Better Late than Never:

Environmental Punishments and Corporate Green Hiring*

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Abstract: Do firms adjust their hiring decisions after receiving environmental punishments? Using data on over 4.3 million job postings for Chinese listed firms from 2015 to 2021, we find that firms subjected to environmental punishments will subsequently increase their corporate green hiring (i.e., employees with green skills). Pressure from local environmental concerns and regulatory efforts incentivizes firms to increase their demand for employees with green skills. Environmental punishments have a more pronounced effect on corporate green hiring for non-state-owned enterprises and firms with lower financial constraints. Moreover, green hiring can have a remediation effect on firms' environmental performance and stimulate their green innovation activities and spillover effects on other firms within the industry. Overall, our findings shed light on corporate hiring decisions under environmental regulations.

Keywords: Environmental punishments; Human capital; Job postings; Green skills

1. Introduction

Developing countries face difficult tradeoffs between economic development and environmental protection. Given the looming problem of ecological degradation, China has placed ecological civilization at the forefront and implemented regulations for the comprehensive management of the atmosphere, water, and soil. Various studies have examined the effects of China's stringent environmental regulations on pollution emissions and related economic consequences (Tanaka, 2015; Chen et al., 2018; Cai et al., 2016; Qi et al., 2023; He et al., 2020), showing their effectiveness in enhancing environmental and social well-being. As firms bear the brunt of pollution control costs while also being job providers, how environmental regulations affect firm behavior and subsequently influence one of the world's largest labor markets is important to understand. Recent studies have explored the impact of environmental regulations on employment in China (Liu et al., 2017; Liu et al., 2021); however, exploration of how environmental regulations affect corporate labor strategies in specific occupations (e.g., employees with green skills) is still lacking.

"Green talent" has been integral to policymaking for environmental protection and economic development since its introduction[1]. In China, the government has caused a boom in employment for those with green skills to help the country achieve its carbon peak and neutrality goals and create a more livable environment[2]. The recently updated *Occupational Classification Code of the People's Republic of China* acknowledges numerous green jobs[3]. However, data, such as the *2022 Global Green Skills Report* issued by LinkedIn, have revealed a persistent shortage of green talent, both in China and globally[4]. Despite the growing recognition of the importance of green talent by the government and the public, empirical research on strategies to increase the green labor force for operating and advancing

[1] We use the terms "green talents," "green human capital," "employees with green skills," "green labor force," "green employment," and "green hiring" interchangeably in this paper.
[2] https://www.chinadaily.com.cn/a/202303/02/WS63fff020a31057c47ebb1a14.html
[3] http://www.mohrss.gov.cn/xxgk2020/fdzdgknr/jcgk/zqyj/202207/t20220712_457477.html
[4] https://news.linkedin.com/2022/february/our-2022-global-green-skills-report

green technologies remains scarce. Porter and Linde (1995) have suggested that rational environmental regulation induces firms to change their production processes and factor inputs, which may spur them to seek greener technologies and a more skilled, adaptable labor force to manage environmental risk proactively (Acemoglu et al., 2016; Hagendorff et al., 2023; Elliott et al., 2024). However, increased costs due to environmental regulations may cause firms to transition to less polluting production or outsource their current production (Li and Tang, 2024), thereby reducing the demand for employees with green skills. Thus, the effect of environmental regulations on corporate green hiring is an empirical question, and understanding whether and how environmental regulations affect the demand for green human capital is imperative.

To answer this question, we explore the relationship between environmental punishments and corporate green hiring in the context of China. The advantages of the Chinese setting are reflected in two aspects. On the one hand, environmental pollution has long been an issue in China (Wang et al., 2021). With China engaged in a war on pollution to achieve economic transformation (Greenstone et al., 2021; Greenstone et al., 2022), environmental regulations have been widely adopted and are dominated by environmental punishments. China's new *Environmental Protection Law* enacted in 2015 is considered the most stringent environmental law in history. It increases the information disclosure of environmental punishments imposed on firms by local law enforcement authorities (Agarwal et al., 2023), enabling the public to have a clearer insight of the environmental punishments. On the other hand, although China has the largest labor market in the world, it is seeking to upskill its workforce to increase value and efficiency[5]. The reshaping of corporate demand for employees with the green skills can help us better understand how firms can achieve green transformation and sustainable development at the micro level.

[5] https://www.china-briefing.com/news/chinas-labor-force-data-trends-and-future-outlook/.

In this study, we utilize job posting data from *51job*, a Chinese online recruitment platform, and identify green jobs through a textual analysis of job descriptions between 2015 and 2021. We then use the natural logarithm of the number of green job postings made by listed firms during the year as a measure of corporate green hiring to represent firms' environmental efforts (Darendeli et al., 2022). We collect all records of environmental punishments announcements issued by listed firms in their interim and annual reports. Accordingly, we find strong evidence that environmental punishments can lead firms to increase their corporate green hiring. Firms subjected to environmental punishments show a 21.1% increase in green hiring relative to the average number of green job postings in our sample. We also conduct a series of robustness tests and confirm the stability of our main results after using alternative measures of green hiring, adding higher-dimensional fixed effects, and ruling out alternative explanations for other types of job postings.

We conduct four analyses to address potential endogeneity concerns. First, we use both propensity score matching (PSM) and entropy balancing (EB) to mitigate the differences between firms subject to environmental punishments and those that are not. Second, we conduct a placebo test to confirm that the influence of environmental punishments on corporate green hiring is unlikely to be driven by chance. In addition, we utilize instrumental variable regression, and adopt (1) the number of firms receiving environmental punishments in the city in which a firm is located in the previous year; (2) the interaction term between the Chinese vertical administration reform in 2016 and the regional legal environment, as the instrumental variable, respectively. The instrumental variable regression results still hold. Finally, we utilize the impact thresholds for confounding variables (ITCV) (Frank, 2000) and coefficient stability tests (Oster, 2019) to estimate the potential effects of omitted variables. The results indicate the limited impact of unobservable omitted variables on our findings.

We next explore the potential mechanisms and find that greater regional environmental concerns and stricter environmental supervision and enforcement will exert greater pressure on local firms, driving them to hire more employees with green skills to improve their environmental governance performance after environmental punishments.

We also perform a battery of heterogeneity analyses, and the results show that the effect of environmental punishments on corporate green hiring is more pronounced for non-state-owned enterprises (non-SOEs) and firms with lower financial constraints. However, we do not find a significant difference in the effect of environmental punishments with different fine amounts on corporate green hiring, suggesting that regardless of the severity of the punishment imposed, firms subjected to environmental punishments will improve their environmental governance by hiring green talent.

Finally, we explore the economic consequences of green hiring for firms subjected to environmental punishments. First, we test whether firms' environmental performance improves after an increase in green hiring, finding that both the likelihood and the fine amount of environmental punishment firms received decrease, consistent with Innes and Sam (2008)'s findings on regulatory reciprocity. Second, the findings indicate that green hiring after environmental punishments can contribute to more green innovation activities, which can help punished firms improve their future environmental governance, reflecting the firms' actual green activities even further. Third, our results show that when a firm is punished, other firms in the same industry also increase their green hiring, suggesting a spillover effect of green hiring on firms subjected to environmental punishments.

Our study contributes to existing literature in several ways. First, this study contributes to the growing body of literature on the economic consequences of environmental regulations. Previous studies have found that environmental regulations may increase production costs and unemployment (Zhang et al., 2019; Walker, 2011; Agarwal et al., 2019), while decreasing firms' profitability and total factor productivity (Fan et al., 2019; He et al., 2020). Moreover, environmental regulatory policies can encourage firms to invest in research and development (R&D) and use "clean" technologies, thereby reducing pollution (Acemoglu et al., 2016; Aghion et al., 2016; Brown et al., 2022). We investigate the potential effects of environmental regulations on corporate labor demand and find that environmental punishments can increase corporate demand for employees with green skills, which may suggest that firms respond to environmental regulations by hiring highly skilled labor to match "clean" technologies. The empirical results on the economic consequences further validate this expectation, showing that firms increase their green innovation activities after green hiring.

Second, this study contributes to the literature on the determinants of corporate hiring decisions. Previous studies have examined the impact of environmental regulations on labor demand but typically focus on regional industry-level employment, reporting mixed conclusions (Berman and Bui, 2001; Gray et al., 2014; Walker, 2011; Liu et al., 2017; Liu et al., 2021). Distinct from the existing literature, we mainly focus on the effects of environmental regulations on firm-level labor demand, particularly that for employees with green skills, which not only contributes to understanding the firms' human capital needs but also provides evidence on how firms can achieve a green transition by adjusting the demand for labor skills.

Third, motivated by Darendeli et al. (2022), we propose a method to evaluate corporate green hiring in China. The existing literature usually obtains information about online job postings and skills in demand in the US from the Lightcast database (formerly known as "Burning Glass"), which standardizes information at the job-posting level through machine learning algorithms. However, developing countries such as China do not have a similar database that can directly capture information about the skills in demand. We use the definition of “green jobs” in *The Occupational Classification Code of the People's Republic of China*, in addition to the *Word2Vec* method to obtain keywords, and identify the green job posting by textual analysis of job descriptions. We posit that this measure of corporate green hiring can effectively capture firms’ environmental efforts and reflect their investments in green human capital by focusing on corporate demand for green labor in online job postings. This method can also be used to measure corporate demand for employees with other skills in the future (Acemoglu et al., 2022; Darendeli et al., 2022; Cao et al., 2023; Gao et al., 2023).

To the best of our knowledge, our work is most relevant to two studies. One is Vona et al. (2018), who find that environmental regulations result in a substantial demand for green skills. However, the main difference between our study and Vona et al. (2018) is that we focus on labor demand related to green skills in hiring decisions at the firm level, whereas they focus on the importance of two types of green skills (i.e., engineering skills for technology design and production and managerial skills for implementing and monitoring environmental organizational practices) at the regional level. To construct the indicator, they directly use the standardized “specific green skills” provided by Occupational Information Network (O*NET) to identify green jobs, and validate to obtain “general green skills” that are highly correlated with green jobs for complements. However, we find that in the process of recruiting employees, the types of jobs required by firms do not correspond exactly to the classification of occupations information provided by the government in China. Thus, we analyze the specific requirements for hiring employees (i.e., the job descriptions) based on those provided in the firms’ job postings so that we can more accurately identify the firms’ demand for employees with green skills.

The other is Li and Tang (2024), which examines the impact of environmental tax laws on the demand for green talent. Environmental taxation aims to protect the environment by internalizing the external costs of environmental pollution through economic tools, thereby inducing polluters to take action to reduce pollution emissions. However, we focus primarily on environmental punishment, an administrative tool used by regulators for environmental governance. After the implementation of the new *Environmental Protection Law* in 2015, environmental punishment became more stringent in terms of enforcement and information disclosure, which may lead to higher costs for penalized firms (Agarwal et al., 2023). Because we have access to detailed information about which and when firms are subject to environmental punishments, we can more clearly observe the changes in firms' hiring decisions[6].

The remainder of this paper is organized as follows. Section 2 provides an overview of the institutional background, reviews the related literature, and develops the hypotheses. Section 3 introduces the study's data and variables. Section 4 presents the main results of the study. Section 5 explores potential mechanisms, heterogeneity, and economic consequences. Section 6 concludes the paper.

2. Institutional Background, Related Literature, and Hypothesis Development

2.1 Institutional background

Environmental punishment is a fundamental environmental regulation tool in China. From the perspective of specific jurisprudential theory, a reasonable division of *administrative power* and *judicial power* helps to achieve public goals, including environmental protection (Wang, 2016). Especially in China, the environmental violations need to be investigated and dealt with as soon as possible, because it may be difficult to obtain evidence after the environmental site has changed over time, and the long-term accumulation of pollutants may exacerbate the damage to the ecological environment. Environmental justice can only judge case by case and must go through complicated

[6] Our results are still consistent when controlling the effect of environmental tax laws.

procedures such as filing a lawsuit, thus it is only used for more serious incidents. On the contrary, administrative enforcement can quickly gather evidence for administrative punishment. Additionally, the number of environmental administrative departments, local ecological and environmental authorities is greater than the number of environmental protection trial courts. Administrative enforcement is low-cost and efficient, and it is crucial to strengthen it. Besides, *Environmental administrative penalties* provide environmental administrative departments adequate investigative tools. These punishments establish a management system that relies on both ex-ante supervision and ex-post punishment. Thus, China relies heavily on administrative punishments for environmental governance.

Environmental punishment is primarily enforced based on *Environmental Protection Law* and *Administrative Punishment Law*. Local ecological and environmental authorities conduct environmental punishment procedures for suspected violations of ecological and environmental protection laws, rules, and regulations. The basic procedure involves several steps. First, except for punishments that can be imposed instantly, the authorities conduct a preliminary examination and file a case. Special personnel are then appointed to investigate and collect evidence, followed by the submission of an investigation report for a detailed examination. Subsequently, the type and content of the punishment are determined. Importantly, the parties involved must be informed before publication and they have the right to request a hearing within five days of receiving the notification. During the hearing, evidence is presented and cross-examined by both parties and authorities. Finally, the authorities issue a *Decision on Administrative Punishment*. It is worth noting that only cases serious enough to be suspected of criminal behavior are referred to the judiciary and held criminally liable, which confirms that China's environmental regulation uses administrative punishments as the most common tool. Appendix A shows the changes in the number of environmental punishment cases and total amount of fines in China in recent years[7]. As the environment has improved, the number of environmental punishment cases and total amount of fines have both shown a downward trend since 2017, although they remain at a relatively large scale. In 2023, China recorded 79,600 environmental punishment cases, with fines totaling 6.27 billion RMB[8].

