a}	−0.121^{a}	−0.069^{a}	0.196^{a}	0.125^{a}	0.060^{a}	−0.111^{a}	0.585^{a}	1	0.146^{a}	−0.225^{a}	−0.256^{a}	0.118^{a}	0.055^{a}	−0.009	−0.046^{a}	0.178^{a}	−0.117^{a}
$SOE_{i,t}$	0.042^{a}	0.063^{a}	−0.015^{c}	−0.058^{a}	−0.030^{a}	0.312^{a}	0.253^{a}	−0.056^{a}	−0.056^{a}	0.143^{a}	0.167^{a}	0.019^{b}	−0.202^{a}	0.310^{a}	0.138^{a}	1	−0.345^{a}	−0.383^{a}	0.303^{a}	0.233^{a}	−0.050^{a}	−0.179^{a}	0.085^{a}	0.072^{a}
$CEO\_SHR_{i,t}$	−0.004	−0.002	0.010	−0.018^{b}	−0.006	−0.276^{a}	−0.249^{a}	0.076^{a}	0.038^{a}	−0.165^{a}	−0.143^{a}	−0.034^{a}	0.201^{a}	−0.355^{a}	−0.192^{a}	−0.217^{a}	1	0.867^{a}	−0.521^{a}	−0.117^{a}	0.028^{a}	0.243^{a}	−0.078^{a}	−0.011
$EXC\_SHR_{i,t}$	−0.004	−0.004	0.013^{c}	−0.021^{a}	−0.007	−0.311^{a}	−0.289^{a}	0.092^{a}	0.044^{a}	−0.187^{a}	−0.178^{a}	−0.044^{a}	0.237^{a}	−0.415^{a}	−0.227^{a}	−0.244^{a}	0.911^{a}	1	−0.578^{a}	−0.127^{a}	0.036^{a}	0.289^{a}	−0.092^{a}	−0.026^{a}
$INS_{i,t}$	0.053^{a}	0.056^{a}	−0.010	−0.072^{a}	−0.035^{a}	0.413^{a}	0.221^{a}	0.115^{a}	0.048^{a}	0.183^{a}	0.115^{a}	−0.074^{a}	−0.231^{a}	0.228^{a}	0.104^{a}	0.307^{a}	−0.463^{a}	−0.527^{a}	1	0.164^{a}	−0.057^{a}	−0.237^{a}	0.150^{a}	0.192^{a}
$BOARD_{i,t}$	0.080^{a}	0.085^{a}	−0.009	−0.090^{a}	−0.032^{a}	0.240^{a}	0.116^{a}	0.059^{a}	−0.020^{a}	0.064^{a}	0.095^{a}	−0.060^{a}	−0.111^{a}	0.138^{a}	0.053^{a}	0.247^{a}	−0.136^{a}	−0.133^{a}	0.172^{a}	1	−0.642^{a}	0.012	0.009	0.095^{a}
$INDE_{i,t}$	−0.017^{b}	0.002	−0.008	0.028^{a}	0.007	−0.055^{a}	−0.002	−0.049^{a}	−0.008	−0.009	−0.045^{a}	0.045^{a}	0.068^{a}	−0.018^{b}	−0.025^{a}	−0.059^{a}	0.097^{a}	0.095^{a}	−0.065^{a}	−0.592^{a}	1	−0.023^{a}	0.031^{a}	−0.030^{a}
$SHAREBALANCE_{i,t}$	−0.002	0.003	0.011	0.081^{a}	0.041^{a}	−0.071^{a}	−0.115^{a}	−0.000	0.066^{a}	−0.033^{a}	−0.088^{a}	−0.006	0.112^{a}	−0.131^{a}	−0.026^{a}	−0.147^{a}	0.055^{a}	0.124^{a}	−0.236^{a}	0.016^{b}	−0.035^{a}	1	0.006	−0.051^{a}
$WAGE_{i,t}$	0.074^{a}	0.108^{a}	−0.002	0.241^{a}	0.108^{a}	0.274^{a}	0.128^{a}	0.052^{a}	0.044^{a}	0.328^{a}	0.052^{a}	0.016^{b}	0.075^{a}	0.239^{a}	0.171^{a}	0.080^{a}	−0.103^{a}	−0.121^{a}	0.147^{a}	0.002	0.033^{a}	0.019^{b}	1	0.018^{b}
$INTCON_{i,t}$	0.074^{a}	0.074^{a}	−0.005	−0.149^{a}	−0.060^{a}	0.132^{a}	−0.114^{a}	0.419^{a}	0.134^{a}	0.068^{a}	−0.035^{a}	−0.393^{a}	−0.039^{a}	−0.124^{a}	−0.126^{a}	0.014^{c}	0.029^{a}	0.034^{a}	0.107^{a}	0.077^{a}	−0.030^{a}	−0.030^{a}	−0.030^{a}	1

Notes: The table shows the correlation matrix for the main variables in model (2). The upper triangle is the pearson correlation matrix, and the lower triangle is the spearman correlation matrix. All variables are defined in Panel A of Appendix A. c, b, and a represent 10 %, 5 %, and 1 % levels of significance, respectively.

Table 5
Baseline results.

	(1)	(2)	(3)	(4)
	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$
$ESOP_i \times POST\_Imple_{i,t}$	0.096***	0.053**	0.098***	0.055**
	(3.01)	(2.15)	(3.07)	(2.24)
$POST\_Imple_{i,t}$	−0.006	0.009	−0.009	0.004
	(−0.27)	(0.54)	(−0.40)	(0.23)
$SIZE_{i,t}$			0.013	0.013
			(0.70)	(0.81)
$LEV_{i,t}$			0.160	0.153**
			(1.62)	(1.98)
$ROA_{i,t}$			0.540***	0.412***
			(3.35)	(3.18)
$GROWTH_{i,t}$			−0.021	−0.019
			(−1.31)	(−1.49)
$SALESPP_{i,t}$			−0.012	−0.013
			(−0.70)	(−0.97)
$FIXEDPP_{i,t}$			0.011	0.001
			(0.87)	(0.07)
$LOSS_{i,t}$			0.058**	0.049**
			(1.97)	(2.06)
$RND_{i,t}$			0.447	0.243
			(1.07)	(0.67)
$AGE_{i,t}$			−0.053	−0.024
			(−0.99)	(−0.61)
$FIRMAGE_{i,t}$			0.399**	0.336***
			(2.37)	(2.88)
$SOE_{i,t}$			−0.007	0.026
			(−0.18)	(0.77)
$CEO\_SHR_{i,t}$			−0.082	−0.030
			(−0.55)	(−0.27)
$EXC\_SHR_{i,t}$			−0.184	−0.075
			(−1.23)	(−0.71)
$INS_{i,t}$			0.021	0.045
			(0.26)	(0.74)
$BOARD_{i,t}$			0.103	0.121
			(0.82)	(1.30)
$INDE_{i,t}$			0.255	0.310
			(0.85)	(1.46)
$SHAREBALANCE_{i,t}$			−0.009	−0.013
			(−0.39)	(−0.80)
$WAGE_{i,t}$			0.003	0.002
			(0.14)	(0.14)
$INTCON_{i,t}$			0.006	0.004
			(1.10)	(0.95)
_cons	0.386***	0.256***	−1.349*	−1.266**
	(49.17)	(41.47)	(−1.90)	(−2.37)
FIRM FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
N	17,311	17,311	17,311	17,311
adj R^2	0.661	0.656	0.664	0.658

Notes: The table shows the results of how ESOPs affect firms' green innovation in the following year. Columns (1) and (2) show the results of model (2) without control for any control variables. Columns (3)–(4) show the results of model (2), which explores the changes in green patents and green invention patents in the following year after implementing the ESOP for companies in the treatment group. The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

The correlation coefficients of the main variables in the model (2) are presented in Table 4. The Pearson and Spearman correlation coefficients for $ESOP_i$ and $ESOP_i \times POST\_Imply_{i,t}$ on $Green\_P_{i,t+1}$ and $Green\_Inv_{i,t+1}$ are positive and significant at the 1 % level. This indicates positive relationships between ESOP and corporate green patents and green invention patents. Although the correlation coefficients of some variables exceed 0.5, all variance inflation factors are below 10, which implies a low possibility of multicollinearity.

4. Main results

4.1. Baseline results

First, we test how ESOPs affect firms' green innovation (H1) with the results of model (2) presented in Table 5. In columns (1) and (2), we regress model (2) without any control variables but firm and year-fixed effects. The coefficients of $ESOP_i \times POST\_Imple_{i,t}$ are both positive and significant, no matter whether $Green\_P_{i,t+1}$ or $Green\_Inv_{i,t+1}$ is the dependent variable, which preliminary verifies our hypothesis H1. After controlling the financial and corporate governance indicators, columns (3) and (4) show the results of model (2). With $Green\_P_{i,t+1}$ as the dependent variable, the coefficient of $ESOP_i \times POST\_Imple_{i,t}$ is positive and significant (0.098, $p < 0.01$), indicating an average increase of 10.30 % ($e^{0.098}$–1) in the number of green patent applications applied for by firms in the following year from the pre- to post-implementation periods of the ESOPs. Taking $Green\_Inv_{i,t+1}$ as the dependent variable, we find a significant increase (0.055, $p < 0.05$) in the number of green invention patents applied for by firms in the following year from the pre-implementation period to the end period, with an average increase of 5.65 % ($e^{0.055}$–1).

4.2. Parallel trend test

The positive relationships between *ESOPs* and $Green\_P_{i,t+1}$ and $Green\_Inv_{i,t+1}$ demonstrated in the previous section may not be sufficient evidence that ESOPs increase green innovation because green innovation may vary between the treatment and control groups in the absence of an ESOP, resulting in a higher rate of green innovation in the treatment group than in the control group. Therefore, the parallel trend assumption is a crucial prerequisite for the DiD model to demonstrate causation. We introduce multiple dummy time-based variables for the parallel trend test and construct the following model:

$$\begin{aligned} Green\_P_{i,t+1}\big|Green\_Inv_{i,t+1} = \alpha_0 + \sum_{t=-2}^{3}\vartheta_t ESOP_i \times POST\_Imlpy\_t \\ + \sum_{t=-2}^{3}\delta_t POST\_Imply\_t + \sum_{k=1}^{19}\beta_k CONTROL_{i,t,k} \\ + FIRM + YEAR + \varepsilon \end{aligned} \tag{3}$$

In model (3), time dummy variables, $POST\_Imply\_t$ ($t = -3, -2, -1, 0, 1, 2, 3$), are constructed to identify the economic effects of each year before and after the implementation of the ESOP by the firm. $POST\_Imply\_t$ ($t = -3, -2, -1, 0, 1, 2, 3$) equals one if the year is three or more years prior to the year of ESOP implementation, two years prior to the year of ESOP implementation, one year the year of ESOP implementation, the year of ESOP implementation, one year after the year of ESOP implementation, two years after the year of ESOP implementation, or three or more years after the year of ESOP implementation, respectively, and 0 otherwise. *POST_Imply_-3* is removed to prevent collinearity problems. By replacing $POST\_Imply_{i,t}$ in model (2) with $POST\_Imply\_t$, model (3) is constructed to verify whether model (2) meets the parallel trend assumption.