2.2 Related literature

2.2.1 Effects of environmental regulation

Environmental regulations have been widely adopted in developing countries such as China (He et al., 2020; Agarwal et al., 2023). Previous studies have found that environmental regulations may increase the cost burden borne by firms (Ryan, 2012). For example, with an increase in the efficiency of environmental enforcement following the establishment of specialized environmental courts in China, local firms increased their expenditures on environmental protection and abnormal audit fees, leading to a decrease in access to bank loans (Wu et al., 2023, 2024; Zhang et al., 2019). Thus, environmental regulations usually decrease a firm's profitability and total factor productivity (Sam and Zheng, 2020). Fan et al. (2019) that stricter environmental regulations account for sharp declines in firms' profits, capital, and labor. He et al. (2020) utilize a water quality monitoring system in China and find that tighter environmental regulations can reduce polluting firms' total factor productivity.

Scholars have also focused on the effects of environmental regulations on the labor market; however, the conclusions have been mixed. Based on air quality regulation in Los Angeles, Berman and Bui (2001) find no evidence that environmental regulation can lead to a substantial reduction in employment, whereas Curtis (2018) show that environmental regulation of the NOx budget trading program leads to a decline in overall employment in the manufacturing industry. In the context of China, both Liu et al. (2017) and Liu et al. (2021)

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[7] Data are collected from the annual work report of the Ministry of Ecology and Environment.
[8] https://www.mee.gov.cn/ywdt/hjywnews/202302/t20230223_1017248.shtml

document that firms may reduce labor demand, as they need to carry out pollution-reduction activities and change their optimal production decisions to respond to stricter environmental regulations.

2.2.2 Corporate hiring decisions

Another literature stream emphasizes that job postings, a crucial labor market activity, are a reasonable measure of a firm's unobservable investment behavior (Hershbein and Kahn, 2018; Gao et al., 2023; Hagendorff et al., 2023).

Firms use job postings to convey their demand for talent with specific skills (Cao et al., 2023; Gao et al., 2023). Skill requirements are evolving in general labor markets and typically reflect firms' investment orientations. For example, Deming (2017) highlights the growing importance of social skills in the labor market. Hershbein and Kahn (2018) and Campello et al. (2023a, 2023b) have demonstrated that firms adjust their hiring and skill requirements in job postings over certain periods. Acemoglu et al. (2022) identify changes in talent types under the influence of artificial intelligence. Gao et al. (2023) observe a significant increase in firms' job postings with accounting skill requirements following the disclosure of internal control weaknesses. Darendeli et al. (2022) evaluate firms' environmental efforts by scoring the concentration of green skills required in job postings, showing that new green hiring can predict future profitability and generate more green patents. Hagendorff et al. (2023) find that firms demand more green skills following an increase in climate change exposure, suggesting that they engage in proactive environmental risk management. Elliott et al. (2024) also find that eco-product innovation will lead increase in green jobs. These findings echo the suggestion of Consoli et al. (2016) that green jobs require higher levels of human capital than non-green jobs. Thus, corporate job postings contain valuable information about corporate demand for human capital, thus providing us with an opportunity to measure corporate green hiring.

2.3 Hypothesis development

Rationalizing environmental regulations induces firms to adjust their production processes and alter the structure of their input factors (Porter and Linde, 1995). The dominant view in the literature on how environmental regulation affects labor demand is that the relative magnitude of the two effects determines the direction of the impact, namely, the *output effect* and the *substitution effect* (Berman and Bui, 2001; Liu et al., 2021). Specifically, the *output effect* means that environmental regulations increase firms' production costs, leading to a reduction in their output and demand for inputs, including labor demand. The *substitution effect* depends on firms' pollution control activities. These activities can be divided into two categories: "*end-of-pipe*", which reduces the pollution already produced and typically increases the labor demand, and "*changes in production processes*", which may increase the demand for labor with specific skills, such as employees who develop and use new production processes but may replace some of the demand for other labor. Consequently, the findings of studies on the relationship between environmental regulations and overall labor demand are mixed (Berman and Bui, 2001; Liu et al., 2017; Vona et al., 2018).

In this study, we focus on environmental punishment, which is a relatively strict form of environmental regulation accompanied by continuous supervision and large fines, which have significant effects on firms' production and operation processes. However, our specific interest lies not in the overall labor demand, but the demand for a specific type of labor: green labor. Following the traditional analytical framework, under the *substitution effect*, whichever approach firms take, there will be a need to increase the demand for green labor when firms are subjected to environmental punishments. This is because green labor is needed both from the direct manipulation of pollution-reducing equipment and for improving production processes at the source. Hiring employees with green skills can bring direct benefits to the firms' development of green transformation. Conversely, under the *output effect*, firms tend to reduce their demand for labor, including green labor, because of the increased production costs induced by environmental punishments. Therefore, the firms' demand for employees with green skills depends on a comparison between the *substitution effect* and *output effect*.

Firms may increase demand for employees with green skills to respond to environmental regulations if the benefits from complying with environmental regulations (*substitution effect*) are higher than the costs of green human capital investments (*output effect*). When firms are subjected to environmental punishments, they have incentives to improve environmental governance to reduce the high penalty costs of continuing to receive environmental punishments in the future, and also to recover the impact of negative reputation (Agarwal et al., 2023; Xu et al., 2012). At the same time, firms usually need to invest in R&D and use "clean" technologies when improving their environmental governance (Acemoglu et al., 2016; Aghion et al., 2016; Brown et al., 2022). Hiring employees with green skills not only signals the investment of human capital in environmental governance, but also the green talents can be adapted to "clean" technologies. Thus, we propose the following hypothesis:

Hypothesis 1a: *Ceteris paribus, firms will increase green job postings after they are subjected to environmental punishments.*

However, firms may also reduce their demand for employees with green skills to respond to environmental regulations if the costs of green human capital investment (*output effect*) are higher than the benefits of compliance (*substitution effect*). First, this may result from the increased costs associated with the lack of green talent as environmental regulations become more stringent. Thus, if the cost of hiring green talent significantly exceeds that of environmental punishments, firms may choose to limit their demand for green talent. Second, environmental fines may incentivize firms to transition to less-polluting production or outsource their polluting production activities, which may be more cost-effective than paying environmental fines or hiring green talent. Thus, we propose the following competing hypotheses.

Hypothesis 1b: *Ceteris paribus, firms will decrease green job postings after they are subjected to environmental punishments.*

3. Data and Methodology

3.1 Data and sample selection

We construct a sample of Chinese A-share listed firms from 2015 to 2021. The sample period is consistent with our novel job posting data, which is from 2016 to 2021. Considering that we examine the impact of environmental punishments on one-year-ahead green job posting, the sample period of environmental punishment is from 2015 to 2020. Notably, the enactment of China's new *Environmental Protection Law* in 2015 significantly strengthened environmental protection incentives and punishments overall. Compared with under the old *Environmental Protection Law*, the disclosure of environmental punishment records is now mandatory and more complete, environmental offense information is recorded in the social credit system, and information is disclosed to the public promptly (Agarwal et al., 2023), enabling us to obtain more comprehensive information on environmental punishments imposed on listed firms and their subsidiaries by authorities.

Our green job posting data are obtained from *51Job*, one of the largest online human resource service providers in China. We collect all job posting data from the website and match the employer names with the names of China's A-share listed firms and their direct subsidiaries, ultimately obtaining approximately 4.3 million online job postings. We then remove duplicate job postings and applied text analysis methods to identify green job postings based on specific *job descriptions*.

Our green job posting data have two unique characteristics suited to this study. First, *51Job* offers extensive coverage of real-time data on online job posts, with a market share of 27.61% in revenue in 2021, which is the largest among Chinese online recruitment platforms. According to a report released by *Analysys*, in 2022, *51Job* maintains a leading position in the scale of active users, with a user share of 73.5%, while also excelling in user reputation and trust as well as other aspects[9]. Second, the dataset provides detailed job-level information, enabling us to capture differences in labor demand across firms. Each job posting includes the employer's name, address, title, function, number of people required, salary range, and posting time. Some job postings also provide information on specific skill requirements, requisite years of experience, and educational qualifications.

However, such job posting data have inherent limitations (Darendeli et al., 2022). First, online hiring only contains job postings that firms make through online platforms and cannot cover offline recruitment, which may underestimate the actual labor demand. However, *51Job*, as one of the largest online recruitment platforms in China, is representative of the labor demand of Chinese firms. Second, job posting data capture employers' labor demands but do not reveal whether such vacancies are eventually filled. Given that the labor market is liquid and labor supply often surpasses labor demand in China, we expect that vacancies are not likely to remain unfilled for long.

We obtain firm-level environmental punishment data from the China Center for Economic Research (CCER) database, which is widely used in studies on Chinese firms. This database records the environmental punishments imposed on all listed firms and their subsidiaries. The data also provide information on when the punishment was announced, the reason for the punishment, the type of punishment, and the amount of the fine.

[9] https://36kr.com/p/1982730042885129

Other corporate financial and stock market data are sourced from the China Stock Market and Accounting Research (CSMAR) and Chinese Research Data Services (CNRDS) databases. We exclude the following: (1) industries that have never been subject to environmental punishments during our sample period, (2) firms that were subject to environmental punishment before 2014, and (3) firms with missing values for the main variables. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate outlier effects. The final dataset includes 18,209 firm-year observations covering 3,555 unique firms.

3.2 Variable definitions

3.2.1 Dependent variable: Green job postings

Our main dependent variable is *Ln(Green posting)*. We focus on firms' online job postings because this information is publicly available, allowing us to extract firms' real labor demand for different skills. Referring to Darendeli et al. (2022), we construct our main measures as follows:

First, we collect and categorize all the information in the online job postings from *51Job*. Then, we further identify green jobs from all the job postings. Specifically, we refer to the definition of "*green jobs"* identified in *The Occupational Classification Dictionary of the People's Republic of China* and select 38 seed words. For each seed word, we use the *Word2Vec* method to find 50 synonyms with the highest degree of similarity. We then manually check these synonyms to ascertain 123 keywords for identifying green job postings. All the keywords are listed in the second row of Appendix B.

Next, we define a job posting as green job if any of the keywords used for screening appear in the *job description*. Conversely, a job posting is classified as non-green if none of the keywords appear. Additionally, we use the information provided in the job posting, such as the *job function*, to mitigate potential measurement errors. The third and fourth rows of

Appendix B list the keywords used, and Appendix C lists examples of the information provided in green job postings[10].

Finally, we define *Ln(Green posting)* as the natural logarithm of one plus the number of green job postings made by a firm in a given year, which measures a firm's demand for green human capital. A higher value of *Ln(Green posting)* indicates that a firm has a higher demand for labor with green skills. We also define *Ln(Other posting)* as the natural logarithm of one plus the number of non-green job postings made by a firm in a given year. In the robustness test, we also use three alternative variables: *Green portion*, defined as the ratio of the number of green job postings released by firms in a given year to the total number of job postings; *Green dummy*, a dummy variable that takes the value of one if a firm releases at least one green job posting in a given year, and zero otherwise; and *Green posting*, defined as the number of green job postings released by a firm in a given year[11].

3.2.2 Independent variable: Environmental punishment

Our independent variable is the environmental punishments imposed on firms. Since the implementation of the New Environmental Protection Law on January 1, 2015, the Ministry of Ecology and Environment of the People's Republic of China has required firms to disclose information on environmental punishments, making this more transparent (Agarwal et al., 2023).

Environmental punishments are issued by the environmental protection administrative authorities according to environmental protection regulations. Once a listed firm or its subsidiaries receive a punishment decision issued by the authorities, the listed firm will

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[10] Ultimately, with the help of the keywords in Appendix B, we define the following two cases in which a job posting is a green job posting: (1) If a job posting's *job description* includes the green keyword in row 2, and the *job function* do not include the keyword in row 3; (2) If a job posting's *job description* does not include the green keyword in row 2, but the *job function* include the keyword in row 4.

[11] In order to preliminarily validate that the green hiring measure can reflect the firms' investment in environment governance, we examine the relationship between green hiring and firms' future ESG performance, green patents applications, whether or not receive environmental honor and award, and whether or not have environmental activities. The results in Appendix D show a positive correlation between green posting and firms' green performance and innovative activities, etc., indicating that green hiring can reflect a firm's investment in environmental improvement.

release an announcement as soon as possible explaining the punishment and steps they will take to rectify the situation and meet their disclosure responsibility. Thus, we construct the variable *Punish*, an indicator variable that equals one if a listed firm or its subsidiaries release at least one announcement of environmental punishment in a given year, and zero otherwise.