Panel A of Table 6 shows the results of model (3), and the graphs demonstrating the results of the parallel trend assumption test are

Table 6
Parallel assumption test and placebo test.

Panel A: parallel assumption test

	(1) $Green\_P_{i,t+1}$		(2) $Green\_Inv_{i,t+1}$	
	Coef.	T-value	Coef.	T-value
$ESOP_i \times POST\_Imple\_\text{-}2$	0.048	(1.23)	0.017	(0.58)
$ESOP_i \times POST\_Imple\_\text{-}1$	0.040	(1.01)	0.037	(1.18)
$ESOP_i \times POST\_Imple\_0$	0.080*	(1.96)	0.048	(1.50)
$ESOP_i \times POST\_Imple\_1$	0.148***	(2.90)	0.104**	(2.54)
$ESOP_i \times POST\_Imple\_2$	0.176***	(3.45)	0.083**	(2.11)
$ESOP_i \times POST\_Imple\_3$	0.071	(1.26)	0.035	(0.83)
$POST\_Imple\_\text{-}2$	−0.043	(−1.59)	−0.039*	(−1.92)
$POST\_Imple\_\text{-}1$	−0.014	(−0.54)	−0.027	(−1.42)
$POST\_Imple\_0$	−0.025	(−0.87)	−0.020	(−0.96)
$POST\_Imple\_1$	−0.015	(−0.38)	−0.026	(−0.90)
$POST\_Imple\_2$	−0.020	(−0.49)	−0.006	(−0.19)
$POST\_Imple\_3$	−0.037	(−0.76)	−0.023	(−0.62)
CONTROLS	Yes		Yes	
FIRM FE	Yes		Yes	
YEAR FE	Yes		Yes	
N	17,311		17,311	
adj. R^2	0.664		0.659	

Panel B: placebo test

	(1)	(2)	(3)	(4)
	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$
$ESOP_i \times POST\_Pseudo\_1_{i,t}$	0.029	0.027		
	(0.85)	(0.97)		
$POST\_Pseudo\_1_{i,t}$	0.008	0.004		
	(0.34)	(0.22)		
$ESOP_i \times POST\_Pseudo\_2_{i,t}$			0.044	0.021
			(1.28)	(0.80)
$POST\_Pseudo\_2_{i,t}$			−0.029	−0.028*
			(−1.25)	(−1.70)
CONTROLS	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
N	9901	9901	9901	9901
adj. R^2	0.717	0.725	0.717	0.725

Notes: The table shows the results of the parallel assumption test and placebo test for model (2). In Panel A, column (1) shows the change in green patents applied by companies in the next year in each year before and after implementing the ESOP, whereas column (2) shows the change in green invention patents applied in the next year as a result. Panel B shows the results of the time-varying placebo test, which investigates the existence of omitted events or policies that may affect the relationship between ESOP and corporate green innovation. By advancing the implemented date of the ESOPs by one year and two years, respectively, the hypothesis that there are no omitted events and policies that lead to the improvement of green innovation may not be rejected if the coefficients of $ESOP_i \times POST\_Pseudo\_1_{i,t}$ and $ESOP_i \times POST\_Pseudo\_2_{i,t}$ are insignificant. The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

shown in Fig. 2 at the 10 % significance level. As can be seen, the null hypothesis that there is no significant difference in the trend of green innovation between the treatment and control groups before implementing the ESOP is not rejected. Thus, the parallel trend assumption is satisfied.

4.3. Placebo test

To rule out omitted variables or other policy factors that may lead to increased green innovation in companies in the treatment group, we perform a time-varying placebo test and a randomly selected pseudo-treatment group test.

We conduct the time-varying placebo test by advancing the implementation dates by one and two years (Kyung et al., 2019). Specifically, we exclude all observations after the (artificial) implementation date of the ESOPs and assume that companies implement their ESOPs 1 or 2 years prior to the actual implementation date. $POST\_Pseudo\_1_{i,t}$ and $POST\_Pseudo\_2_{i,t}$, which equal one if the firm-year is in the year and subsequent years of the date that is one year or two years prior to the implementation date of the ESOPs, respectively, and 0 otherwise. We conduct the time-varying placebo test by replacing $POST\_Imply_{i,t}$ in model (2) with $POST\_Pseudo\_1_{i,t}$ and $POST\_Pseudo\_2_{i,t}$. As Panel B of Table 6 shows, the coefficients of $ESOP_i \times POST\_Pseudo\_1_{i,t}$ and $ESOP_i \times POST\_Pseudo\_2_{i,t}$ in columns (1)–(4) are all non-significant, which indicates that there is a weak probability of omitted events (rather than ESOPs) leading to improved corporate green innovation.

Next, using companies at the pre-implementation date of their ESOP as the sample, we randomly select 546 observations as the pseudo-

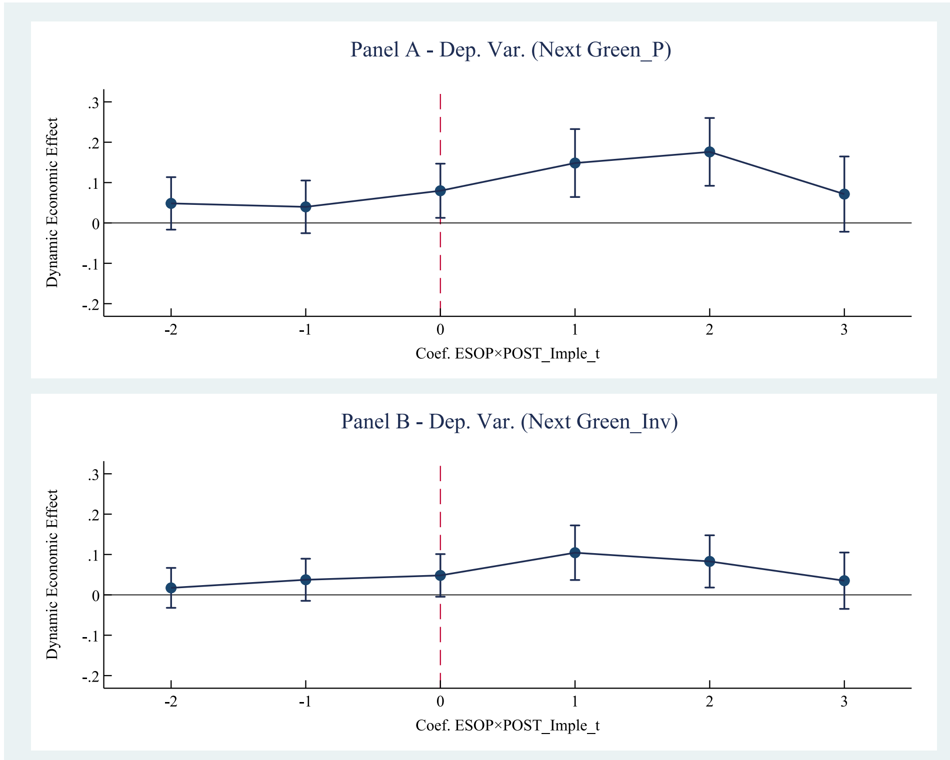

Fig. 2. Parallel trend test.
Notes: The figure shows the results of whether the assumption of parallel trends is met for model (2). Panel A and Panel B correspond to model (3), with $Green\_P_{i,t+1}$ and $Green\_Inv_{i,t+1}$ as dependent variables, respectively. The horizontal coordinates are the time points for each year before and after the implementation of the ESOP, and the vertical coordinates correspond to the values of the solid dots in blue, which measure the coefficients of the time-based dummy variables in the model (3). The vertical blue solid line identifies the significance level of the coefficients on the time-based dummy variables at each time point. If the vertical blue solid line does not cross the horizontal line of zero, the coefficient on the dummy variable is significant at the 10 % level or above. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

treatment group companies and the remaining companies as the pseudo-control group (1626 observations).[11] Based on these groups, we construct the pseudo-independent variable ESOP and substituted it into the model (2). We calculate $ESOP_i$ in the same way as in the previous section. By repeating the random sampling 500 times and re-testing model (2) on this basis, we plot the coefficients of the key variables $ESOP_i \times POST\_Imple_{i,t}$ for the 500 sampling tests. The results are presented in Panels A and B of Fig. 3. It is evident that the coefficients of $ESOP_i \times POST\_Imple_{i,t}$ have an approximately normal distribution, which greatly excludes the possibility of omitted factors contributing to the regression results. Therefore, these tests indicate that our results remain robust.

4.4. Entropy balancing and alternative PSM techniques

As considerable sample loss is a shortcoming of PSM, the entropy balancing approach effectively minimises the potential pre-trends in our control variables without sampling loss. We perform third-order entropy balancing on the full sample before PSM (Hainmueller, 2012; Darendeli et al., 2022). DiD model (4) is constructed following Bertrand and Mullainathan (2003) and Chan et al. (2013) and tested using the full sample and the entropy-balanced sample. The definition of $ESOP_i \times Imply_{i,t}$ for the treatment group companies remains the same as before, and it equals zero for companies in the control group. The control variables are the same as those in the model (2).

$$Green\_P_{i,t+1} \big| Green\_Inv_{i,t+1} = \alpha_0 + \alpha_1 ESOP_i \times POST\_Imply_{i,t} + \sum_{k=1}^{19} \beta_k CONTROL_{i,t,k} + FIRM + YEAR + \varepsilon \quad (4)$$

Panel A of Table 7 shows the matching results of entropy balancing. Compared with pre-matching, the differences in firm characteristics between the treatment and control groups are largely eliminated after adopting this approach. It is evident from columns (1)–(4) of Panel B that the main results hold for the full sample before and after entropy balancing.

As there are more observations in the control group than in the treatment group, we use the one-to-three PSM method for the main analyses. This aids in matching the treatment group companies with those with the closest covariates in the control group. In addition, we allow the same control group companies to be matched with different treatment group companies in different years to minimise the differences in covariates among companies that are successfully matched. However, to eliminate potential mistakes arising from this method, we

[11] Some control group companies may have multiple observations in the same pre-implementation year with the same artificial implementation date and duration period because of the one-to-three putback PSM technique. We keep the selected pseudo treatment group companies with different (artificial) implementation dates and duration periods when randomly selecting.

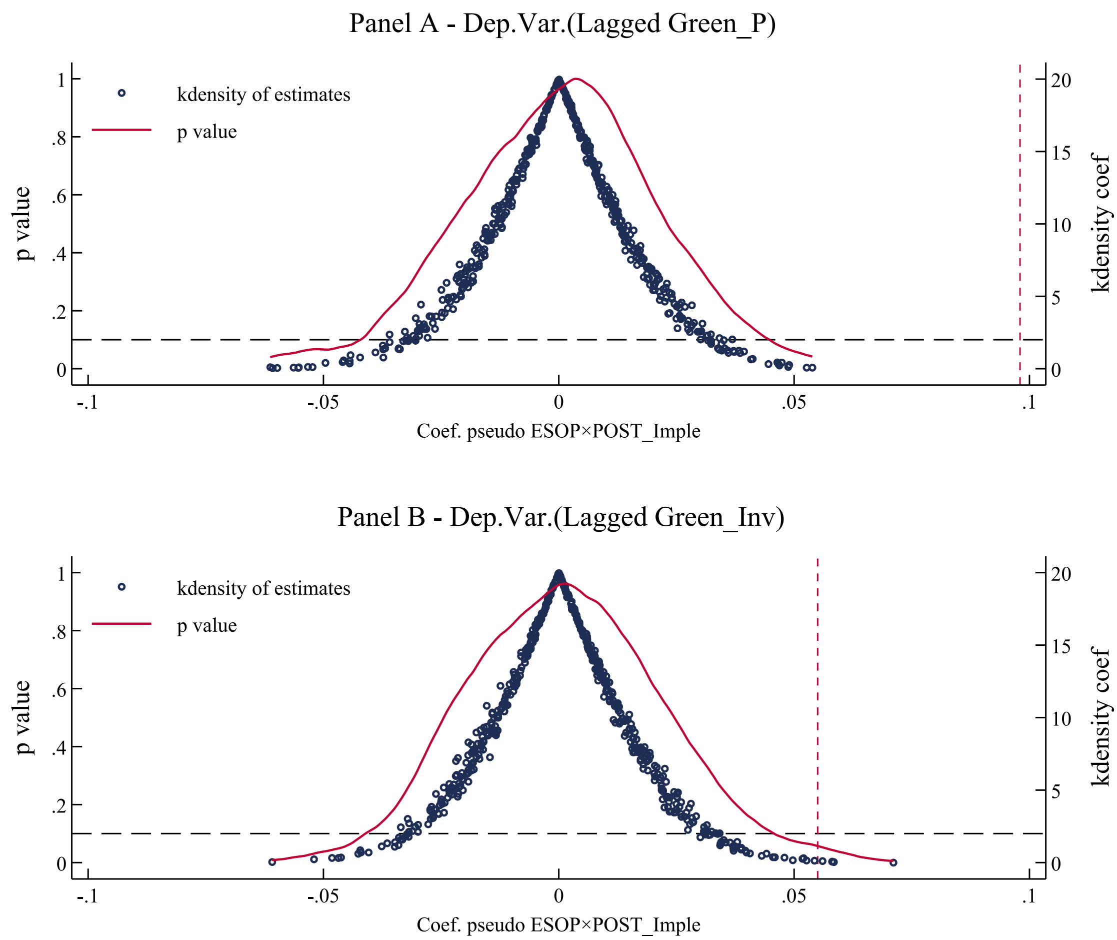

Fig. 3. Placebo test.

Notes: Placebo tests for model (2) are presented in the figure. The horizontal coordinate measures the coefficient of the independent variable $ESOP_i \times POST\_Imple_{i,t}$. The vertical coordinate on the left measures the significance of the coefficient on the independent variable $ESOP_i \times POST\_Imple_{i,t}$, while the vertical coordinate on the right measures the kernel density of the coefficient on the variable $ESOP_i \times POST\_Imple_{i,t}$. The red dashed line horizontally refers to the 10 % significance level, while the red dashed line vertically refers to the corresponding coefficient of the independent variable $ESOP_i \times POST\_Imple_{i,t}$. in model (2). Standard errors for all regressions are clustered at the firm level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

modify the PSM conditions and use the one-to-one without replacement method of nearest-neighbour matching as a robustness check.

Table 8 presents the results of this robustness check. Panel A shows the t-tests for the mean of the covariates between the treatment and control groups after matching and finds that none are significant. Panel B shows the regression results after modifying the PSM conditions. We find that firms in the treatment group experienced a significant increase in green innovation after the implementation of ESOPs.

4.5. Heckman two-stage model

We construct the Heckman treatment effect model (5) to test for possible self-selection problems. We use two instrumental variables as exogenous variables: $IV1_{i,t\text{-}1}$ is the percentage of firms implementing ESOPs in the industry to which the focal firm belongs in the previous year, and $IV2_{i,t\text{-}1}$ is the capital size of the ESOPs implemented by each industry in each city to the total size of the ESOPs implemented in that industry in the previous year. We select $IV1_{i,t\text{-}1}$ and $IV2_{i,t\text{-}1}$ as the instrumental variables for two main reasons. First, rivals in the same industry or region influence each other through competition (Durnev and Mangen, 2020) and imitation (Aerts et al., 2006). Therefore, a high implementation ratio within an industry may lead to an increasing trend of ESOP adoption by firms within the industry. In particular, when the size of ESOPs within an industry in a city is large relative to that industry as a whole, companies without an ESOP are likely to have strong incentives to adopt an ESOP. Hence, we anticipate that $IV1_{i,t\text{-}1}$ and $IV2_{i,t\text{-}1}$ may have strong explanatory power on ESOPs, which we test in model (5). Second, an industry's ESOP adoption ratio and the region's ESOP size are exogenous indicators that cannot be directly influenced by a single company and do not directly affect corporate green innovation.

$$Probit(ESOP_i) = \alpha_0 + \alpha_1 IV1_{i,t-1} + \alpha_2 IV2_{i,t-1} + \sum_{k=1}^{19} \beta_k CONTROL_{i,t,k} + IND + YEAR + \varepsilon \tag{5}$$

Using $ESOP_i$ as the dependent variable and $IV1_{i,t\text{-}1}$ and $IV2_{i,t\text{-}1}$ as the independent variables, we construct a model (5) for Heckman selection

Table 7
Entropy balancing.

Panel A: The difference between treatment and control groups before and after the entropy balancing

Variable	$ESOP_i = 1$			PRE				POST			
				$ESOP_i = 0$			S.D.	$ESOP_i = 0$			S.D.
	Mean	Var.	Skewness	Mean	Var.	Skewness	Diff.	Mean	Var.	Skewness	Diff.
$SIZE_{i,t}$	22.185	1.320	0.711	22.207	1.768	0.594	−0.020	22.185	1.320	0.711	0.000
$LEV_{i,t}$	0.412	0.041	0.288	0.452	0.045	0.213	−0.202	0.412	0.041	0.288	0.000
$ROA_{i,t}$	0.041	0.004	−2.415	0.031	0.005	−2.322	0.154	0.041	0.004	−2.415	0.000
$GROWTH_{i,t}$	0.229	0.222	4.154	0.183	0.278	4.187	0.099	0.229	0.222	4.154	0.000
$SALESPP_{i,t}$	13.742	0.715	0.602	13.792	0.781	0.554	−0.059	13.742	0.715	0.603	0.000
$FIXEDPP_{i,t}$	12.342	1.050	−0.242	12.589	1.356	−0.093	−0.241	12.342	1.050	−0.242	0.000
$LOSS_{i,t}$	0.077	0.071	3.169	0.117	0.103	2.382	−0.150	0.077	0.071	3.169	0.000
$RND_{i,t}$	0.042	0.002	2.112	0.033	0.002	2.530	0.219	0.042	0.002	2.112	0.000
$AGE_{i,t}$	2.028	0.476	−0.193	2.264	0.571	−0.595	−0.343	2.028	0.476	−0.193	0.000
$FIRMAGE_{i,t}$	2.793	0.134	−0.754	2.889	0.111	−0.973	−0.262	2.793	0.134	−0.754	0.000
$SOE_{i,t}$	0.139	0.120	2.085	0.442	0.247	0.232	−0.876	0.139	0.120	2.085	0.000
$CEO\_SHR_{i,t}$	0.070	0.016	2.044	0.041	0.010	2.881	0.229	0.070	0.016	2.044	0.000
$EXC\_SHR_{i,t}$	0.099	0.024	1.735	0.059	0.016	2.550	0.261	0.099	0.024	1.735	0.000
$INS_{i,t}$	0.396	0.061	0.093	0.452	0.058	−0.177	−0.228	0.396	0.061	0.093	0.000
$BOARD_{i,t}$	2.229	0.026	−0.366	2.251	0.033	−0.173	−0.136	2.229	0.026	−0.366	0.000
$INDE_{i,t}$	0.377	0.003	1.273	0.375	0.003	1.391	0.038	0.377	0.003	1.273	0.000
$SHAREBALANCE_{i,t}$	0.768	0.341	1.217	0.686	0.351	1.283	0.142	0.768	0.341	1.217	0.000
$WAGE_{i,t}$	9.194	1.108	−0.510	9.307	1.267	−0.526	−0.107	9.194	1.108	−0.510	0.000
$INTCON_{i,t}$	6.459	1.730	−3.295	6.203	3.000	−2.624	0.195	6.459	1.730	−3.295	0.000

Panel B: Test before (Full Sample) and after entropy balancing

	Full Sample		Entropy balancing	
	(1)	(2)	(3)	(4)
	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$
$ESOP_i \times POST\_Imple_{i,t}$	0.059***	0.031*	0.067***	0.044**
	(2.66)	(1.70)	(2.95)	(2.35)
CONTROLS	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
N	24,471	24,471	24,471	24,471
adj. R^2	0.650	0.633	0.648	0.629

Notes: The table shows the matches for entropy matching, tests based on the full sample, and tests based on the full sample with entropy matching. Panel A shows the differences in control variables between the treatment and control groups before and after entropy matching. Columns (1) and (2) in Panel B show the results of model (4) before entropy matching, whereas columns (3) and (4) show the results of model (4) after entropy balancing. The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. Regressions of entropy balancing are estimated based on weights (pweight) taken from the entropy balancing estimation. Standard errors for all regressions are clustered at the firm level.

Table 8
Alternative techniques of propensity score matching.