3.2.3 Control variables

Considering other factors that may influence firms' investments in green human capital, we control for a range of firm characteristics. *Size* is defined as the natural logarithm of a firm's total assets, *Leverage* is total liabilities divided by total assets, *ROA* is net income divided by total assets, *Growth* is the annual change in sales scaled by lagged total sales, *MTB* is the market value at the end of the fiscal year over the book value of equity, *CAPX/TA* is capital expenditure divided by total assets, *R&D/Sales* is R&D expenses over sales, *SG&A/Sales* is selling and administrative expenses over sales; *Largest* is the percentage of shares owned by the largest shareholder, *INS* is the percentage of shares owned by institutional investors, *Analyst_Coverage* is a dummy variable that equals one if the firm is followed by at least one analyst and zero otherwise, and *CSR/ESG Report* is a dummy variable that equals one if the firm releases a corporate social responsibility (CSR) or ESG report in a given year and zero otherwise. Appendix E provides detailed descriptions of all variables.

3.3 Model specification

To investigate the effects of environmental punishments on corporate green hiring, we estimate the following model:

$$Green\ job\ postings_{i,t+1} = \alpha + \beta_1 Punish_{it} + \beta' Controls_{it} + \delta_j + \lambda_t + \varepsilon_{i,t+1} \quad (1)$$

where *i*, *j*, and *t* denote firm, industry, and year respectively, and $\varepsilon_{i,t+1}$ is the random error term. We use the firm-level one-year-ahead $Green\ job\ postings_{i.t+1}$ as the dependent variable because a time lag may exist between environmental punishment and a firm's green hiring behavior. The main measurement variable, *Ln(Green posting)*, is defined as the natural logarithm of one plus the total number of green job postings in a given year. We also use the *Green portion*, *Green dummy*, and *Green posting* for the robustness test. The key independent variable, $Punish_{it}$, is an indicator variable that equals one if a listed firm or its subsidiaries release at least one environmental punishment announcement in a given year and 0 otherwise. $Controls_{it}$ reflects a series of firm characteristics used as control variables. We also include industry-fixed effects δ_j and year-fixed effects λ_t to control for unobservable time-invariant industry characteristics, as well as common time trends. We use standard errors clustered at the firm level to estimate the *t*-values. This study focuses on the coefficient of $Punish_{it}$, β_1, which captures the marginal effect between environmental punishments and corporate green hiring.

3.4 Descriptive statistics

Table 1 presents the sample distribution of environmental punishments across years and industries. Panel A of Table 1 shows that the percentage of listed firms subject to environmental punishment gradually increased until remaining steady at approximately 20%. Panel B of Table 1 shows that the three industries subjected to the most environmental punishment are chemical raw materials and products (12.46%), special equipment (6.68%), and pharmaceuticals (6.36%).

/*Insert Table 1 about here*/

Table 2 provides the descriptive statistics of the main variables. On average, a firm issues 2.129 green job postings and 163.872 non-green job postings per year, with the standard deviation of *Green posting* being 5.943, indicating wide variation in green job postings across firms. The mean value of *Punish* is 0.123, indicating that 12.3% of the samples received punishments related to environmental protection during our sample period.

/*Insert Table 2 about here*/

4. Effects of Environmental Punishments on Green Hiring

4.1 Baseline results

We estimate Equation (1) and report the results in Table 3. In column (1), we include only industry- and year-fixed effects and find that the coefficient of *Punish* is significantly positive at the 1% level. In column (2), we include a series of firm characteristics as control variables, and the coefficient of *Punish* remains significantly positive at the 1% level. These results suggest that firms tend to release more job postings requiring green skills after being subjected to environmental punishments, thereby increasing their investment in green human capital. According to the results in column (2), firms subjected to environmental punishment will display a 21.1% (= 0.111/0.526) increase in green hiring relative to the unconditional mean value of the number of green job postings, which is economically significant. In summary, the baseline results suggest that the pressure generated by environmental punishment encourages firms to increase their investment in green human capital to cope with stringent environmental enforcement, thus supporting *Hypothesis 1a*.

The results for the control variables also align with our expectations. Specifically, the coefficients of *RD/Sales* and *CAPX/TA* are both significantly positive, indicating that firms that invest more in R&D and make long-term asset purchases tend to invest more in green human capital as well.

/*Insert Table 3 about here*/

4.2 Robustness checks

First, we adopt alternative measures of green job postings to confirm the robustness of our results. To replace the dependent variables, we use (1) *Green portion*, the ratio of the number of green job postings released by firms in a given year to the total number of job postings; (2) *Green dummy*, a dummy variable that takes the value of one if a firm releases at least one green job posting in a given year and zero otherwise; and (3) *Green posting*, defined as the number of green job postings released by the firm in a given year. In columns (1)–(3) of Table 4, the coefficients of *Punish* are all positive and significant, further supporting our previous findings.

Second, we control for higher dimensional-fixed effects. In column (4) of Table 4, we induce province-fixed effects to control for province-level time-invariant potential unobservable characteristics. In column (5) of Table 4, we control for the province × year and industry × year fixed effects to control for industry- and province-level time-varying characteristics. The results indicate that the coefficients of *Punish* remain positive and significant.

One potential concern is that firms subjected to environmental punishments may have an increased need for all types of employees, which would lead us to observe similar results. Thus, to rule out this potential explanation, we construct a new variable, *Ln(Other posting)*, defined as the natural logarithm of one plus the number of non-green job postings released by listed firms in a given year. In column (6) of Table 4, we do not find a significant relationship between environmental punishments and firms' demand for non-green human capital, thus verifying that the observed increase in green job postings is specific to the impact of environmental punishments rather than a general expansion of overall labor demand.

Finally, the environmental protection tax law implemented in 2018 may confound our estimation. It was designed to encourage firms to improve their environmental investment and implement environmental protection, by increasing the environmental costs and legitimacy pressure of polluters. To exclude the potential distortion of environmental protection tax law, following Li and Tang (2024), we construct the variable *Polluter*, which takes value of one if a firm belongs to a highly polluting industry[12], and zero otherwise; and the variable *Taxation*, which takes value of one in years after the implementation of environmental protection tax law, and zero otherwise. Then, we introduce Polluter, Taxation, and their interaction Polluter×Taxation into Eq. (1). The results in column (7) of Table 4 indicate that our results are still consistent even controlling the effect of the environmental protection tax law.

/*Insert Table 4 about here*/

4.3 Endogeneity tests

Our study may still be subject to endogeneity concerns. Omitted variables may cause firms to experience more environmental punishments while simultaneously boosting green job creation. Although we control for industry- and year-fixed effects, exhausting all omitted factors that could explain the relationship between environmental punishments and corporate green hiring is not possible. Therefore, in this section, we implement several approaches to address possible endogeneity issues.

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[12] The industry codes of highly polluting industry are B06 (Coal Mining and Washing), B07 (Oil and Natural Gas Extraction), B08 (Ferrous Metal Mining and Dressing), B09 (Non-ferrous Metal Mining and Dressing), C17 (Textiles), C19 (Leather, Fur, Feather (down) and Footwear), C22 (Papermakign and Paper Products), C25 (Petroleum Refining, Coking, and Nuclear Fuel Processing), C26 (Chemical Raw Materials and Products), C27 (Pharmaceuticals), C28 (Chemical Fibers), C30 (Non-metallic Mineral Products), C31 (Ferrous Metal Metallurgy and Rolling), C32 (Non-ferrous Metal Metallurgy and Rolling), C33 (Metal Products), D44 (Electricity and Heat Production and Supply).

4.3.1 Matching

To mitigate possible systematic differences between samples with and without environmental punishments. We first adopt the PSM method to construct a comparable control group. Specifically, we define the treatment group as firms subjected to the first environmental punishment during the sample period (*Treat = 1*) and firms that have never been punished as the control group (*Treat = 0*). We employ a logit model to regress the indicator variable *Treat* on a set of one-period lagged control variables in Eq. (1) as well as industry-fixed effects to estimate the propensity score and construct a matching sample year-by-year. We then re-estimate the baseline model with the matched samples, and the results in column (1) of Table 5 show that the coefficient of *Punish* remains significantly positive at the 1% level.

Next, we use the EB method to match the samples. Similar to PSM, EB considers various moments of covariates simultaneously to achieve more accurate matching by balancing multidimensional covariates between the treatment and control groups. The core idea is to provide a set of moment constraints to the control group covariates, weighting them to balance with the covariates of the treatment group. In column (2) of Table 5, the coefficient of *Punish* remains significantly positive at the 1% level after sample matching using the EB method, providing robust support for our main conclusions. Appendix F presents the balance test results for matched samples.

/*Insert Table 5 about here*/

4.3.2 Falsification test

To address the possibility of unobservable factors driving the effect of environmental punishments on corporate green hiring, we randomly assign firms to the treatment and control groups while ensuring that the number of firms punished each year matches the actual data. We construct a new variable, *Punish_placebo*, instead of *Punish* in Eq. (1), and then re-estimate the baseline model. After repeating the above steps 1000 times, we obtain descriptive statistics on the coefficients of *Punish_placebo* and plot the distribution, as shown in Table 6 and Figure 1, respectively. For comparison, we also plot the actual coefficient estimated in column (2) of Table 3 (0.111) in the figure with a red dashed line. It is positioned beyond the right tail of the distribution of placebo coefficients, suggesting that unobserved omitted factors do not drive the effect of environmental punishments on corporate green hiring.

/*Insert Table 6 about here*/

/*Insert Figure 1 about here*/

4.3.3 Instrumental variables

We use instrumental variable regression to mitigate potential endogeneity issues. Specifically, we construct an instrumental variable, *L1_Punish_city*, defined as the natural logarithm of the number of punished firms in the city plus one in the previous year. Given that environmental punishments are usually issued by local environmental protection authorities, a higher number of punished firms in a city suggests stronger environmental regulatory intensity and enforcement, which in turn increases the likelihood that firms in the city will receive punishments in the future. However, this does not directly affect firms' hiring decisions.

Additionally, in 2016, the Chinese government launched a vertical administration reform by empowering provincial environmental protection bureaus to administer lower-level environmental protection bureaus through personnel control, which potentially result in stricter environmental enforcement (Chen et al., 2024). As the effectiveness of reform may also depend on the regional legal environment, following Bettinger et al. (2017), we consider an interaction-instrument strategy to construct another instrument with the interaction of two variables: (1) *Reform*, an indicator equals one if the province where the firm is located has implemented the verticalization reform, and zero otherwise[13]; (2) *High Legal Score*, which equals one if the rule-of-law level scores from Fan et al. (2019) are above the median value of scores based on the scores in 2013, and zero otherwise[14].

Table 7 reports the instrumental variable regression results. In column (1), the coefficient of *L1_Punish_city* is significantly positive at the 1% level, indicating that the total number of punished firms in the city where the firm was located in the last year is positively associated with the likelihood of the firm being punished. The *F*-statistic in the first stage is 16.983, which is larger than 10, and rejects the null hypothesis that the instrumental variable is weak based on the rule of thumb suggested by Staiger and Stock (1997). The column (2) of Table 7 reports the second stage regression result, the coefficient of *Punish (Instrument)* remains significant and positive at the 1% level.

The instrument variable regression results by using the interaction-instrument strategy are presented in column (3) and (4). The first stage regression result in column (3) indicates that regions with better legal environments increase the probability of local firms being penalized after the verticalization reform. In the second stage regression result in column (4), the coefficient of *Punish (Instrument)* remains significant and positive at the 1% level.

We also introduce both *L1_Punish_city* and *Reform×High Legal Score* into the two-stage instrumental regression. The results in column (5) and (6) remain consistent,

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[13] We obtain the timing of the verticalization reform across provinces from the Table A1 in the online appendix of Chen et al. (2024). The timing of the reform in each province is as follows: 2016 (Hubei, Chongqing); 2017 (Jiangsu, Shandong, Qinghai, Fujian, Jiangxi, Hubei); 2018 (Shanghai, Tianjin, Shaanxi, Xinjiang); 2019 (Guangdong, Inner Mongolia, Ningxia, Guizhou, Henan, Jilin, Yunnan, Beijing, Zhejiang, Anhui, Sichuan, Gansu, Heilongjiang, Shanxi, Liaoning, Hunan, Hainan).

[14] We use the province-level rule of law level scores in 2013 to avoid the interference from changes in the legal environment during our sample.

indicating that the positive effect of environmental punishments on corporate green hiring holds after using the instrumental variables approach to mitigate the endogeneity problem.

/*Insert Table 7 about here*/

4.3.4 Impact threshold for a confounding variable and coefficient stability test

Finally, we use two methods to estimate the potential impact of the omitted variables. First, referring to Frank (2000), we use the ITCV method, which calculates the product of the smallest correlation coefficient between the omitted variables and both the explained and explanatory variables. This serves as a lower bound for the correlation required for omitted variables to invalidate the conclusions. The results are shown in Panel A of Table 8, indicating that the omitted variable must have a correlation threshold of 16% and an impact threshold of 0.16*0.16=0.0256 to invalidate the conclusions. The control variable with the greatest impact on both the explanatory and explanatory variables is *Size*, with an impact magnitude of 0.0983*0.2313=0.0227. This indicates that, even if another variable with the same impact as *Size* is introduced, it will still be insufficient to invalidate our conclusion.