Panel A: Differences in covariates between the treatment and control groups after PSM

Variables	Treatment	Control	Diff.
	(N = 467)	(N = 467)	T-Value
$SIZE_{i,t-1}$	22.16	22.11	0.617
$LEV_{i,t-1}$	0.395	0.385	0.792
$ROA_{i,t-1}$	0.048	0.046	0.629
$GROWTH_{i,t-1}$	0.293	0.293	−0.005
$SALESPP_{i,t-1}$	13.71	13.72	−0.193
$FIXEDPP_{i,t-1}$	12.41	12.39	0.266
$LOSS_{i,t-1}$	0.045	0.044	0.363
$RND_{i,t-1}$	0.047	0.049	−0.153
$AGE_{i,t-1}$	1.956	1.895	1.304
$FIRMAGE_{i,t-1}$	2.797	2.779	0.806
$SOE_{i,t-1}$	0.120	0.139	−0.876
$CEO\_SHR_{i,t-1}$	0.083	0.079	0.390
$EXC\_SHR_{i,t-1}$	0.115	0.111	0.327
$INS_{i,t-1}$	0.383	0.399	−0.957
$BOARD_{i,t-1}$	2.223	2.226	−0.249
$INDE_{i,t-1}$	0.377	0.378	−0.405
$SHAREBALANCE_{i,t-1}$	9.23	9.219	0.162
$WAGE_{i,t-1}$	0.765	0.776	−0.304
$INTCON_{i,t-1}$	6.544	6.549	−0.076

Panel B: Regression results after ‘one-to-one, without replacement’ PSM

	(1)	(2)
	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$
$ESOP_i \times POST\_Imple_{i,t}$	0.077**	0.049*
	(2.33)	(1.87)
$POST\_Imple_{i,t}$	−0.007	−0.001
	(−0.23)	(−0.02)
CONTROLS	Yes	Yes
FIRM FE	Yes	Yes
YEAR FE	Yes	Yes
N	7270	7270
adj. R^2	0.661	0.653

Notes: The table shows the differences in covariates and regression results under the ‘one-to-one, without replacement’ propensity score matching. Panel A shows the differences in the mean values of the covariates between the treatment and control groups after propensity score matching. Panel B shows the results of model (2) after propensity score matching for ‘one to one, no put-back. The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

testing with industry and year-fixed effects. Model (5) uses a probit regression with the same control variables as model (2), and the results are presented in column (1) of Table 9. $IMR_{i,t}$ is obtained from the first-stage regression (model (5)), and we add it to model (2) as the second stage of the Heckman selection test. The results of the second stage are presented in columns (2)–(3) of Table 9. In column (1), the coefficients of both $IV1_{i,t-1}$ and $IV2_{i,t-1}$ are positive and significant, indicating the strong explanatory power of the IVs for the tendency of companies to implement ESOPs. In columns (2)–(3), the baseline test results persist after considering the self-selection problem by controlling $IMR_{i,t}$, which indicates that our main test is robust. In addition, the coefficients of $IMR_{i,t}$ are not significant, which indicates that self-selection problems are unlikely to influence our study.

Table 9
Heckman two stage.

	(1)	(2)	(3)
	$ESOP_i$	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$
$ESOP_i \times POST\_Imple_{i,t}$		0.076**	0.047*
		(2.36)	(1.88)
$POST\_Imple_{i,t}$		−0.004	0.007
		(−0.18)	(0.43)
$IV1_{i,t-1}$	1.555**		
	(2.17)		
$IV2_{i,t-1}$	1.630***		
	(13.76)		
$IMR_{i,t}$		0.040	0.040
		(0.37)	(0.48)
CONTROLS	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes
YEAR FE	No	Yes	Yes
IND FE	Yes	No	No
N	14,935	14,924	14,924
pseudo R^2	0.027	–	–
adj. R^2	–	0.681	0.674

Notes: The table shows the tests for self-selection problems for our sample. Column (1) shows the first stage of the treatment effects model, while columns (2) and (3) show the second stage of the treatment effects model. The definitions of all variables can be found in Panel A of Appendix A. Z-values are shown in parentheses in column (1) and T-values are shown in parentheses in columns (2)-(3). *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

Table 10
Omitted variables test.

$Green\_P_{i,t+1}$		$Green\_Inv_{i,t+1}$	
1.3 R^2; δ = 1	Estimated β from Eq. (2) = 0	1.3 R^2; δ = 1	Estimated β from Eq. (2) = 0
‘True’ β Bound [0.080, 0.091]	δ −49.245	‘True’ β Bound [0.0449, 0.0452]	δ 9.791

Notes: The table shows the tests for omitted variables of model (2). The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

4.6. Omitted variable test

We follow Oster (2019) to test omitted variable bias in the basic model. We assume that there is an omitted variable of comparable importance to $ESOP_i \times POST\_Imple_{i,t}$ in the model (2). The R^2 of the model (2) becomes 1.3 times better after adding the omitted variable. We test the intervals for the true coefficient of $ESOP_i \times POST\_Imple_{i,t}$ after including the omitted variable, using $Green\_P_{i,t+1}$ and $Green\_Inv_{i,t+1}$ as the dependent variables. As shown in Table 10, the intervals for the true coefficients of $ESOP_i \times POST\_Imple_{i,t}$ are [0.080, 0.091] and [0.0449, 0.0452] for the two dependent variables, respectively, which are included in the 99.5 % confidence interval for the coefficients of $ESOP_i \times POST\_Imple_{i,t}$ without the critical omitted variable. Moreover, after adding the omitted variable, the true interval of $ESOP_i \times POST\_Imple_{i,t}$ does not contain zero. This indicates that the coefficients of $ESOP_i \times POST\_Imple_{i,t}$ remain positive after including the important omitted variable. For these reasons, the possibility that an important

Table 11
Mechanism test.

	Risk-taking	Employees' productivity	
	(1)	(2)	(3)
	$RISK_{i,t+1}$	$EMP\_PROD1_{i,t+1}$	$EMP\_PROD2_{i,t+1}$
$ESOP_i \times POST\_Imple_{i,t}$	0.002**	0.005**	0.002*
	(2.26)	(2.12)	(1.94)
$POST\_Imple_{i,t}$	−0.000	−0.002	−0.000
	(−0.59)	(−1.33)	(−0.13)
CONTROLS	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes
N	16,839	16,336	16,336
adj. R^2	0.621	0.581	0.594

Notes: The table shows the results of the mechanism tests. Column (1) shows the mechanism test of corporate risk-taking as well as columns (2)–(3) show the mechanism tests of green innovation productivity. When using $RISK_{i,t+1}$ as the dependent variables, firm size ($SIZE_{i,t}$), leverage ($LEV_{i,t}$), return on assets ($ROA_{i,t}$), sales growth ($GROWTH_{i,t}$), whether the firm is loss-making ($LOSS_{i,t}$), fixed assets ratio ($TANGIBLES_{i,t}$), cash holding ($CASH_{i,t}$), cash flow ($CFO_{i,t}$), capital expenditure ($CAPEX_{i,t}$), investment in research and development ($RND_{i,t}$), years since the listing date of the firm ($AGE_{i,t}$), firm age ($FIRMAGE_{i,t}$), nature of property rights ($SOE_{i,t}$), CEO shareholding ($CEO\_SHR_{i,t}$), institutional shareholding ($INS_{i,t}$), board size ($BOARD_{i,t}$), the proportion of independent directors ($INDE_{i,t}$), compensation of top3 executives ($Top3Salary_{i,t}$) and the level of internal control ($INTCON_{i,t}$) are used as the control variables. When the dependent variables are $EMP\_PROD1_{i,t+1}$ and $EMP\_PROD2_{i,t+1}$, the control variables are the same as model (2). The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

omitted variable exists is low, indicating that our model is robust.

Next, we test the importance of the omitted variable relative to $ESOP_i \times POST\_Imple_{i,t}$ based on the assumption that the coefficient of $ESOP_i \times POST\_Imple_{i,t}$ becomes zero or negative after including the omitted variable. Oster (2019) argues that if the absolute value of the relative importance of the omitted variable is greater than one, there is a low possibility that the omitted variable exists. We find that the values of the relative importance of the omitted variable are −49.245 and 9.791 in our study, which strongly rejects the assumption that important variables are omitted in the basic model.

4.7. Additional robustness tests

In this section, we present additional untabulated analyses to ensure the robustness of our results. First, we employed diverse alternative methodologies to measure corporate green innovation: (1) we additionally add green and green invention patents that companies joint applied with other entities to calculate corporate green and green invention innovation; (2) we use the number of green patents granted as an alternative measure of corporate green innovation (Liu and Li, 2022); (3) we use the number of patent citations as an alternative measure of green innovation (Kim and Valentine, 2021); (4) we use the number of green utility patents as an alternative measure of green innovation. Our untabulated results indicate a significant increase in green innovation after the implementation of an ESOP.

Second, the distribution of industries in our sample demonstrates that although most industries in China engage in green innovation to some extent, green innovation is most prevalent in the manufacturing sector (Jiang and Bai, 2022). Following the literature (Quan et al., 2023), we restrict the sample to the manufacturing industry for robustness testing. The untabulated results show that our main findings hold when the sample is restricted to the manufacturing industry.

Next, we modify the baseline model (2) using two approaches to test the robustness of the main findings. For one, we modify model (2) to a Tobit model restricted on the left. For two, we refer to the PSM technique of Chan et al. (2013), which uses the same staggered DiD method as model (2) but removes the dummy variable $POST\_Imply_{i,t}$. Our untabulated results show the main findings hold after modifying the basic model.

Finally, we examine the impact of the SDGs on the relationship between ESOP and green innovation. In September 2015, the United Nations adopted the 2030 Agenda for Sustainable Development, where the Sustainable Development Goals (SDGs) were formulated and adopted.[12] The SDGs encompass three key dimensions: social, economic, and environmental, and comprise 17 global development goals aimed at guiding global development efforts from 2015 through 2030. Following the release of the SDGs, China has been dedicated to their implementation, both in terms of action and policymaking. For instance, in April 2016, the Ministry of Foreign Affairs of the People's Republic of China issued "China's Position Paper on the Implementation of the 2030 Agenda for Sustainable Development".[13] The SDGs' introduction and enforcement may increase environmental regulatory pressures on firms, prompting green innovation to comply with regulations. Industries like manufacturing and high-pollution sectors are significantly affected, and these firms make up a substantial part of our sample. The SDGs' adoption in 2015 aligns with the rise of ESOPs among Chinese listed companies starting in 2014. A concern is that our study's main findings could be due to SDGs' influence on green innovation, not ESOPs. We construct the model (6) to empirically assess the SDG's impact.

$$\begin{aligned} Green\_P_{i,t+1}\middle|Green\_Inv_{i,t+1} = {} & \alpha_0 + \alpha_1 SDG_{i,t} \times ESOP_i \times POST\_Imply_{i,t} \\ & + \alpha_2 SDG_{i,t} \times POST\_Imply_{i,t} + \alpha_3 SDG_{i,t} \\ & + \alpha_4 ESOP_i \times POST\_Imply_{i,t} + \alpha_5 POST\_Imply_{i,t} \\ & + \sum_{k=1}^{19} \beta_k CONTROL_{i,t,k} + FIRM + YEAR + \varepsilon \end{aligned} \tag{6}$$

The dummy variable $SDG_{i,t}$ is assigned a value of 1 for enterprises in the manufacturing or high-pollution sectors during the period post-2015, and 0 for all other cases. $SDG_{i,t}$, along with its interaction with the terms $ESOP_i \times POST\_Imply_{i,t}$ and $POST\_Imply_{i,t}$, are integrated into model (2). In the untabulated results, it is observed that the coefficient of $SDG_{i,t} \times ESOP_i \times POST\_Imply_{i,t}$ is insignificant, indicating that the execution of the SDGs does not substantially influence the findings of this study.