We also employ coefficient stability tests following Oster (2019) to estimate the potential omitted variable bias. Oster (2019) introduced a scaling factor, δ, to indicate the change in coefficients and explanatory power between unrestricted and restricted regressions. We set *R_max* to 1.3 times the R^2 of the baseline regression model, as suggested by Oster (2019). *R_max* is the maximum goodness-of-fit of the regression if all the unobservable omitted variables can be observed. The results presented in Panel B of Table 8 show that the value of scaling factor δ is 2.412, indicating that the importance of unobservable omitted variables needs to be at least 2.412 times that of the available observable variables to invalidate our conclusions.

Combining the above approaches, we conclude that the unobservable omitted variables have very little impact on our findings.

/*Insert Table 8 about here*/

5. Further Analysis

5.1 Potential mechanisms

Local rule of law environments are closely related to environmental punishments, and different levels of local environmental concern, supervision, and governance will lead to different outcomes for firms subjected to environmental punishments. Stricter local rule of law environments, especially for the regulation of local environmental protection, will exert pressure on punished firms to take active steps to improve their environmental governance. Therefore, in this section, we discuss how the local environment in which a firm is located influences the effect of environmental punishment on corporate green hiring.

First, the level of concern and importance attached to the environment in the region where the firm is located may influence the effectiveness of environmental punishments. In areas where the environment is more emphasized, local governments and the public are more concerned about environmental issues. Therefore, the pressure created from outside the firm is more likely to force the firm to pay attention to environmental governance. Inside the firm, a supportive social atmosphere encourages it to consciously make efforts to improve its environmental performance. We expect firms in areas with higher local environmental concerns to be more likely to increase their green hiring after receiving environmental punishments. Specifically, the government work report announces the local government's work plan and goals for the year. Therefore, we use the ratio of the number of environment-related keywords in provincial government work reports to the total number of words as a proxy for the level of local governments' environmental concern (*Government Concern*)[15]. From the perspective of public concern, previous studies indicate that environmental letters and visits can directly reflect the degree of public participation in environmental governance and contribute to green development (Zhang et al., 2022). Thus, we use the number of environmental letters at the provincial level as a proxy for local public environmental concern (*Public Concern*)[16].

For these two variables (*Government Concern* and *Public Concern*), we divide the sample based on the median value for each year. Firms with higher values of *Government Concern* or *Public Concern* are considered to be in areas with higher environmental concern (*High Government Concern* Group and *High Public Concern* Group), whereas the remaining firms are considered to be in areas with lower environmental concern (*Low Government Concern* Group and *Low Public Concern* Group). In Panel A of Table 9, although the coefficients of *Punish* are positive and significant for both subsamples, the magnitudes of the coefficients are larger in the *High Government Concern* and *High Public Concern* group*s.* We also conduct tests for the difference in coefficients between subsamples, and the *p*-value suggests that the difference is significant, indicating that greater government and public concern about environmental issues drives firms to invest more in green human capital when they are subjected to environmental punishments.

Second, we consider the perspective of local environmental supervision. With the comprehensive green transformation of China's economic and social development, the central government has increasingly mandated energy-saving and emission-reduction goals every five years. In response, local governments may establish energy-saving and emission-reduction targets in their work reports. Unlike discussions on environmental

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[15] The keywords related to environmental regulation include: environmental protection, environmental protection, pollution, energy consumption, emission reduction, sewage discharge, ecology, green, low-carbon, air, chemical oxygen demand, sulfur dioxide, carbon dioxide, PM10, and PM2.5.
[16] The data are from China Environmental Yearbook.

protection, which highlight the importance of the environment, clear targets signal the local government's determination and capability to monitor the environment. Therefore, we expect that the clearer the energy-saving and emissions-reduction targets set by the local government, the stronger the positive effect of environmental punishments on corporate green hiring.

We collect descriptions of energy-saving and emission-reduction targets from each year's provincial government work report. Then, we classify provinces into three groups based on the nature of their targets: (1) those with explicit quantitative targets, (2) those with qualitative targets, and (3) those with no targets mentioned. In Panel B of Table 9, we estimate the regression for each group of subsamples separately, showing that the coefficients of *Punish* are only significantly positive in provinces with either quantitative or qualitative energy-saving and emission-reduction targets, indicating that local firms will increase green hiring more after environmental punishments under supervision pressure from local government environmental governance targets.

Finally, the coordination of environmental judicial and administrative powers is considered an important guarantee to enhance the effective implementation of environmental regulations. Traditional legal theory posits that judicial and administrative powers are essentially the rights to judgment and management. However, with the increasing complexity of public affairs, an environmental case usually requires a good interactive relationship between the judiciary and the administration. In China currently, judicial methods remain insufficient compared to environmental administrative enforcement, highlighting the need for an enhanced environmental justice system (Zhang et al., 2019; Wu et al., 2023, 2024).

Therefore, we measure the degree of local judicial development in two ways. First, we use the establishment of specialized environmental courts (*Environmental Court*) as an indicator variable that takes the value of one if the city where the firm is located has set up a specialized environmental court and zero otherwise. Second, we obtain the province-level rule-of-law level scores from Fan et al. (2019) and define those above (below) the median as *High Legal Score* Group (*Low Legal Score* Group) based on the scores in 2013[17]. The establishment of specialized environmental courts and a higher level of rule of law can reflect stricter enforcement and deterrent effects. Thus, we expect that the positive effect of environmental punishments on corporate green hiring will be more pronounced for firms located in areas with specialized environmental courts or higher levels of the rule of law. In Panel C of Table 9, although the coefficients of *Punish* are positive and significant for both sub-samples, the magnitudes of the coefficients are larger in the *With Environmental Court* and *High Legal Score* Group. We also conduct tests to assess the difference in coefficients between the subsamples, and the *p*-value suggests that the difference is significant, indicating that stricter law enforcement drives firms to invest more in green human capital when they are subjected to environmental punishments.

Overall, our results confirm that greater regional environmental concerns and stricter environmental supervision and enforcement exert greater pressure on local firms, driving them to hire more employees with green skills to improve their environmental governance performance after environmental punishment.

/*Insert Table 9 about here*/

5.2 Heterogeneity analyses

In this section, we conduct several heterogeneity analyses to investigate how the effects of environmental punishments on corporate green hiring vary according to firm characteristics.

[17] We use the province-level rule of law level scores in 2013 to avoid the interference from changes in the legal environment during our sample.

First, we examine whether the effect of environmental punishment on corporate green hiring differs between SOEs and non-SOEs. As government enterprises, SOEs in China usually undertake other tasks such as maintaining social stability, in addition to operating and producing (Jiang and Kim, 2020). The existing literature also finds that SOEs typically receive preferential treatment, such as financing (Brandt and Li, 2003; Allen et al., 2005; Li et al., 2008). In terms of judicial regulation, SOEs typically receive less regulation and less disclosure of litigation cases (Liu et al., 2022). Thus, we expect environmental punishments to have a greater effect on corporate green hiring for non-SOEs. in the results in columns (1) and (2) of Table 10 show that the coefficients of *Punish* are positive and significant for SOEs and non-SOEs, while the magnitude of the coefficient is larger for non-SOEs. We also conduct tests for the difference in coefficients between the subsamples, and the p-value suggests that the difference is significant, which is consistent with our expectations.

Second, we examine how firms' financing constraints influence the effect of environmental punishments on corporate green hiring. Firms with fewer financing constraints have more resources available to attract human capital and pursue growth. Therefore, we expect the effect of environmental punishment on corporate green hiring to be stronger for firms with fewer financing constraints. We measure financing constraints using two methods. First, we employ the KZ index, referring to Kaplan and Zingales (1997), as a proxy for financing constraints. Firms with a KZ index above the median value of the sample in a given year are defined as the financing-constrained group (*High KZ*), while those below the median are defined as the financing-unconstrained group (*Low KZ*). Second, we use firm size to divide firms into two groups, with those above the median considered as the financing-unconstrained group (*Big Size*) and the others as the financially constrained group (*Small Size*). The results in columns (3)–(6) of Table 10 show that the coefficients of *Punish* are positive and significant for all groups; however, the magnitude of the coefficients is larger in the *Low KZ* and *Big Size* groups. We also conduct tests for the differences in coefficients between subsamples, and the *p*-value suggests that the difference is significant, indicating that financial resources can affect hiring decisions after a firm is subjected to environmental punishments.

/*Insert Table 10 about here*/

Finally, we investigate whether punishment fines in different amounts have a heterogeneous effect on firms' hiring decisions. We aggregate the amount of fines that firms pay for environmental punishments each year and then split our variable *Punish* into two new indicators: *Punish_High_Fines* and *Punish_Low_Fines*. *Punish_High_Fines* (*Punish_Low_Fines*) is a dummy variable that takes the value of one if the firm's total amount of fines is above (below) the median in a given year, and zero otherwise. In Table 11, we add these two indicators to Eq. (1) instead of *Punish*, and find that the coefficients of *both Punish_High_Fines* and *Punish_Low_Fines* are positive and significant. We do not find a significant difference between the two indicators, suggesting that, regardless of the differences in the severity of the punishments imposed, firms subjected to environmental punishments will improve their environmental governance by hiring green talent.

/*Insert Table 11 about here*/

5.3 Economic consequences

5.3.1 Remediation of firms subjected to environmental punishments

Our findings suggest that firms increase their demand for green human capital to improve environmental governance after receiving environmental punishments. A natural question is whether green hiring facilitates improvements in environmental performance and, ultimately, more successful remediation. In this section, we answer this question in terms of firms' future punishment and estimate the following Probit regression model:

$$Improvement_{i,t+2} = \alpha + \beta_1 Ln(Green\ posting)_{i,t+1} + \beta' Controls_{it} + \delta_j + \lambda_t + \varepsilon_{i,t+2} \quad (2)$$

$$Fines\_reduction_{i,t+2} = \alpha + \beta_1 Ln(Green\ posting)_{i,t+1} + \beta' Controls_{it} + \delta_j + \lambda_t + \varepsilon_{i,t+2}$$

(3)

We use firm-level environmental performance two years ahead as the dependent variable. $Improvement_{i,t+2}$ is a dummy variable that equals one if the firm is subject to environmental punishment in year *t* but not in year *t+2* and zero otherwise. $Fines\_reduction_{i,t+2}$ is a dummy variable that equals one if the amount of fines imposed on the firm in year *t+2* is less than that in year *t*. The control variables are identical to those in Eq. (1). We focus on the estimated coefficient of *Ln(Green posting)*.

Panel A of Table 12 shows the results of this analysis. The coefficients of *Ln(Green posting)* are significantly positive at the 10% level, suggesting that as the demand for green talent increases, a firm will be less likely to be subject to environmental punishment, and the amount of fines will also decrease.

5.3.2 Effect of green hiring for firms subjected to environmental punishments on green innovation

To verify whether firms take real action to improve their environmental performance after demanding green talent, we estimate the following regression model to discuss the effect of punished firms' decisions regarding whether to hire green talent in the case of green innovation:

$$Ln(Green\ Patent_{i,t+2}) = \alpha + \beta_1 Punish_{it} \times Green\ Dummy_{i,t+1} + \beta_2 Punish_{it} + \beta_3 Green\ Dummy_{i,t+1} + \beta' Controls_{it} + \delta_j + \lambda_t + \varepsilon_{i,t+2} \quad (4)$$

We use the firm-level two-year-ahead $Ln(Green\ Patent_{i,t+2})$ as the dependent variable, which is the natural logarithm of the total number of green patent applications by firms plus one in year *t+2*. The dummy variable *Green Dummy* takes the value of one if a firm releases at least one green job posting in year *t+1*, and zero otherwise. The control variables are the same as those in Eq. (1). We focus on the estimated coefficient of the interaction term between *Punish* and *Green Dummy*. Panel B of Table 12 presents these results. In column (1), the coefficient of $Punish_{it} \times Green\ Dummy_{i,t+1}$ is significantly positive at the 10% level, indicating that green hiring after environmental punishment can contribute firms' greater participation in green innovation activities.

5.3.3 Spillover effects of green hiring for firms subjected to environmental punishments

Environmental punishments typically act as a deterrent for other firms; therefore, we also explore the potential spillover effects. When a firm is punished, other firms in the same industry will give more consideration to environmental governance to avoid also receiving punishment owing to their similar business operations. Thus, environmental punishments not only cause the punished firm to make improvements but also motivate other firms in the industry to respond (i.e., hire green talent). To test for spillover effects, we estimate the following regression:

$$Green\ job\ postings_{i,t+1} = \alpha + \beta_1 Peer\ Punish_{it} + \beta' Controls_{it} + \delta_j + \lambda_t + \varepsilon_{i,t+1} \quad (5)$$

We construct an indicator variable, *Peer Punish*, which takes the value of one if there is an environmental punishment in the industry to which a firm belongs, and zero otherwise. We exclude all samples subjected to environmental punishments to avoid their influence on themselves with respect to hiring more green talent. The control variables are the same as those in Eq. (1). The results are presented in Panel B of Table 12, and column (2) shows that the coefficient of *Peer Punish* is significantly positive, thereby confirming that the impact of environmental punishments on corporate green hiring has a spillover effect on other firms within the same industry.

/*Insert Table 12 about here*/

6. Conclusion

In this study, we investigate the impact of environmental punishments on corporate green hiring. Using over 4.3 million online job postings by Chinese listed firms from 2015 to 2021, we measure firms' environmental efforts and investments in green human capital. In the baseline regression, our results show that firms subjected to environmental punishments will increase their green hiring. To mitigate the potential endogeneity issues, we use matching approaches, a placebo test, instrumental variables, and an omitted variable test, and find that the baseline results hold.

Our results show that the effect of environmental punishment on corporate green hiring is more significant in areas with higher local environmental concerns, clearer local energy-saving and emission-reduction targets, and improved local judicial infrastructure, thus indicating that the pressure exerted by greater regional environmental concerns and stricter environmental supervision and enforcement will drive firms to increase their green hiring after environmental punishments. Moreover, the effect of environmental punishment on corporate green hiring is more significant for non-SOEs, and firms with lower financial constraints. Notably, the amount of punishment does not influence the effects of environmental punishment on corporate green hiring, suggesting that environmental punishments of varying severity will all have a deterrent effect on corporate environmental governance.

Finally, we conduct an extensive analysis of the economic consequences of green hiring. We find that green hiring can have a remediation effect on firms' environmental performance, thereby reducing the probability of future environmental punishment and penalties. Furthermore, the main effect is accompanied by an increase in firms' green innovation, indicating that firms make environmental protection efforts. Additionally, within-industry spillover effects exist in which the punishment of one firm leads to preventive green human capital investments by other firms in the same industry.

Overall, our results highlight the effectiveness of strong environmental punishments in China. We provide insights for regulators, administrative enforcement authorities, and justice authorities. Our findings suggest that environmental punishment encourages firms to proactively invest in green human capital, which is meaningful for conducting environmental governance with greater efficiency and appropriate intensity to guide firms' actions. In addition, a green transition in the labor market is foreseeable; however, more vocational training and education are needed.

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Table 1: Distribution of environmental punishments by year and industry

Panel A: Distribution by year

Year	Frequency	Percent (%)
2015	182	8.15
2016	326	14.61
2017	456	20.43
2018	459	20.56
2019	427	19.13
2020	382	17.11
Total	2232	100.00

Panel B: Distribution by industry

Industry Code	Industry Name	Frequency	Percent (%)
A	Agriculture, Forestry, Livestock, and Fishery	46	2.06
B	Mining	90	4.03
C13	Processed Agricultural Products	54	2.42
C14	Food Production	36	1.61
C15	Beverage and Refined Tea Production	30	1.34
C17	Textiles	22	0.99
C18	Apparel and Accessories	4	0.18
C19	Leather, Fur, Feather (down) and Footwear	8	0.36
C20	Wood Processing and Products of Bamboo, Rattan, Palm, and Straw	12	0.54
C21	Furniture	9	0.40
C22	Papermaking and Paper Products	40	1.79
C23	Printing and Recorded Media	14	0.63
C24	Cultural, Educational, and Sports Goods	3	0.13
C25	Petroleum Refining, Coking, and Nuclear Fuel Processing	20	0.90
C26	Chemical Raw Materials and Products	278	12.46
C27	Pharmaceuticals	142	6.36
C28	Chemical Fibers	24	1.08
C29	Rubber and Plastics	58	2.60
C30	Non-metallic Mineral Products	65	2.91
C31	Ferrous Metal Metallurgy and Rolling	47	2.11
C32	Non-ferrous Metal Metallurgy and Rolling	50	2.24
C33	Metal Products	34	1.52
C34	General Equipment	90	4.03

C35	Special Equipment	149	6.68
C36	Automobiles	71	3.18
C37	Railway, Shipbuilding, Aerospace, and Other Transport Equipment	22	0.99
C38	Electrical Machinery and Equipment	91	4.08
C39	Computer, Communications, and Other Electronic Equipment	138	6.18
C40	Instruments and Meters	15	0.67
C41	Other Manufacturing	7	0.31
D	Electricity, Heat, Gas and Water Production and Supply	83	3.72
E	Construction	91	4.08
F	Wholesale Trade and Retail Trade	74	3.32
G	Transport, Warehousing and Postal Services	49	2.20
Total		2232	100.00

Table 2: Summary statistics

Variable	N	Mean	SD	Min	p50	Max
Green posting	18209	2.129	5.943	0.000	0.000	40.000
Other posting	18209	163.872	267.933	0.000	66.000	1595.000
Ln(Green posting)	18209	0.526	0.878	0.000	0.000	3.714
Ln(Other posting)	18209	3.786	2.008	0.000	4.205	7.375
Green dummy	18209	0.350	0.477	0.000	0.000	1.000
Punish	18209	0.123	0.328	0.000	0.000	1.000
Size	18209	22.173	1.192	19.688	22.059	25.628
Leverage	18209	0.424	0.206	0.060	0.412	0.953
ROA	18209	0.028	0.083	-0.429	0.034	0.192
Growth	18209	0.154	0.455	-0.661	0.086	2.918
MTB	18209	2.226	1.609	0.854	1.715	10.844
Largest	18209	33.165	14.419	8.410	30.950	72.620
INS	18209	42.538	24.266	0.230	43.921	90.351
Analyst Coverage	18209	0.117	0.321	0.000	0.000	1.000
SGA/Sales	18209	0.177	0.146	0.015	0.135	0.811
RD/Sales	18209	0.021	0.035	0.000	0.000	0.188
CAPX/TA	18209	0.043	0.043	0.000	0.030	0.209
CSR/ESG Report	18209	0.236	0.424	0.000	0.000	1.000

Table 3: Baseline results: Effects of environmental punishments on corporate green hiring

This table explores the effect of environmental punishments on corporate green hiring. Specifically, it presents estimates of the coefficient β_1 from Equation (1). *Ln(Green posting)* is defined as the natural logarithm of the number of green job postings made by a firm in a given year plus one. *Punish* is a dummy variable that equals one if a listed firm or its subsidiaries release at least one announcement of environmental punishment in a given year, and zero otherwise. Column (1) estimates Equation (1) without including controls; column (2) estimates Equation (1) including controls. For a detailed description of the variables, see Appendix D. We control for industry-fixed effects and year-fixed effects in all columns. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Ln(Green posting)*	(2) *Ln(Green posting)*
Punish	0.256***	0.111***
	(8.227)	(4.065)
Size		0.273***
		(18.880)
Leverage		0.064
		(1.153)
ROA		0.252***
		(2.637)
Growth		0.036**
		(2.504)
MTB		0.039***
		(6.277)
Largest		-0.003***
		(-2.801)
INS		-0.001*
		(-1.891)
Analyst Coverage		-0.028
		(-0.903)
SGA/Sales		0.050
		(0.695)
RD/Sales		0.880***
		(3.074)
CAPX/TA		2.259***
		(9.255)
CSR/ESG Report		0.044

		(1.529)
Intercept	0.495***	-5.662***
	(41.644)	(-17.901)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	18,209	18,209
Adj R^2	0.084	0.198

Table 4: Robustness checks

This table reports the results of the robustness tests. In columns (1) to (3), we conduct robustness tests on alternative green job postings measures. Specifically, in column (1), we replace the dependent variable with the *Green portion*, the ratio of the number of green job postings released by a firm divided by the total number of job postings in the given year. In column (2), we replace the dependent variable with the *Green dummy*, a dummy variable that equals one if the firm releases at least one green job posting in a given year, and zero otherwise, and estimate using a Logit model. In column (3), we replace the dependent variable with *Green posting*, the original number of green job postings released by a firm, and estimated using a Poisson model. Then we conduct robustness tests in columns (4) and (5) for adding high-dimensional fixed effects. In column (4), we add province-fixed effects to Equation (1). In column (5), we replace industry and year fixed effects with industry × year and province × year fixed effects. In column (6), we conduct a falsification test regarding the impact of environmental punishment on non-green job postings. We replace the dependent variable with *Ln(Other posting)*, the natural logarithm of the number of non-green job postings made by a firm in a given year plus one. Finally, in column (7), we exclude the effects of the environmental protection tax law, following Li and Tang (2024), *Polluter* is a duumy variable that takes one if firm belongs to a highly polluting industry, and zero otherwise, *Taxation* is a dummy variable that takes one in years after the implementation of environmental protection tax law in 2018, and zero otherwise..For a detailed description of the variables, see Appendix D. We control for industry-fixed effects and year-fixed effects in columns (1), (2), (3), (6) and (7). The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	*Green portion*	*Green dummy*	*Green posting*	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Other posting)*	*Ln(Green posting)*
Punish	0.004***	0.235***	0.195***	0.116***	0.122***	0.040	0.112***
	(3.485)	(3.806)	(2.842)	(4.452)	(4.511)	(0.757)	(4.116)
Polluter×Taxation							0.085***
							(3.239)
Polluter							-0.412***

							(-3.552)
Size	0.003***	0.601***	0.621***	0.274***	0.274***	0.703***	0.274***
	(5.026)	(17.859)	(17.610)	(19.598)	(19.204)	(22.712)	(18.966)
Leverage	0.003	-0.050	0.169	0.098*	0.108*	-0.175	0.071
	(1.063)	(-0.318)	(0.812)	(1.789)	(1.916)	(-1.126)	(1.286)
ROA	-0.004	0.960***	1.200***	0.217**	0.202**	2.260***	0.251***
	(-1.065)	(2.953)	(2.720)	(2.272)	(2.053)	(9.324)	(2.629)
Growth	0.001	0.125***	0.044	0.038***	0.036**	0.255***	0.034**
	(0.758)	(3.100)	(1.070)	(2.643)	(2.436)	(7.730)	(2.357)
MTB	-0.000	0.045***	0.038**	0.037***	0.037***	0.072***	0.039***
	(-0.065)	(2.618)	(2.012)	(6.046)	(5.745)	(4.200)	(6.317)
Largest	-0.000	-0.006***	-0.002	-0.003***	-0.003***	-0.003*	-0.002***
	(-0.927)	(-2.964)	(-0.848)	(-3.478)	(-3.531)	(-1.666)	(-2.788)
INS	0.000	-0.002	-0.004**	-0.001	-0.001	-0.006***	-0.001*
	(0.069)	(-1.470)	(-2.003)	(-0.998)	(-0.911)	(-4.575)	(-1.868)
Analyst Coverage	-0.001	0.142	-0.068	-0.045	-0.049	0.337***	-0.036
	(-1.132)	(1.560)	(-0.542)	(-1.452)	(-1.547)	(4.311)	(-1.129)
SGA/Sales	-0.010***	0.227	0.103	0.090	0.063	1.657***	0.039
	(-3.654)	(1.014)	(0.341)	(1.243)	(0.837)	(8.071)	(0.544)
RD/Sales	0.014	2.503***	2.273***	0.632**	0.886**	5.451***	0.975***
	(1.424)	(3.380)	(2.674)	(2.250)	(2.497)	(8.859)	(3.365)
CAPX/TA	0.056***	4.769***	4.688***	2.065***	2.068***	2.051***	2.244***
	(5.368)	(8.716)	(8.062)	(8.465)	(8.284)	(4.048)	(9.199)
CSR/ESG Report	-0.001	0.068	0.029	0.052*	0.050*	0.061	0.045
	(-0.422)	(1.012)	(0.386)	(1.852)	(1.752)	(0.952)	(1.560)
Intercept	-0.045***	-15.411***	-13.309***	-5.703***	-5.700***	-12.189***	-5.612***

	(-4.002)	(-19.265)	(-17.281)	(-18.623)	(-18.237)	(-18.100)	(-17.737)
Industry FE	Yes	Yes	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	Yes	Yes
Province FE	No	No	No	Yes	No	No	No
Industry×Year FE	No	No	No	No	Yes	No	No
Province×Year FE	No	No	No	No	Yes	No	No
Observations	18,209	18,209	18,209	18,209	18,207	18,209	18,209
Pseudo R^2/Adj R^2	0.092	0.113	0.272	0.222	0.216	0.310	0.203

Table 5: Endogeneity issues: Propensity score matching and entropy balance matching

This table reports the results of using sample matching methods to address possible endogeneity issues. we define the treatment group as firms subjected to the first environmental punishment during the sample period (*Treat = 1*) and firms that have never been punished as the control group (*Treat = 0*). First, we employ a logit model to regress the indicator variable *Treat* on a set of one-period lagged control variables in Eq. (1) as well as industry-fixed effects to estimate the propensity score and construct a matching sample year-by-year. After obtaining the matched samples, the results of the regression are presented in column (1). Second, we directly match the control samples and treatment samples with the help of the overall entropy balance method. Specifically, it uses weighting to balance the mean, variance, and skewness of two sets of samples. After obtaining the matched samples, the results of the regression are presented in column (2). For a detailed description of the variables, see Appendix D. We control for industry-fixed effects and year-fixed effects. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
VARIABLES	*Ln(Green posting)*	*Ln(Green posting)*
Punish	0.077***	0.102***
	(2.861)	(3.700)
Size	0.289***	0.293***
	(14.192)	(16.665)
Leverage	-0.056	0.013
	(-0.716)	(0.193)
ROA	0.358**	0.390***
	(2.550)	(3.308)
Growth	0.051***	0.043**
	(2.612)	(2.352)
MTB	0.059***	0.056***
	(5.765)	(6.520)
Largest	-0.002	-0.003***
	(-1.505)	(-2.800)
INS	-0.002**	-0.001*
	(-2.139)	(-1.866)
Analyst Coverage	-0.082**	-0.031
	(-2.043)	(-0.820)
SGA/Sales	0.035	0.105
	(0.332)	(1.094)
RD/Sales	1.481***	2.372***

	(2.855)	(5.547)
CAPX/TA	2.242***	2.527***
	(6.264)	(8.555)
CSR/ESG Report	0.053	0.046
	(1.450)	(1.449)
Intercept	-6.017***	-6.173***
	(-13.437)	(-15.947)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	10,419	18,209
Adj R^2	0.212	0.222

Table 6: Falsification test

This table presents the result of the falsification test. We randomly assign firms to the treatment and control groups while ensuring that the number of firms punished each year matches the actual data. We construct a new variable, *Punish_placebo*, instead of *Punish* in Eq. (1), and then re-estimate the baseline model. After repeating the above steps 1000 times, we summarize the estimates of *Punish_placebo* and plot the Kdensity and *p*-value distribution of the placebo coefficient estimates. For comparison, we also include a red dashed line for the actual estimated value of *Punish* from the baseline model in Table 3 column (2).