5. Mechanism tests

We have determined that ESOPs can increase corporate green innovation over their duration. However, the potential mechanism remains unclear. First, innovation requires that companies take risks (Chang et al., 2015), but management may be risk-averse and oppose R&D innovation to safeguard their personal interests (John et al., 2008). This phenomenon is increasingly prevalent in relation to green innovation. Although green innovation has positive environmental externalities (Xie and Teo, 2022), it involves high risks and inputs (Berrone et al., 2013; Kopyrina et al., 2023) and makes it difficult to reap immediate benefits (Zhao et al., 2023). Consequently, the risks for companies and executives to innovate green innovation are even more severe than for other types of innovation.

Although employees are key participants in corporate production and operations who receive valuable first-hand information (Babenko and Sen, 2016), they lack the power and earnings incentives to work

[12] For more detail, see https://sdgs.un.org/2030agenda.

[13] For more detail, see https://www.mfa.gov.cn/web/ziliao_674904/zt_674979/dnzt_674981/qtzt/2030kcxfzyc_686343/zw/201604/t20160422_9279988.shtml.

Table 12
Cross-sectional tests.

Panel A: SOE vs Non-SOE

Dep. Var	$Green\_P_{i,t+1}$		$Green\_Inv_{i,t+1}$	
	(1) $SOE_{i,t}=1$	(2) $SOE_{i,t}=0$	(3) $SOE_{i,t}=1$	(4) $SOE_{i,t}=0$
$ESOP_i \times POST\_Imple_{i,t}$	0.045	0.104***	0.003	0.058**
	(0.59)	(3.01)	(0.05)	(2.21)
$POST\_Imple_{i,t}$	−0.038	−0.006	−0.013	0.007
	(−0.81)	(−0.24)	(−0.32)	(0.36)
CONTROLS	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
N	2525	14,752	2525	14,752
adj. R^2	0.773	0.644	0.767	0.635

Panel B: high CEO power vs low CEO power

Dep. Var	$Green\_P_{i,t+1}$		$Green\_Inv_{i,t+1}$	
	(1) $CEO\_Power_{i,t}$ High	(2) $CEO\_Power_{i,t}$ Low	(3) $CEO\_Power_{i,t}$ High	(4) $CEO\_Power_{i,t}$ Low
$ESOP_i \times POST\_Imple_{i,t}$	0.085*	0.138***	0.032	0.077**
	(1.93)	(3.07)	(0.96)	(2.18)
$POST\_Imple_{i,t}$	−0.023	0.009	0.001	0.020
	(−0.85)	(0.30)	(0.05)	(0.85)
CONTROLS	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
N	9288	7500	9288	7500
adj. R^2	0.694	0.675	0.685	0.679

Panel C: pollute industries vs non-pollute industries

Dep. Var	$Green\_P_{i,t+1}$		$Green\_Inv_{i,t+1}$	
	(1) Pollute industries	(2) Non-pollute industries	(3) Pollute industries	(4) Non-pollute industries
$ESOP_i \times POST\_Imple_{i,t}$	0.132**	0.067**	0.078	0.036
	(2.16)	(2.16)	(1.48)	(1.48)
$POST\_Imple_{i,t}$	−0.039	0.007	−0.003	0.009
	(−1.31)	(0.44)	(−0.10)	(0.67)
CONTROLS	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
N	2415	14,882	2415	14,882
adj. R^2	0.713	0.654	0.734	0.639

Notes: The table reports the results of cross-sectional tests. Panel A shows the differences between state-owned and non-state-owned enterprises in terms of the impact of ESOP on corporate green innovation, while Panel B shows the differences in main results between enterprises with high and low CEO power, and Panel C shows the differences in main results between enterprises in heavy and low polluting industries. The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses. *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

hard to use their internal information for supervision purposes. By granting employees ownership, ESOPs give them greater management power and combine employees' earnings with longer-term corporate development (Aubert et al., 2017). ESOPs improve employees' motivation and abilities to co-monitor executives (Kim and Ouimet, 2014). Consequently, ESOPs could aid in restricting executives' suboptimal decisions relevant to green innovation stemming from risk aversion (Chen et al., 2020).

Furthermore, green innovation requires employees to work hard and avoid free riding. Profit-sharing through ESOPs arouses executives' initiative (Kandel and Lazear, 1992), which can alleviate free riding by employees (Chang et al., 2015) and thus improve their productivity in green innovation (Jones and Kato, 1995). In summary, ESOPs may boost corporate green innovation through mechanisms such as restricting executives' risk aversion and reducing employees' free riding.

We use corporate risk-taking to measure the extent of executives' risk aversion and green innovation outputs per employee in the ESOP to calculate employee productivity in green innovation. Using risk-taking ($RISK_{i,t+1}$) and employee efficiency in green innovation ($EMP\_PROD1_{i,t+1}$, $EMP\_PROD2_{i,t+1}$) as the dependent variables, we construct DiD model (7) to test the mechanisms. The key variables $ESOP_i$ and $POST\_Imply_{i,t}$ in the model (7) are defined as before, and the regression results are presented in Table 11.

$$RISK_{i,t+1}|EMP\_PROD_{i,t+1} = \alpha_0 + \alpha_1 ESOP_i \times POST\_Imply_{i,t} + \alpha_2 POST\_Imply_{i,t} + CONTROLS + FIRM + YEAR + \varepsilon \tag{7}$$

$RISK_{i,t+1}$ refers to the annualised standard deviation of weekly stock returns. Next, we measure employee productivity in green innovation as the ratio of the number of green patents to the number of employees in the ESOP ($EMP\_PROD1_{i,t+1}$) and the number of green invention patents to the number of employees in the ESOP ($EMP\_PROD2_{i,t+1}$).

Table 11 reports the results of the mechanism tests. Columns (1) shows that the ESOPs implemented by companies can facilitate

Table 13
Features of ESOPs and the impact of the ESOPs on companies' environmental performance.

	Whether the ESOP is self-administered			
	(1)	(2)	(1) $Green\_Increase_i = 1$	(2) $Green\_Increase_i = 0$
	$Green\_P_{i,t+1}$	$Green\_Inv_{i,t+1}$	oprobit($ENV_{i,t+1}$)	oprobit($ENV_{i,t+1}$)
$Self\_1_i \times POST\_Imple_{i,t}$	0.052	0.032		
	(1.33)	(1.01)		
$Self\_2_i \times POST\_Imple_{i,t}$	0.111***	0.062**		
	(3.18)	(2.28)		
$ESOP_i \times POST\_Imple_{i,t}$			0.442***	0.259
			(3.04)	(0.99)
$POST\_Imple_{i,t}$	−0.008	0.004	−0.006	0.350**
	(−0.38)	(0.25)	(−0.05)	(2.28)
CONTROLS	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
N	17,311	17,311	2937	1181
adj. R^2	0.664	0.658	–	–
pseudo R^2	–	–	0.265	0.267

Notes: In the table, Columns (1)–(2) show the impact of whether the employee self-administered ESOP on the ESOPs' ability to increase the number of green patent and green invention patent applications in the following year. Columns (3)–(4) show the results of the ordered logit model (9) in the sub-groups $Green\_Increase_i = 1$ and $Green\_Increase_i = 0$, which further explore how the impact of the ESOP on corporate green innovation further affects environmental performance and the willingness to report information related to the environment and substantial. The definitions of all variables can be found in Panel A of Appendix A. T-values are shown in parentheses in columns (1)-(2) and Z-values are shown in parentheses in columns (3)-(4). *, **, and *** represent 10 %, 5 %, and 1 % levels of significance, respectively. All regressions are estimated based on weights (_weight) taken from the propensity score match. Standard errors for all regressions are clustered at the firm level.

corporate risk-taking in long-term investments involving high risks and high rewards. Columns (2)–(3) show that ESOPs significantly improve employee productivity in green innovation, both in terms of green and green invention patent applications. These results strongly support the hypothesis above.

6. Cross-sectional tests

6.1. The nature of property rights

The nature of property rights may influence the relationship between ESOPs and corporate green innovation, that is, whether enterprises are state-owned or have other ownership types. SOEs have a stronger incentive to engage in green innovation than non-SOEs. Indeed, although SOEs are profit-seeking, they are also required to promote government goals, such as environmental improvement and pollution reduction. Chang et al. (2015) argue that companies with a higher proportion of state ownership are more likely to comply with government-initiated corporate social responsibility (CSR) requirements and to increase CSR spending compared with other companies. The report of the 20th National Congress of the Communist Party of China (Xi, 2022) established overall goals for China's development by 2035,[14] including that 'a green production and lifestyle should be widely formed, carbon emissions should be steadily reduced after reaching the peak, the ecological environment should be fundamentally improved, and the goal of a beautiful China should be basically achieved'. In response to national policy guidance, SOEs are more likely than other companies to proactively implement green innovation strategies for the sustainable development of their enterprises and the reduction of environmental pollution. ESOPs motivate employees to actively engage in corporate operations and governance by giving them ownership and a 'voice' through shareholding, which enhances their monitoring capability. Thus, although SOEs may be more likely to engage in green innovation than non-SOEs, the ability of ESOPs to enhance corporate green innovation may be limited in SOEs, given that green innovation is already at a higher level than in non-SOEs, resulting in a weaker governance role for ESOPs than in non-SOEs. Thus, how the nature of property rights affects the relationship between ESOPs and green innovation is tested for various groups.

Using the nature of property rights as the grouping criterion, we examine the impact of ESOPs on corporate green innovation in the SOE and non-SOE subsamples, respectively. According to the findings in Panel A of Table 12, the promotion effect of ESOPs on corporate green innovation is stronger in non-SOEs than in SOEs.

6.2. CEO power

We examine how CEO power influences the effect of ESOPs on green innovation, given that the CEO plays a crucial role in the strategic decisions of the firm (Finkelstein, 1992). Especially when CEO power is high, CEOs have strong discretionary power over corporate decisions and even influence executives' group decision-making (Adams et al., 2005). In contrast, employees' ability to influence corporate decisions is constrained by their relatively small equity holdings through ESOPs. Furthermore, studies indicate that more powerful CEOs focus more on innovation projects than CEOs with less power, who fear dismissal for declining short-term performance if they adopt long-term goals. Thus, firms with more powerful CEOs tend to invest more in high-risk projects (such as greater innovation) than firms with weaker CEOs. Furthermore, CEOs can improve their reputation and status among stakeholders through environmental innovation (Zhang et al., 2022). Zhao and Qu (2023) provide evidence supporting the point that higher CEO power is conducive to promoting corporate green innovation. Thus, as the power of a CEO increases, so does the initial level of green innovation, resulting in a diminished capacity for employees to enhance these aspects. Consequently, ESOPs may be less effective in promoting green innovation in such firms than in firms with less powerful CEOs.