	N	Mean	SD	Min	p5	Median	p95	Max
Coefficient	1000	-0.0002	0.0218	-0.0750	-0.0360	-0.0003	0.0364	0.0700
p-value	1000	0.4979	0.2845	0.0005	0.0581	0.5054	0.9465	0.9995

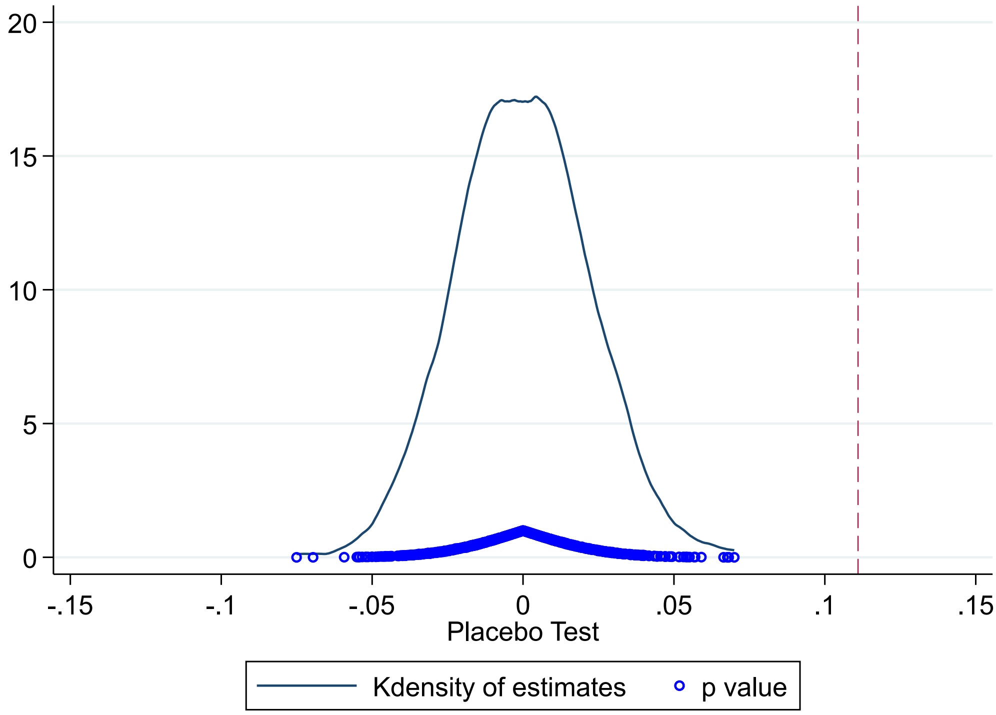

Figure 1: Falsification test

Table 7: Instrumental variable regression

This table presents the results of instrumental variable estimation. In Column (1) and (2), we report the first and second regression results by introducing the *L1_Punish_city* as the instrument variable. *L1_Punish_city* is defined as the natural logarithm of the total number of punished firms in the city plus one in which the focal firm is located in year *t-1*. In Column (3) and (4), we report the the first and second regression results by introducing the *Reform*× *High Legal Score* as the instrument variable. *Reform*, an indicator equals one if the province where the firm is located has implemented the verticalization reform, and zero otherwise. *High Legal Score*, which equals one if the rule-of-law level scores from Fan et al. (2019) are above the median value of scores based on the scores in 2013, and zero otherwise. In Column (5) and (6), we report the first and second regression results by introducing both the instrument variables. For a detailed description of the variables, see Appendix D. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Punish*	*Ln(Green posting)*	*Punish*	*Ln(Green posting)*	*Punish*	*Ln(Green posting)*
L1_Punish_city	0.012***				0.010***	
	(4.121)				(3.233)	
Reform× *High Legal Score*			0.022***		0.019**	
			(3.405)		(2.441)	
Punish (Instrument)		5.841***		4.671***		5.143***
		(6.486)		(3.054)		(4.418)
Size	0.054***	-0.028	0.046***	0.065	0.055***	0.010
	(14.675)	(-0.548)	(15.258)	(0.903)	(14.720)	(0.155)
Leverage	0.077***	-0.406***	0.048***	-0.150	0.078***	-0.353***
	(4.281)	(-4.466)	(3.255)	(-1.424)	(4.346)	(-2.646)
ROA	-0.024	0.296***	-0.039	0.429**	-0.024	0.280
	(-0.604)	(2.870)	(-1.150)	(2.287)	(-0.603)	(1.240)

Growth	-0.020***	0.147***	-0.014***	0.099***	-0.020***	0.132***
	(-3.038)	(6.340)	(-2.581)	(2.828)	(-3.048)	(3.056)
MTB	0.003	0.019**	0.003*	0.025**	0.003	0.021*
	(1.546)	(2.548)	(1.692)	(2.371)	(1.578)	(1.657)
Largest	-0.000	-0.002**	-0.000	-0.002*	-0.000	-0.002
	(-0.532)	(-2.050)	(-1.028)	(-1.647)	(-0.581)	(-1.561)
INS	-0.000	-0.001	-0.000	-0.001	-0.000	-0.001
	(-0.417)	(-1.260)	(-0.753)	(-0.923)	(-0.426)	(-0.989)
Analyst Coverage	-0.038**	0.184***	-0.034***	0.118*	-0.041**	0.158
	(-2.364)	(3.045)	(-3.447)	(1.649)	(-2.558)	(1.576)
SGA/Sales	-0.107***	0.625***	-0.086***	0.450***	-0.105***	0.552***
	(-4.318)	(5.069)	(-4.185)	(2.628)	(-4.211)	(2.988)
RD/Sales	-0.268**	2.189***	-0.332***	2.332***	-0.271**	2.029***
	(-2.516)	(5.630)	(-3.650)	(3.436)	(-2.544)	(3.121)
CAPX/TA	-0.036	2.692***	-0.019	2.355***	-0.034	2.660***
	(-0.483)	(9.471)	(-0.333)	(7.752)	(-0.461)	(6.403)
CSR/ESG Report	0.012*	-0.042	0.006	0.016	0.012*	-0.033
	(1.648)	(-1.286)	(1.006)	(0.473)	(1.668)	(-0.755)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,110	14,110	18,209	18,209	14,110	14,110
Cragg-Donald Wald F	16.983	-	11.591	-	-	-
Sargan-Hansen test (*p*-value)	-	-	-	-	-	0.310

Table 8: Impact of omitted variables

This table presents the results of measuring the effect of potential omitted variables. Panel A presents the results using the impact threshold for a confounding variable (ITCV) test from Frank (2000) based on the results in column (2) of Table 3. This method uses the correlation of each control variable with the independent and dependent variables to estimate the minimum theoretical value of the correlation that a possible omitted variable would need to have to invalidate our inference. Panel B presents the results of using the coefficient stability test to evaluate the unobservable selection and possible omitted variable bias (Bereskin et al., 2023; Oster, 2019). The coefficient of proportionality (δ) indicates the change in the coefficient of the independent variable and explanatory power between the unrestricted and restricted regressions.

Panel A: ITCV

Variable	Partial correlation of the control variable with the independent variable	Partial correlation of the control variable with the dependent variable	Impact
Size	0.0983	0.2313	0.0227
Leverage	0.0169	0.0243	0.0004
ROA	0.0015	0.0383	0.0001
Growth	-0.0127	0.0311	-0.0004
MTB	-0.0132	0.057	-0.0008
Largest	-0.003	-0.0529	0.0002
INS	-0.01	-0.0433	0.0004
Analyst Coverage	-0.1035	-0.0233	0.0024
SGA/Sales	-0.038	0.0021	-0.0001
RD/Sales	-0.0359	0.1049	-0.0038
CAPX/TA	0.0172	0.1209	0.0021
CSR/ESG Report	0.0103	0.0075	0.0001

Panel B: Oster (2019) Coefficient Stability

	Coefficient		R^2		
Model	Uncontrolled	Controlled	Uncontrolled	Controlled	δ
Industry and Year FE	0.235	0.111	0.008	0.201	2.412

Table 9: Potential mechanisms

In this table, we discuss how the local environment in which a firm is located influences the effect of environmental punishment on corporate green hiring. Panel A shows the results of grouping the samples based on the degree of local environmental concern. We use the word frequency of environmental keywords in provincial local government work reports (*Government Concern*) and the number of environmental letters and visits from the public at the provincial level (*Public Concern*) as proxies for the degree of environmental concern. Specifically, column (1) uses the subsample with higher values of *Government Concern*, and column (2) uses subsample with lower values of *Government Concern*. Column (3) uses the subsample with higher values of *Public Concern*, and column (4) uses the subsample with lower values of *Public Concern*. Panel B shows the results of grouping the samples by the intensity of local environmental supervision. We use the environmental emission reduction targets proposed in provincial local government work reports as a proxy variable for local environmental monitoring intensity, respectively. Specifically, column (1) uses the subsample with quantitative emission reduction targets proposed in the provincial local government work reports, column (2) uses the subsample with qualitative emission reduction targets proposed, and column (3) uses the subsample with no targets. Panel C shows the results of grouping the sample based on the degree of local judicial development. We use the establishment of environmental courts in cities (*Environmental Court*) and the provincial legal system environment score (*Legal Score*) as proxy variables. Specifically, column (1) uses the subsample whose city has established an intermediate environmental court, and column (2) uses the subsample whose city has not yet established an environmental court. Column (3) uses the subsample with higher *Legal Score*, and column (4) uses the subsample with lower *Legal Score*. For a detailed description of the variables, see Appendix D. We control for industry-fixed effects and year-fixed effects in all columns. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Level of local environmental concern

VARIABLES	(1) Government Concern High *Ln(Green posting)*	(2) Government Concern Low *Ln(Green posting)*	(3) Public Concern High *Ln(Green posting)*	(4) Public Concern Low *Ln(Green posting)*
Punish	0.154***	0.080**	0.140***	0.091***
	(3.902)	(2.436)	(3.440)	(2.643)
Size	0.279***	0.266***	0.346***	0.216***
	(13.983)	(16.618)	(16.604)	(11.254)
Leverage	0.119	0.030	0.241***	-0.054
	(1.481)	(0.496)	(2.804)	(-0.776)
ROA	0.222	0.259**	0.255*	0.184
	(1.453)	(2.429)	(1.730)	(1.497)
Growth	0.028	0.042**	0.012	0.047***
	(1.343)	(2.279)	(0.510)	(2.595)
MTB	0.026***	0.050***	0.041***	0.033***
	(3.006)	(6.756)	(4.540)	(4.251)
Largest	-0.002	-0.003***	-0.001	-0.003**
	(-1.361)	(-3.419)	(-1.095)	(-2.524)
INS	-0.001	-0.001	-0.001	-0.001
	(-1.270)	(-1.454)	(-1.403)	(-0.935)
Analyst Coverage	-0.043	-0.013	-0.060	0.008
	(-0.983)	(-0.322)	(-1.366)	(0.189)
SGA/Sales	0.164	-0.033	0.200	0.042
	(1.606)	(-0.436)	(1.529)	(0.539)
RD/Sales	0.619	1.143***	1.100**	0.425
	(1.416)	(3.026)	(2.556)	(1.125)
CAPX/TA	2.333***	2.148***	2.014***	2.178***
	(7.049)	(7.568)	(6.404)	(5.957)
CSR/ESG Report	0.024	0.065**	0.049	0.070**
	(0.608)	(2.004)	(1.040)	(2.113)
Intercept	-5.817***	-5.521***	-7.307***	-4.437***
	(-13.402)	(-15.663)	(-15.919)	(-10.564)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,183	10,026	8,876	9,333
Adj R^2	0.209	0.206	0.256	0.168
Coefficient difference *p*-value	0.000		0.008	