Following Finkelstein (1992), we identify four aspects of CEO power: structural, ownership, expert, and prestige power. We construct eight dummy variables to identify the four dimensions of CEO power (Zhang et al., 2022). $Dual_{i,t}$ and $Insider\text{-}Director_{i,t}$ refer to the CEO's structural power. $Dual_{i,t}$ takes a value of 1 if the CEO is also the chairman of the board, and zero otherwise, and $Insider\text{-}Director_{i,t}$ equals one if the CEO is an internal director, and zero otherwise. $CEO\_SHR_{i,t}$ and $Institute\_share_{i,t}$ are constructed to identify the ownership power of the CEO. $CEO\_SHR_{i,t}$ equals one if the CEO holds shares in the firm, and zero otherwise. $Institute\_share_{i,t}$ equals one if the firm's institutional shareholding is below the median industry shareholding, and zero otherwise. $Rank_{i,t}$ and $Tenure_{i,t}$ are constructed to identify the CEO's expert power. $Rank_{i,t}$ equals one if the CEO has a senior professional title, and zero otherwise. $Tenure_{i,t}$ equals one if the CEO's tenure exceeds the median of the industry, and zero otherwise. Finally, $Degree_{i,t}$ and $Part\text{-}time\ job_{i,t}$ identify the CEO's prestige power. $Degree_{i,t}$ equals one if the CEO has a master's degree or higher educational qualifications, and aero otherwise. $Part\text{-}time\ job_{i,t}$ equals one if the CEO holds part-time jobs outside the firm, and zero otherwise.

Using principal component analysis, we obtain three principal components with eigenvalues greater than one among the eight dummy variables and fit an indicator of CEO power, $CEO\_Power_{i,t}$, according to

[14] For more details, see http://www.gov.cn/xinwen/2022-10/25/content_5721685.htm.

the weights of the principal components. A higher (lower) value of $CEO\_Power_{i,t}$ indicates a more (less) powerful CEO. We examine the impact of ESOPs on corporate green innovation separately within different groupings using the median of $CEO\_Power_{i,t}$ in the same industry each year as the grouping criterion. As shown in Panel B of Table 12, the contribution of ESOPs to corporate green innovation is only significant in the sample with less CEO power. Therefore, high CEO power may restrict the potential for ESOPs to promote corporate green innovation.

6.3. Heavily polluting industries

As discussed, ESOPs can increase green innovation by motivating executives' risk-taking and reducing employees' free riding, and these effects may be stronger in heavily polluting industries. As the main source of environmental pollution, heavily polluting industries are more accountable for environmental issues than other industries. As public, government, and media concerns over resource exhaustion and environmental pollution grow, they experience greater public pressure than other industries (C. Hu et al., 2021), and they have more incentive to ease the pressure by increasing green investment (Gu et al., 2021), which created a compelling need to actively explore and adopt advanced technologies that effectively reduce pollution emissions and enhance resource efficiency (Zor, 2023). Moreover, employees in the heavily polluted industry care more about their health. They could be more proactive in green innovation once they have the capability to affect corporate decision-making. For the reasons above, employees in heavily polluting industries are more likely to actively promote corporate green innovation than employees in other industries. Especially when ESOPs give them responsibility for governance to foster long-term corporate growth, react to market pressures, and maintain their corporation's reputation. Accordingly, we examine the impact of ESOPs on corporate green innovation for groups that vary depending on whether the company belongs to a heavily polluting industry.

The classification of heavily polluting industries is based on the definition in the *Industry Classification and Management Directory for Environmental Verification of Listed Companies*, issued by the Ministry of Environmental Protection of China.[15] We examine the impact of ESOPs on corporate green innovation in polluting and non-polluting industries. Columns (1)–(4) of Panel C of Table 12 show the results. Although the effect of ESOPs on firms' green invention patents is not significant in both polluting and non-polluting industries in columns (3)–(4), they are both significant in both polluting and non-polluting industries in columns (1)–(2), and there are more (less) green patents and green invention patents in firms with ESOPs that belong to polluting (non-polluting) industries.

7. Additional tests

7.1. Heterogeneity tests for whether ESOPs are self-administered by employees

Companies implement two types of management of the ESOPs: self-management and delegated management. Under self-managed ESOPs, dominant shareholders may influence and even restrict the voting rights of employee shareholdings, resulting in restricted co-monitoring by employees. Conversely, when ESOPs are managed by professional asset management organisations, employees are more likely to actively exercise their voting rights and promote green innovation within their company.

$$Green\_P_{i,t+1} \middle| Green\_Inv_{i,t+1} = \alpha_0 + \alpha_1 Self\_1_i \times POST\_Imply_{i,t} + \alpha_2 Self\_2_i \times POST\_Imply_{i,t} + \alpha_3 POST\_Imply_{i,t} + \sum_{k=1}^{19} \beta_k CONTROL_{i,t,k} + FIRM + YEAR + \varepsilon \tag{8}$$

We construct $Self\_1_i$ and $Self\_2_i$ to classify the ESOPs implemented by companies in the treatment group as self-managed and managed by professional asset management organisations. When the ESOPs implemented by companies in the treatment group are self-managed (delegated), $Self\_1_i$ ($Self\_2_i$) takes a value of 1, and 0 otherwise. $Self\_1_i$ and $Self\_2_i$ are both 0 for the control group firms. Replacing $ESOP_i$ in the model (2) with $Self\_1_i$ and $Self\_2_i$, we construct the model (8). The results are shown in columns (1)–(2) of Table 13. We find that ESOPs involving delegated (self-) management have a stronger (weaker) effect on promoting green innovation.

7.2. Eliminating the confounded effects of firms adopting multiple ESOPs in various years

Multiple ESOPs may be implemented by various companies within a single year, potentially complicating the preliminary conclusions drawn in Section 7.1. These sections focus on analyzing the characteristics of the initial ESOP adopted by companies. Specifically, if a company routinely offers a range of ESOPs to both current and new employees, it becomes challenging to precisely attribute green innovation to a particular ESOP that is currently in force or has been exercised. This difficulty arises because these plans may be managed under various approaches.

Of the 991 ESOPs that were successfully executed between 2014 and 2020, as recorded in the CNRDS database, 289 were subsequent ESOPs for the companies involved. For those companies that introduced ESOPs more than once during the sample period, we exclude all observations from their second ESOP implementation until the end of the sample period. Utilizing this refined dataset, we re-examine the tests in Section 7.1. The untabulated results confirm that the presamble results remain consistent when observations are only influenced by the companies' initial ESOP.

7.3. The impact of ESOPs on companies' environmental performance

Improving environmental pollution caused by production and promoting sustainable development are the original purposes of green innovation (Zhou et al., 2021a; Cui et al., 2023). Therefore, if a company engages in high-quality green innovation, it will contribute to improving its environmental performance. Therefore, we further explore the impact of ESOPs on the environmental performance of companies. Suppose the green innovation activities promoted by ESOPs do contribute to companies' sustainable development. In that case, environmental performance will be better (worse) among companies that have (have not) increased green innovation after implementing their ESOPs. To calculate environmental performance, we construct an indicator of environmental advantages using the environment, social, and governance (ESG) ratings in the CNRDS database. We introduce six dummy variables to measure environmental advantages, such as whether the firm has products that benefit the environment or obtained environmental certification that year. We sum the values of these dummy variables to construct the indicator $ENV_{i,t+1}$, which measures each firm's environmental performance.

$$oprobit\left(ENV_{i,t+1}\right) = \alpha_0 + \alpha_1 ESOP_i \times POST\_Imply_{i,t} + \alpha_2 POST\_Imply_{i,t} + CONTROLS + FIRM + YEAR + \varepsilon \tag{9}$$

We introduce an ordered probit model (9) to investigate the impact

[15] More details, please see https://www.gov.cn/gzdt/2008-07/07/content_1038083.htm.

of ESOPs on corporate environmental performance and willingness to disclose environmental information. $Green\_Increase_i$ is constructed to measure the trend of $Green\_P_{i,t+1}$ across the pre- to post-implementation periods of the ESOP. If the mean value of $Green\_P_{i,t+1}$ after implementing the ESOP is higher than that of before, $Green\_Increase_i$ equals one, and zero otherwise. The definitions of $ESOP_i$ and $POST\_Imply_{i,t}$ are the same as before. As Table 13 columns (3)–(4) show, ESOPs improve companies' environmental performance when the companies increase their number of green patent applications after implementing ESOPs.

8. Conclusion

The question of how companies can achieve sustainability and address climate change has become urgent. In terms of product design and service delivery, innovation, particularly green innovation, is well documented as a key to enhancing a firm's capability to address environmental issues. Considering the long-term and highly uncertain nature of green innovation and the considerable externalities involved, it is challenging to design incentive mechanisms to promote corporate innovation activities (Chang et al., 2015). Our study bridges a gap in the literature by investigating whether and how ESOPs can be an efficient mechanism that promotes corporate green innovation.

Based on a large sample of Chinese listed firms during the 2010–2020 period, we use a time-varying DiD model to provide solid causal evidence of the positive and significant impact of ESOPs on corporate green innovation. Our results are robust after addressing potential endogeneity issues through parallel trend, placebo, and omitted variable tests. The results remain robust after using entropy balancing and PSM techniques, a Heckman two-stage model, and alternative model specifications. We find that the underlying mechanisms through which ESOPs promote firms' green innovative practices are enhanced risk-taking capability and increased employee productivity in green innovation. To provide in-depth insights into variations in the relationship between ESOP adoption and corporate green innovation, we conduct a series of cross-sectional analyses by considering the nature of property rights, CEO characteristics, industry features, and types of ESOP management. In addition, we find that companies with increased green innovation after adopting an ESOP experience an improvement in environmental performance. To the best of our knowledge, our study is the first to comprehensively investigate the real impact of ESOPs on corporate green innovation practices.

This study's empirical evidence has important implications for corporate strategic management regarding the design of incentive mechanisms to address climate change and for policymakers and regulators concerning how to improve and regulate ESOP programmes. Our study is based on the Chinese setting, so the results may not necessarily be generalisable to other settings. Yet, we believe that our study indicates that employees, being a company's most valuable asset in the new millennium, should play a core role in addressing environmental issues. Thus, our study offers a source of motivation and may spark ideas on ways companies can motivate employees, particularly rank-and-file employees, to boost their productivity and promote corporate green practices.