Panel B: Intensity of local environmental supervision

	(1)	(2)	(3)
	Local environmental emission reduction targets		
	Quantitative targets	Qualitative targets	No targets
VARIABLES	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Green posting)*
Punish	0.161**	0.113***	0.039
	(2.407)	(3.602)	(0.627)
Size	0.240***	0.291***	0.241***
	(8.242)	(17.168)	(9.169)
Leverage	-0.070	0.163**	-0.054
	(-0.543)	(2.467)	(-0.593)
ROA	-0.065	0.340***	0.220
	(-0.285)	(2.888)	(1.236)
Growth	0.060*	0.016	0.070**
	(1.920)	(0.896)	(2.035)
MTB	0.031**	0.040***	0.042***
	(2.472)	(5.408)	(3.166)
Largest	-0.002	-0.002**	-0.004***
	(-0.849)	(-2.286)	(-2.757)
INS	-0.001	-0.001	-0.001
	(-0.885)	(-1.390)	(-1.400)
Analyst Coverage	0.039	-0.057	0.005
	(0.588)	(-1.483)	(0.070)
SGA/Sales	-0.113	0.165*	-0.070
	(-0.889)	(1.709)	(-0.598)
RD/Sales	-0.588	1.576***	0.311
	(-1.121)	(4.283)	(0.536)
CAPX/TA	2.382***	2.273***	2.342***
	(3.972)	(8.138)	(5.060)
CSR/ESG Report	0.033	0.028	0.075
	(0.590)	(0.792)	(1.315)
Intercept	-4.818***	-6.133***	-4.885***
	(-7.650)	(-16.436)	(-8.517)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	3,775	12,130	2,304
Adj R^2	0.203	0.215	0.220
Coefficient difference	(1)-(2)	(2)-(3)	(1)-(3)
p-value	0.127	0.000	0.000

Panel C: Degree of local judicial development

	(1)	(2)	(3)	(4)
	Environmental Court		Legal Score	
	Court=1	Court=0	High	Low
VARIABLES	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Green posting)*
Punish	0.151***	0.069*	0.173***	0.055*
	(3.795)	(1.905)	(3.760)	(1.721)
Size	0.254***	0.294***	0.291***	0.258***
	(12.768)	(14.522)	(13.322)	(13.731)
Leverage	0.063	0.060	0.194**	0.006
	(0.749)	(0.837)	(2.050)	(0.096)
ROA	0.186	0.309**	0.145	0.320***
	(1.283)	(2.445)	(0.876)	(2.803)
Growth	0.042**	0.027	0.016	0.046***
	(2.157)	(1.279)	(0.664)	(2.606)
MTB	0.025***	0.057***	0.026***	0.042***
	(3.059)	(5.979)	(2.789)	(5.138)
Largest	-0.001	-0.004***	-0.003*	-0.003***
	(-0.575)	(-3.810)	(-1.776)	(-2.900)
INS	-0.001	-0.001	-0.000	-0.001*
	(-1.110)	(-1.604)	(-0.340)	(-1.911)
Analyst Coverage	0.006	-0.066	-0.007	-0.090**
	(0.125)	(-1.596)	(-0.154)	(-2.264)
SGA/Sales	0.048	0.041	-0.034	0.166*
	(0.497)	(0.373)	(-0.287)	(1.893)
RD/Sales	0.657*	1.073***	0.127	1.320***
	(1.649)	(2.584)	(0.304)	(3.446)
CAPX/TA	1.828***	2.630***	2.008***	2.336***
	(5.197)	(7.963)	(5.188)	(7.515)
CSR/ESG Report	-0.005	0.096**	-0.009	0.068*
	(-0.122)	(2.177)	(-0.198)	(1.919)
Intercept	-5.261***	-6.117***	-5.985***	-5.372***
	(-12.100)	(-13.736)	(-12.612)	(-12.967)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,113	9,096	7,644	10,565
Adj R^2	0.186	0.235	0.235	0.200
Coefficient difference *p*-value	0.000		0.000	

Table 10: Heterogeneity analyses: firm characteristics

This table examines the differential impact of environmental punishment on green job postings across firms' characteristics. We use the nature of firm equity, the KZ index of financing constraints, and firm size for our analyses, respectively. Specifically, column (1) uses a subsample of state-owned firms, and column (2) uses a subsample of non-state-owned firms. Column (3) uses the subsample of firms whose KZ index is higher than the median of all firms in the year, and column (4) uses the subsample of firms whose KZ index is lower than the median of all firms in the year. Column (5) uses a subsample of firms whose size is greater than the median of all firms in that year, and column (6) uses a subsample of firms whose size is less than the median of all firms in that year. For a detailed description of the variables, see Appendix D. We control for industry-fixed effects and year-fixed effects in all columns. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	SOE		KZ		Size	
	SOE=1	SOE=0	High	Low	High	Low
VARIABLES	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Green posting)*	*Ln(Green posting)*
Punish	0.084**	0.124***	0.086**	0.140***	0.137***	0.066*
	(2.083)	(3.419)	(2.276)	(4.035)	(3.844)	(1.872)
Size	0.279***	0.289***	0.297***	0.252***	0.312***	0.235***
	(11.782)	(15.625)	(15.045)	(14.311)	(11.767)	(10.907)
Leverage	-0.143*	0.248***	-0.157**	0.271***	0.041	0.067
	(-1.682)	(3.422)	(-1.997)	(3.804)	(0.411)	(1.219)
ROA	0.278*	0.260**	0.248**	0.305**	0.500***	0.208**
	(1.756)	(2.153)	(2.131)	(2.175)	(2.620)	(2.181)
Growth	0.018	0.031*	0.047**	0.021	0.033	0.031*
	(0.820)	(1.667)	(2.476)	(1.015)	(1.514)	(1.919)
MTB	0.041***	0.035***	0.044***	0.035***	0.041**	0.017***
	(3.536)	(4.766)	(5.440)	(4.013)	(2.552)	(2.967)
Largest	-0.002	-0.002	-0.003**	-0.002**	-0.002	-0.002*
	(-1.479)	(-1.576)	(-2.095)	(-2.051)	(-1.492)	(-1.707)
INS	-0.003**	0.000	-0.001*	-0.001	-0.002	-0.001
	(-1.997)	(0.100)	(-1.748)	(-1.411)	(-1.637)	(-1.128)
Analyst Coverage	-0.117**	-0.045	-0.079	-0.013	-0.001	-0.031
	(-2.453)	(-1.193)	(-1.626)	(-0.361)	(-0.016)	(-1.051)
SGA/Sales	0.021	0.070	-0.028	0.071	-0.029	0.058

	(0.167)	(0.778)	(-0.311)	(0.749)	(-0.194)	(0.821)
RD/Sales	1.178**	0.962***	1.861***	0.302	1.628***	0.787**
	(2.202)	(2.733)	(4.201)	(0.853)	(2.951)	(2.401)
CAPX/TA	1.990***	2.020***	2.146***	2.307***	3.214***	1.237***
	(4.508)	(6.940)	(6.722)	(7.624)	(8.036)	(5.061)
CSR/ESG Report	0.070*	0.025	0.058	0.026	0.053	-0.002
	(1.689)	(0.627)	(1.482)	(0.749)	(1.457)	(-0.059)
Intercept	-5.706***	-6.068***	-6.078***	-5.283***	-6.662***	-4.726***
	(-11.209)	(-14.888)	(-13.978)	(-13.683)	(-11.296)	(-10.367)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,356	10,853	8,843	9,366	9,102	9,107
Adj R^2	0.204	0.225	0.226	0.183	0.245	0.093
Coefficient difference *p*-value	0.008		0.005		0.000	

Table 11: Heterogeneity analyses: Amount of environmental punishment fines

This table shows the results of the heterogeneity analysis based on the amount of environmental punishment fines received by firms. We construct two new variables, *Punish_High_Fines*, a dummy variable that equals one if the firm's annual fine amount is higher than the median annual fine amount for all firms in that year and zero otherwise, and *Punish_Low_Fines*, a dummy variable that equals one if the firm's annual fine amount is lower than the median annual fine amount for all firms in that year and zero otherwise. In column (1), we include only *Punish_High_Fines* and *Punish_Low_Fines* in the regression; in column (2), we further include all control variables in the regression. For a detailed description of the variables, see Appendix D. We control for industry-fixed effects and year-fixed effects in all columns. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
VARIABLES	*Ln(Green posting)*	*Ln(Green posting)*
Punish_High_Fines	0.241***	0.082**
	(6.034)	(2.256)
Punish_Low_Fines	0.225***	0.113***
	(6.603)	(3.747)
Size		0.273***
		(18.921)
Leverage		0.064
		(1.163)
ROA		0.251***
		(2.629)
Growth		0.036**
		(2.507)
MTB		0.039***
		(6.283)
Largest		-0.003***
		(-2.804)
INS		-0.001*
		(-1.882)
Analyst Coverage		-0.029
		(-0.922)
SGA/Sales		0.050
		(0.688)
RD/Sales		0.877***
		(3.063)

CAPX/TA		2.259***
		(9.249)
CSR/ESG Report		0.044
		(1.528)
Intercept	0.497***	-5.676***
	(41.736)	(-17.934)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	18,209	18,209
Adj R^2	0.086	0.201
Coefficient difference		
p-value	0.732	0.459

Table 12: Economic consequences

Table 12 shows the results of economic consequences. Panel A reports the remediation of firms subjected to environmental punishments. *Improvement* is a dummy variable that equals one if the firm is subject to environmental punishment in year *t* but not in year *t+2*, and zero otherwise. *Fines_reduction* is a dummy variable that equals one if the amount of fines imposed on the firm in year *t+2* is less than the amount in year *t*. In Panel B, column (1) reports the real effect of green hiring for firms subjected to environmental punishments. We replace the dependent variable with *Ln(Green patent)*, which is the natural logarithm of the total number of green patent applications by firms plus one in year *t+1*. We also introduce the *Green dummy*, a dummy variable that equals one if the firm releases at least one green job posting in year *t* and zero otherwise, and the interaction term of *Green dummy* and *Punish* in the regression. Column (2) reports the spillover effects within industries. First, we exclude all firm-year samples with environmental punishments. Then we replace the independent variable with *Peer Punish*, a dummy variable that equals one if a firm in the focal firm's industry receives punishment in year *t*, and zero otherwise. For a detailed description of the variables, see Appendix D. We control for industry-fixed effects and year-fixed effects in all columns. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Remediation of firms subjected to environmental punishments

	(1)	(2)
VARIABLES	*Improvement*	*Fines_reduction*
Ln(Green posting)	0.044*	0.041*
	(1.892)	(1.705)
Size	0.103***	0.182***
	(3.899)	(6.690)
Leverage	0.075	0.235*
	(0.609)	(1.886)
ROA	-0.212	-0.205
	(-0.703)	(-0.674)
Growth	-0.035	-0.063
	(-0.778)	(-1.398)
MTB	0.008	0.019
	(0.442)	(1.064)
Largest	-0.002	0.001
	(-0.978)	(0.324)
INS	-0.001	-0.001
	(-0.490)	(-1.398)
Analyst Coverage	-0.209**	-0.179

	(-1.962)	(-1.547)
SGA/Sales	-0.754***	-0.760***
	(-3.951)	(-3.795)
RD/Sales	-1.715	-0.953
	(-1.564)	(-0.864)
CAPX/TA	0.026	0.093
	(0.052)	(0.187)
CSR/ESG Report	0.069	0.029
	(1.408)	(0.594)
Intercept	-3.262***	-5.169***
	(-5.468)	(-8.438)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	9,255	9,255
Pseudo R^2	0.057	0.084

Panel B: Effect of green hiring for firms subjected to environmental punishments on green innovation and Spillover effects on other firms

VARIABLES	(1) *Ln(Green patent)*	(2) *Ln(Green posting)*
Punish×Green dummy	0.099*	
	(1.863)	
Punish	-0.016	
	(-0.548)	
Green dummy	0.318***	
	(14.171)	
Peer Punish		0.078**
		(2.218)
Size	0.312***	0.259***
	(17.436)	(18.014)
Leverage	0.149**	0.118**
	(2.328)	(2.215)
ROA	0.553***	0.248**
	(5.038)	(2.564)
Growth	0.021	0.040***
	(1.154)	(2.664)
MTB	0.045***	0.034***
	(6.103)	(5.496)
Largest	0.000	-0.003***
	(0.203)	(-3.330)
INS	-0.000	-0.001*
	(-0.655)	(-1.699)
Analyst Coverage	-0.039	-0.037
	(-1.258)	(-1.243)
SGA/Sales	0.135*	0.053
	(1.664)	(0.756)
RD/Sales	2.426***	0.771***
	(6.775)	(2.689)
CAPX/TA	0.220	2.101***
	(0.839)	(8.808)
CSR/ESG Report	0.123***	0.036
	(3.738)	(1.266)
Intercept	-6.709***	-5.414***
	(-17.071)	(-17.170)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	14,113	15,977

Adj R^2	0.327	0.185

Appendix A: The time changes in the number of environmental punishments cases and the total amount of fines

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023
Environmental punishments cases	9.7	12.4	23.3	18.6	16.3	12.6	13.3	9.1	8.0
Amount of fine	42.5	66.3	115.8	152.8	119.2	82.4	116.9	76.7	62.7

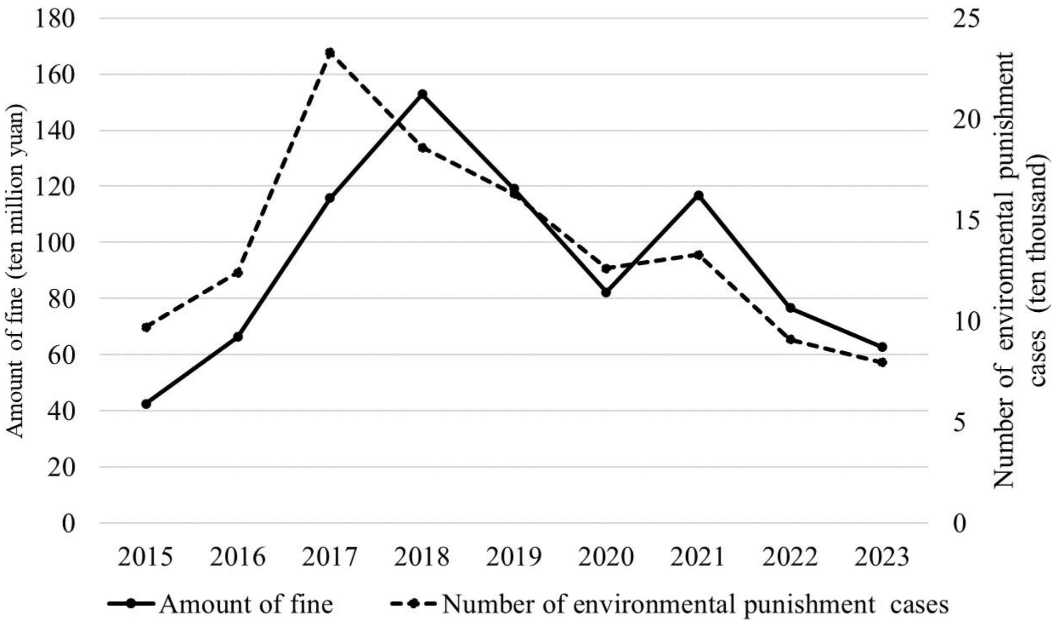

Figure A1: The time changes in the number of environmental punishments cases and the total amount of fines

Notes: This figure presents the time changes in the number of environmental punishments cases and the total amount of fines. Data are collected from the annual work report of the Ministry of Ecology and Environment.