Credit authorship contribution statement

Wenjun Liu: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Qian He:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **June Cao:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Amina Kamar:** Conceptualization, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Acknowledgment

We would like to acknowledge financial support from the National Natural Science Foundation of China (Grant No.71702032), the Humanities and Social Science Project of the Ministry of Education of China (Grant No.21YJC630085), the Science and Technology Innovation Special Fund of Fujian Agriculture and Forestry University (Grant No. KFb22107XA), and School of Accounting, Economics and Finance of Curtin University.

Appendix A

Panel A: variable definition	
Dependent variables	
Green_P	Green patents, the logarithm of one plus the number of green patents applied independently by listed companies.
Green_Inv	Green invention patents, the logarithm of one plus the number of green invention patents applied independently by listed companies.
Green_Um	Green utility patents, the logarithm of one plus the number of green utility patents applied independently by listed companies.
Independent variables	
ESOP	Dummy variable, one if the listed company has implemented an ESOP during the sample period, and zero otherwise.
POST_Imply	The dummy variable, equals one if the firm year falls in the year in which the ESOP is implemented and subsequent years, and zero otherwise.
Control variables	
SIZE	Firm size, the logarithm of total assets.
LEV	Leverage, total debt/total assets.
ROA	Return on assets, net income/total assets.
GROWTH	Sales growth, growth in operating income divided by operating income in the previous year.
SALESPP	Sales per person, operating income/the number of employees.
FIXEDPP	Fixed assets per person, fixed assets/the number of employees.
LOSS	Whether it is a loss, the value equals one if the enterprise's net income for the year is less than zero, and zero otherwise.

(continued on next page)

(*continued*)

Panel A: variable definition	
CASH	Cash holdings, the balance of cash and cash equivalents/(total asset-the balance of cash and cash equivalents).
RND	Investment in research and development, annual R&D investment/total assets.
AGE	Years since the listing date of the firm, the logarithm of one plus the gap between the IPO year and the event year.
FIRMAGE	Firm age, the logarithm of one plus the gap between the established year and the event year of the firm.
SOE	Nature of property rights, the value takes one if the enterprise is state-owned, and zero otherwise.
CEO_SHR	CEO shareholding, CEO shareholdings/total number of shares.
EXE_SHR	Executive shareholding, executive shareholdings/total number of shares.
INS	Institutional shareholding, institution shareholdings/total number of shares.
BOARD	The number of board members, the logarithm of one plus board members.
INDE	The proportion of independent directors, Number of independent directors/total number of board members.
SHAREBALANCE	Equity restriction, shareholdings of second to fifth largest shareholder/shareholding of largest shareholder.
WAGE	Employee wage, (employee pay payable-executives' compensation)/(employee number - executive number).
INTCON	Level of internal control, the internal control index from the Internal Control and Risk Management (DIB) database/100.

Panel B: sample selection	
Total observations	34,906
Less: companies listed in the B-share market	(1130)
Less: financial firms	(733)
Less: missing variables of continuous variables	(7845)
Add: control group samples that are replicated because of matching with different treatment group companies	6430
Less: samples excluded by propensity score matching	(12,764)
Less: the period after the end of the ESOP's duration	(1553)
Less: firms with less than one sample before or after implementing the ESOP	(0)
Final sample	17,311
Treatment observations	4373
Control observations	12,938
Number of unique firms	1466
Treatment firms	546
Control firms	920

References

Adams, R.B., Almeida, H., Ferreira, D., 2005. Powerful CEOs and their impact on corporate performance. Rev. Financ. Stud. 31, 1403–1432.

Aerts, W., Cormier, D., Magnan, M., 2006. Intra-industry imitation in corporate environmental reporting: an international perspective. J. Account. Public Policy 25 (3), 299–331.

Amore, M.D., Bennedsen, M., 2016. Corporate governance and green innovation. J. Environ. Econ. Manag. 75, 54–72.

Amore, M.D., Bennedsen, M., Larsen, B., Rosenbaum, P., 2019. CEO education and corporate environmental footprint. J. Environ. Econ. Manag. 94, 254–273.

Arena, C., Michelon, G., Trojanowski, G., 2018. Big egos can be green: a study of CEO hubris and environmental innovation. Br. J. Manag. 29 (2), 316–336.

Aubert, N., Kern, A., Hollandts, X., 2017. Employee stock ownership and the cost of capital. Res. Int. Bus. Financ. 41, 67–78.

Babenko, I., Sen, R., 2016. Do non-executive employees have valuable information? Evidence from employee stock purchase plans. Manag. Sci. 62 (7), 1878–1898.

Bao, D., Fung, S.Y.K., Su, L., 2018. Can shareholders be at rest after adopting clawback provisions? Evidence from stock price crash risk. Contemp. Account. Res. 35 (3), 1578–1615.

Beck, M.J., Nicoletti, A.K., Stuber, S.B., 2022. The role of audit firms in spreading depositor contagion. Account. Rev. 97 (4), 51–73.

Berrone, P., Fosfuri, A., Gelabert, L., Gomez-Mejia, L.R., 2013. Necessity as the mother of 'green' inventions: institutional pressures and environmental innovations. Strateg. Manag. J. 34 (8), 891–909.

Bertrand, M., Mullainathan, S., 2003. Enjoying the quiet life? Corporate governance and managerial preferences. J. Polit. Econ. 111 (5), 1043–1075.

Blasi, J., Conte, M., Kruse, D., 1996. Employee stock ownership and corporate performance among public companies. Ind. Labour Relat. Rev. 50 (1), 60–79.

Bova, F., Dou, Y., Hope, O.K., 2015. Employee ownership and firm disclosure. Contemp. Account. Res. 32 (2), 639–673.

Cao, J., Li, W., Bilokha, A., 2022. Low-carbon city initiatives and analyst behaviour: a quasi-natural experiment. J. Financ. Stab. 62, 101042.

Cazier, R.A., Merkley, K.J., Treu, J.S., 2020. When are firms sued for qualitative disclosures? Implications of the safe harbour for forward-looking statements. Account. Rev. 95 (1), 31–55.

Chan, L.H., Chen, K.C.W., Chen, T.Y., 2013. The effects of firm-initiated clawback provisions on bank loan contracting. J. Financ. Econ. 110, 659–679.

Chang, S., Jo, H., 2019. Employee-friendly practices, product market competition and firm value. J. Bus. Financ. Acc. 46 (1–2), 200–224.

Chang, X., Fu, K., Low, A., Zhang, W., 2015. Non-executive employee stock options and corporate innovation. J. Financ. Econ. 115 (1), 168–188.

Chen, C., Chen, Y., Hsu, P.H., Podolski, E.J., 2016. Be nice to your innovators: employee treatment and corporate innovation performance. Finance 39, 78–98.

Chen, J., King, T.H.D., Wen, M.M., 2020. Non-executive ownership and private loan pricing. Finance 64, 101638.

Cui, X., Wang, C., Sensoy, A., Liao, J., Xie, X., 2023. Economic policy uncertainty and green innovation: evidence from China. Econ. Model. 118, 106104.

Darendeli, A., Fiechter, P., Hitz, J.M., Lehmann, N., 2022. The role of corporate social responsibility (CSR) information in supply-chain contracting: evidence from the expansion of CSR rating coverage. J. Account. Econ. 10, 101525.

Dong, H., Zhang, L., Zheng, H., 2024. Green bonds: fueling green innovation or just a fad? Energy Econ. 25, 107660.

Du, L., Lin, W., Du, J., Jin, M., Fan, M., 2022. Can vertical environmental regulation induce enterprise green innovation? A new perspective from automatic air quality monitoring station in China. J. Environ. Manag. 317 (1), 115349.

Durnev, A., Mangen, C., 2020. The spillover effects of MD&A disclosures for real investment: the role of industry. J. Account. Econ. 70 (1), 101299.

Erkens, M.H.R., Gan, Y., Yurtoglu, B.B., 2018. Not all clawbacks are the same: consequences of strong versus weak clawback provisions. J. Account. Econ. 66 (1), 291–317.

European Commission, 2014. The promotion of employee ownership and participation. https://eprints.staffs.ac.uk/2616/1/Final%20Study%20%27The%20Promotion%20of%20Emp%20ownership%20and%20Particip%27%20for%20DG%20MARKT_feb%202015.pdf.

Fang, H., Nofsinger, J.R., Quan, J., 2015. The effects of employee stock option plans on operating performance in Chinese firms. J. Bank. Financ. 54, 141–159.

Fauver, L., McDonald, M.B., Taboada, A.G., 2018. Does it pay to treat employees well? International evidence on the value of employee-friendly culture. Finance 50, 84–108.

Feng, G., Niu, P., Wang, J., Liu, J., 2022a. Capital market liberalization and green innovation for sustainability: evidence from China. Econ. Anal. Policy 75, 610–623.

Feng, Y., Yu, Q., Nan, X., Cai, Y., 2022b. Can employee stock ownership plans reduce corporate financialization? Evidence from China. Econ. Anal. Policy 73, 140–151.

Finkelstein, S., 1992. Power in top management teams: dimensions, measurement, and validation. Acad. Manag. J. 35 (3), 505–538.

Fiorillo, P., Meles, A., Mustilli, M., Salerno, D., 2022. How does the financial market influence firms' green innovation? The role of equity analysts. J. Int. Financ. Manag. Acc. 33 (3), 428–458.

Gu, Y., Ho, K., Yan, C., Gozgor, G., 2021. Public environmental concern, CEO turnover, and green investment: evidence from a quasi-natural experiment in China. Energy Econ. 100, 105379.

Hainmueller, J., 2012. Entropy balancing for causal effects: a multivariate reweighting method to produce balanced samples in observational studies. Polit. Anal. 20, 25–46.

Hall, J., Vredenburg, H., 2003. The challenge of innovating for sustainable development. MIT Sloan Manag. Rev. 45 (1), 61–68.

Hao, J., He, F., 2022. Corporate social responsibility (CSR) performance and green innovation: evidence from China. Financ. Res. Lett. 48, 102889.

He, K., Chen, W., Zhang, L., 2021. Senior management's academic experience and corporate green innovation. Technol. Forecast. Soc. Chang. 166, 120664.
He, N., Yang, J., Ren, J., 2024. Pollution and green innovation: evidence from CEOs' early-life experience. Int. Rev. Econ. Financ. 93, 65–79.
Hennig, J.C., Ahrens, C., Oehmichen, J., Wolff, M., 2023. Employee stock ownership and firm exit decisions: a cross-country analysis of rank-and-file employees. Acc. Organ. Soc. 104, 101390.
Hochberg, Y.V., Lindsey, L., 2010. Incentives, targeting, and firm performance: an analysis of non-executive stock options. Rev. Financ. Stud. 23 (11), 4148–4186.
Holmstrom, B., 1989. Agency costs and innovation. J. Econ. Behav. Organ. 12 (3), 305–327.
Hu, C., Mao, J., Tian, M., Wei, Y., Guo, L., Wang, Z., 2021a. Distance matters: investigating how geographic proximity to ENGOs triggers green innovation of heavy-polluting firms in China. J. Environ. Manag. 279 (1), 111542.
Hu, G., Wang, X., Wang, Y., 2021b. Can the green credit policy stimulate green innovation in heavily polluting enterprises? Evidence from a quasi-natural experiment in China. Energy Econ. 98, 105134.
Huang, J., Zhao, J., Cao, J., 2021. Environmental regulation and corporate R&D investment - evidence from a quasi-natural experiment. Int. Rev. Econ. Financ. 72, 154–174.
Huang, J.W., Li, Y.H., 2017. Green innovation and performance: the view of organizational capability and social reciprocity. J. Bus. Ethics 145 (2), 309–324.
Huang, X., Liu, W., Zhang, Z., Zhao, Z., 2022. Intensive judicial oversight and corporate green innovations: evidence from a quasi-natural experiment in China. China Econ. Rev. 101799.
International Energy Agency (IEA), 2021. An energy sector roadmap to carbon neutrality in China. https://www.iea.org/reports/an-energy-sector-roadmap-to-carbon-neutrality-in-china.
Jaffe, A.B., Newell, R.G., Stavins, R.N., 2005. A tale of two market failures: technology and environmental policy. Ecol. Econ. 54 (2–3), 164–174.
Javed, M., Wang, F., Usman, M., Gull, A.A., Zaman, Q.U., 2023. Female CEOs and green innovation. J. Bus. Res. 157, 113515.
Jiang, L., Bai, Y., 2022. Strategic or substantive innovation? -the impact of institutional investors' site visits on green innovation evidence from China. Technol. Soc. 68, 101904.
John, K., Litov, L., Yeung, B., 2008. Corporate governance and risk-taking. J. Financ. 4, 1679–1728.
Jones, D.C., Kato, T., 1995. The productivity effects of employee stock-ownership plans and bonuses: evidence from Japanese panel data. Am. Econ. Rev. 85 (3), 391–414.
Kandel, E., Lazear, E.P., 1992. Peer pressure and partnerships. J. Polit. Econ. 100, 801–817.
Kesting, P., Ulhøi, J.P., 2010. Employee-driven innovation: extending the license to foster innovation. Manag. Decis. 48 (1), 65–84.
Kim, E.H., Ouimet, P., 2014. Broad-based employee stock ownership: motives and outcomes. J. Financ. 69 (3), 1273–1319.
Kim, I., Pantzalis, C., Zhang, Z., 2021. Multinationality and the value of green innovation. Finance 69, 101996.
Kim, J., Valentine, K., 2021. The innovation consequences of mandatory patent disclosures. J. Account. Econ. 71 (2–3), 101381.
Klein, K.J., 1987. Employee stock ownership and employee attitudes: a test of three models. J. Appl. Psychol. 72 (2), 319–332.
Kock, C.J., Santaló, J., Diestre, L., 2012. Corporate governance and the environment: what type of governance creates greener companies? J. Manag. Stud. 49 (3), 492–514.
Kong, D., Wang, Y., 2021. Employee Stock Ownership Plans and Corporate Environmental Engagement. Available at SSRN. 3915366.
Kopyrina, O., Wu, K., Ying, Z., 2023. Greening through central inspection: the role of legitimacy pressure and risk-taking. Pac. Basin Financ. J. 77, 101894.
Kyung, H., Lee, H., Marquardt, C., 2019. The effect of voluntary clawback adoption on non-GAAP reporting. J. Account. Econ. 67 (1), 175–201.
Leiponen, A., 2005. Skills and innovation. Int. J. Ind. Organ. 23 (5–6), 303–323.
Li, X., Shao, X., Chang, T., Albu, L.L., 2022. Does digital finance promote the green innovation of China's listed companies? Energy Econ. 114, 106254.
Li, Z., Liao, G., Wang, Z., Huang, Z., 2018. Green loan and subsidy for promoting clean production innovation. J. Clean. Prod. 187, 421–431.
Liu, M., Li, Y., 2022. Environmental regulation and green innovation: evidence from China's carbon emissions trading policy. Financ. Res. Lett. 48, 103051.
Macias, A., Pirinsky, C., 2015. Employees and the market for corporate control. Finance 31, 33–53.
Malen, J., Marcus, A.A., 2019. Environmental externalities and weak appropriability: influences on firm pollution reduction technology development. Bus. Soc. 58 (8), 1599–1633.
Meng, R., Ning, X., Zhou, X., Zhu, H., 2011. Do ESOPs enhance firm performance? Evidence from China's reform experiment. J. Bank. Financ. 35 (6), 1541–1551.
Oster, E., 2019. Unobservable selection and coefficient stability: theory and evidence. J. Bus. Econ. Stat. 37 (2), 187–204.
Oyer, P., Schaefer, S., 2005. Why do some firms give stock options to all employees?: an empirical examination of alternative theories. J. Financ. Econ. 76 (1), 99–133.
Pang, C., Wang, Y., 2020. Stock pledge, risk of losing control and corporate innovation. Finance 60, 101534.
Quan, X., Ke, Y., Qian, Y., Zhang, Y., 2023. CEO foreign experience and green innovation: evidence from China. J. Bus. Ethics 182, 535–557.
Sha, Y., Zhang, P., Wang, Y., Xu, Y., 2022. Capital market opening and green innovation-evidence from Shanghai-Hong Kong stock connect and the Shenzhen-Hong Kong stock connect. Energy Econ. 111, 106048.
Shen, H., Hua, L., Xu, J., 2018. Business performance of employee stock ownership plans in state-owned enterprises: incentive compatibility or incentive deficiency. J. Manag. World 34 (11), 121–133 (In Chinese).
Sun, G., Fang, J., Li, J., Wang, X., 2024. Research on the impact of the integration of digital economy and real economy on enterprise green innovation. Technol. Forecast. Soc. Chang. 200, 123097.
Sun, H., Edziah, B.K., Sun, C., Kporsu, A.K., 2019. Institutional quality, green innovation and energy efficiency. Energy Policy 135, 111002.
Tang, C., Xu, Y., Hao, Y., Wu, H., Xue, Y., 2021. What is the role of telecommunications infrastructure construction in green technology innovation? A firm-level analysis for China. Energy Econ. 103, 105576.
The State of Employee Ideas, 2018. access on 2023. https://ideas.sideways6.com/article/infographic-the-state-of-employee-ideas.
The Wall Street Journal. Who Has Innovative Ideas? Employees. https://www.wsj.com/articles/SB10001424052748704100604575146083310500518.
Wang, H., Li, J., 2024. Professional experience of CEOs in industry associations and corporate green innovation-empirical evidence from China. Pac. Basin Financ. J. 85, 102383.
Wei, Y., Nan, H., Wei, G., 2020. The impact of employee welfare on innovation performance: evidence from China's manufacturing corporations. Int. J. Prod. Econ. 228, 107753.
Wong, T.J., 2016. Corporate governance research on listed firms in China: Institutions, governance and accountability. Found. Trends Acc. 9 (4), 259–326.
Xi, J., 2022. Hold high the great banner of socialism with Chinese characteristics and strive in unity to build a modern socialist country in all respects. http://www.gov.cn/xinwen/2022-10/25/content_5721685.htm.
Xie, R., Teo, T.S.H., 2022. Green technology innovation, environmental externality, and the cleaner upgrading of industrial structure in China - considering the moderating effect of environmental regulation. Technol. Forecast. Soc. Chang. 184, 122020.
Xu, L., Fan, M., Yang, L., Shao, S., 2021. Heterogeneous green innovations and carbon emission performance: evidence at China's city level. Energy Econ. 99, 105269.
Zhang, D., Zhang, T., Ma, G., 2020b. Can non-executive equity incentives reduce internal control ineffectiveness? Evidence from China. Account. Finance 60 (5), 4467–4496.
Zhang, J., Liang, G., Feng, T., Yuan, C., Jiang, W., 2020a. Green innovation to respond to environmental regulation: how external knowledge adoption and green absorptive capacity matter? Bus. Strateg. Environ. 29 (1), 39–53.
Zhang, Y., Li, J., Deng, Y., Zheng, Y., 2022. Avoid or approach: how CEO power affects corporate environmental innovation. J. Innov. Knowl. 7 (4), 100250.
Zhao, J., Qu, J., 2023. Decision-making of powerful CEOs on green innovation: The roles of performance feedback and institutional investors. Int. J. Financ. Econ. https://doi.org/10.1002/ijfe.2870.
Zhao, J., Qu, J., Wei, J., Yin, H., Xi, X., 2023. The effects of institutional investors on firms' green innovation. J. Prod. Innov. Manag. 40 (2), 195–230.
Zheng, Z., Yong, H., Huang, J., 2021. Motivation of launching ESOP: to motivate or to defend. China Ind. Econ. 3, 118–136 (In Chinese).
Zhou, B., Li, Y., Sun, F., Zhou, Z., 2021b. Executive compensation incentives, risk level and corporate innovation. Emerg. Mark. Rev. 47, 100798.
Zhou, D., Huang, J., Zhao, Y.J., 2019. Employee stock ownership plans and corporate innovation. Account. Res. 3, 63–70 (In Chinese).
Zhou, K., Luo, H., Ye, D., Tao, Y., 2022. The power of anti-corruption in environmental innovation: evidence from a quasi-natural experiment in China. Technol. Forecast. Soc. Chang. 182, 121831.
Zhou, M., Govindan, K., Xie, X., Yan, L., 2021a. How to drive green innovation in China's mining enterprises? Under the perspective of environmental legitimacy and green absorptive capacity. Resour. Policy 72, 102038.
Zor, S., 2023. A neural network-based measurement of corporate environmental attention and its impact on green open innovation: evidence from heavily polluting listed companies in China. J. Clean. Prod. 432, 139815.

Wenjun Liu is an Associate Professor from Fujian Agriculture and Forestry University. His main research interests include accounting and auditing issues in capital markets.

Qian He is a phd student from Central University of Finance and Economics. Her main research interests include accounting and corporate governance.

June Cao is an assistant professor (Senior Lecturer) at Curtin University. She is a both quantitative and qualitative researcher in burgeoning area such as climate change, carbon emissions, green innovations, ESG/CSR, financial and non-financial information disclosure, and the cutting edge of sustainability reporting and IFRS. June is good at using advanced methodologies to solve multifaceted global issues from multidisciplinary perspectives. June's research has been published in A*/Q1/A journals such as the *British Accounting Review, Energy Economics, Journal of Business Research*, *International Journal of Auditing*, *Journal of Accounting Literature*, *Accounting and Finance*, *Journal of Financial Stability*, *China Accounting and Finance Review*, *International Review of Financial Analysis*, *Financial Markets, Institutions and Instruments*, *the Review of Business*, and *International Review of Economics & Finance*.

Amina Kamar is a visiting researcher at Imperial College London. She had positions in the American University of Beirut as a lecturer.