Appendix B: Keywords used in green job postings identifying

Row 1 shows the 38 seed words we select from the descriptions of the 133 green occupations in the newly revised Occupational Classification Dictionary of the People's Republic of China. Row 2 shows the 123 keywords we ultimately use for identifying green job postings when analyzing *job descriptions*. We employ the word2vec method to find 50 synonyms with the highest similarity for each seed word, and then manually check these synonyms. Rows 3 and 4 are the keywords we use when we additionally check with the help of the *job function* in the job postings. Ultimately, we define the following two cases in which a job posting is a green job posting: (1) If a job posting's *job description* includes the green keyword in row 2 and the *job function* do not include the keyword in row 3; (2) If a job posting's *job description* does not include the green keyword in row 2, but the *job function* includes the keyword in row 4.

Seed words	Low carbon (低碳), scrap (报废), discarded (废弃), waste (废物), recycling (回收), biphenyl (联苯), pollution (污染), toxic (有毒), clean (清洁), nitrogen (氮), air (空气), carbon (碳), fossil (化石), coal (煤), resources (资源), atmosphere (大气), emissions (排放), greenhouse (温室), gas (气体), footprint (足迹), wind (风), green (绿色), sun (太阳), regeneration (再生), warming (变暖), climate (气候), fuel (燃料), biology (生物), species (物种), freshwater (淡水), water (水), logging (砍伐), pesticides (农药), agriculture (农业), forests (森林), wetlands (湿地), protection (保护), environment (环境)
Keywords included in the *job description*	Atmosphere (大气), geographic information (地理信息), wastewater (废水), photovoltaics (光伏), environmental protection (环保), energy conservation (节能), sewage (污水), new energy (新能源), protecting the environment (保护环境), grassland resources (草地资源), municipal wastewater (城市污水), geodesy (大地测量), atmospheric environment (大气环境), geography (地理国情), geothermal resources (地热资源), groundwater (地下水), geohazards (地质灾害), sand control (防沙), flood control (防汛), waste water treatment (废水处理), wind power (风力发电), solid waste (固废), solid waste (固体废弃物), solid waste (固体废物), marine measurement (海洋测量), marine environment (海洋环境), marine meteorology (海洋气象), marine hydrography (海洋水文), marine pollution (海洋污染), environmental protection (环境保护), waste reduction (减废), emission reduction (减排), carbon reduction (减碳), healthy and safe environment (健康安全环境), energy saving facilities (节能设施), renewable (可再生), air pollution (空气污染), air quality (空气质量), forestry resources (林业资源), energy management (能源管

	理), emission monitoring (排放监测), climate change (气候变化), forest protection (森林保护), forest resources (森林资源), ecological restoration (生态恢复), ecological restoration (生态修复), biodiversity (生物多样性), biomass (生物质), biomass energy (生物质能), water treatment (水处理), water purification (水净化), hydropower (水力发电), soil and water conservation (水土保持), soil and water erosion remediation (水土流失整治), hydrology (水文), hydrogeology (水文地质), water pollution (水污染), solar energy (太阳能), carbon sink (碳汇), carbon measurement (碳计量), carbon emission (碳排放), carbon cycle (碳循环), soil environment (土壤环境), sludge (污泥), polluted environment (污染环境), pollution monitoring (污染监测), pollutant (污染物), pollutant source (污染源), sewage treatment (污水处理), sewage station (污水站), waste heat (余热), waste pressure (余压), renewable energy (再生能源), renewable resources (再生资源), biogas (沼气), nature conservation (自然保护), HSE (健康、安全和环境), power generation (发电), 环境 (environment), greening (绿化), drainage (排水), ecology (生态), protected areas (保护区), geophysics (地球物理), geothermal (地热), geology (地质), geological mapping (地质测绘), geological hazards (地质灾害), low carbon (低碳), waste (废弃), waste (废弃物), waste (废物), waste liquid (废液), reclamation (复垦), heating (供热), water supply (供水), electricity supply (供用电), solar thermal (光热), seawater desalination (海水淡化), marine resources (海洋资源), environmental pollution (环境污染), energy conservation (节约能源), seedling cultivation (苗木培育), emission (排放), sewage (排污), meteorology (气象), meteorological observation (气象观测), meteorological disasters (气象灾害), thermal energy utilization (热能利用), ecological environment (生态环境), wetlands (湿地), municipal engineering design (市政工程设计), water quality (水质), water resources (水资源), land use (土地利用), land remediation (土地整治), non-hazardous (无害化), non-hazardous treatment (无害化处理), remote sensing (遥感), harmful organisms (有害生物), organic fertilizer (有机肥料), recycling (再生), remanufacturing (再制造)
Keywords excluded from the *job function*	Safety (安全), handling (搬运), office (办公室), security (保安), cleaning (保洁), customs clearance (报关), programming (编程), editing (编辑), finance (财务), procurement (采购), catering (餐饮), storage (仓储), warehouse manager (仓管), warehouse (仓库), tea ceremony (茶艺), workshop (车间), cost (成本), cashier (出纳), chef (厨师), husbandry (畜牧), multimedia (多媒体), legal affairs (法务), distribution (分销), service (服务), vice president (副总), public relations (公关), logistics (后勤), nurse (护士), chemistry (化学), accounting (会计), driver (驾驶员), finance (金融), economy (经济), manager (经理), development (开发), customer service (客服), customer (客户), teacher (老

	师), green (绿化), media (媒介), secretary (秘书), agriculture (农), trainee (培训生), channel (渠道), human resources (人事), finance (融资), software (软件), business (商务), design (设计), audit (审计), production manager (生产经理), production supervisor (生产主管), biological (生物), marketing (市场), after-sales (售后), pre-sales (售前), veterinary (兽医), tax affairs (税务), driver (司机), breeding (饲养), group buying (团购), promotion (推广), health (卫生), logistics (物流), property (物业), project management (项目管理), project manager (项目经理), sales (销售), information technology (信息技术), industry (行业), industry research (行业研究), administration (行政), farming (养殖), medical (医疗), doctor (医生), physician (医师), trade (营业), operations (营运), preschool education (幼教), operations (运营), securities (证券), quality (质量), assistant (助理), general manager (总经理)
Keywords included in the *job function*	EHS (环境、健康、安全管理), waste gas (废气), wind power (风电), solid waste (固废), photovoltaic (光伏), environmental protection (环保), environment (环境), energy saving (节能), water treatment (水处理)

Appendix C: Examples of green job postings

Stock code	*Job title*	*Job description*	*Job function*
000016	R&D Engineer-Solid Waste Treatment Direction (研发工程师-固废处理方向)	<u>Job responsibilities</u>: 1. Responsible for kitchen waste disposal technology research and new technology development. (负责餐厨垃圾处置技术研究和新技术开发) 2. Responsible for the development of technical solutions and engineering design for kitchen waste disposal projects, and organizing the evaluation. (负责餐厨垃圾处置项目技术方案、工程设计方案制订，并组织评审) 3. Responsible for technical support during the construction and operation of kitchen waste disposal projects. (负责餐厨垃圾处置项目建设和运营期间技术支持工作) 4. Cooperate with the maintenance of high-tech enterprise qualification, such as paper publication, patent application, etc. (配合高新技术企业资质维护工作，例如论文发表、专利申请等) <u>Job requirements</u>: 1. Between 28-40 years old, with a master's degree or above in environmental engineering, thermal engineering, engineering thermophysics, chemical engineering or other related majors. (年龄 28-40 岁之间，环境工程、热能工程、工程热物理、化工等相关专业硕士及以上学历) 2. More than three years of experience in engineering design and research and development of kitchen waste disposal and poultry waste disposal is preferred. (有三年以上餐厨垃圾处置、禽粪污处置工程设计和研发经验者优先) 3. Can independently carry out the preparation of technical programs, drawing process flow diagrams, equipment layout, PID diagrams, construction drawings, etc.,	Solid Waste Engineer (固废工程师)

		skilled operation of office, CAD, solidworks and other commonly used software. (能独立开展技术方案编制，绘制工艺流程图、设备布置图、PID 图、施工图等，熟练操作 office、CAD、solidworks 等常用软件) 4. Excellent verbal and written communication skills, strong learning ability. (优秀的语言和书面表达能力、较强的学习能力)	
000969	Fuel Cell Technology R&D (燃料电池技术研发)	Job responsibilities: 1. Master's degree or above. (硕士以上学历) 2. Main research interests include new energy materials and fuel cell technology. (主要研究方向为新能源材料、燃料电池技术等方面) 3. Professional background in fuel cells or related project experience is preferred. (有燃料电池专业背景或相关项目经验优先) 4. Team player, good interpersonal communication, good oral presentation skills. (具备团队合作精神，善于人际交流，具有良好的口才表达能力) 5. Serious and responsible work attitude. (工作态度认真负责) Job requirements: 1. Master's degree or above. (硕士以上学历) 2. Main research interests include new energy materials and fuel cell technology. (主要研究方向为新能源材料、燃料电池技术等方面) 3. Professional background in fuel cells or related project experience is preferred. (有燃料电池专业背景或相关项目经验优先) 4. Team player, good interpersonal communication, good oral presentation skills. (具备团队合作精神，善于人际交流，具有良好的口才表达能力) 5. Serious and responsible work attitude. (工作态度认真负责)	Other (其他)
002717	Wastewater Treatment R&D	Job responsibilities: 1. Responsible for wastewater treatment research and development, project	Water Treatment Engineer (水处理工程师)

Engineer (污水处理研发工程师)	declaration, patent development, technical data preparation and organization, etc. (负责污水处理研发，开展项目申报，专利开发，技术资料编写整理等) 2. Conduct technical analysis, program preparation, provide professional technical support, and solve technical problems for environmental protection engineering in engineering projects. (对工程项目中的环保工程进行技术分析、方案编写，提供专业技术支持，并解决技术难题) 3. Responsible for the development of new methods, technologies and products, such as sewage treatment equipment and processes. (负责污水处理处理设备和工艺等新方法、新技术、新产品的开发) 4. Completion of other work assigned by superiors. (完成上级交办的其他工作) <u>Job requirements</u>: 1. Master's degree or above, majoring in environmental engineering, wastewater treatment or other related fields, junior engineer or above is preferred, and outstanding freshmen are also eligible. (硕士及以上学历，环境工程、污水处理等相关专业，初级工程师或以上职称者优先考虑，优秀应届生亦可) 2. Experience in writing technical documents such as patents, thesis, technical programs, etc., and able to independently write technical feasibility analysis reports. (具有专利、论文、技术方案等技术性文件方面的撰写经验，能独立进行技术可行性分析报告的撰写) 3. Familiar with the principles, methods and equipments of the treatment process of environmental protection engineering, and familiar with the relevant design norms and standards, and the new technology of domestic environmental protection treatment. (熟悉环保工程的处理工艺原理、方法及设备，熟悉相关设计规范及标准，国内环保处理的新技术) 4. Have rich experience in sewage biochemical treatment process, familiar with all

		kinds of common industrial wastewater treatment projects, able to independently complete the sewage treatment engineering program writing. (有丰富的污水生化处理工艺经验，熟悉各类常见工业污水处理项目，能够独立完成污水处理工程方案撰写) 5. Proficiency in AutoCAD, office and other office software. (熟练 AutoCAD，office 及其他办公软件) 6. Strong judgment, analytical and execution skills, strong learning ability, good communication and presentation skills. (具有较强的判断、分析和执行能力，学习能力较强，良好的沟通表达能力) 7. Meticulous work, clear thinking, initiative and responsibility. (工作细心，思维清晰，主动性强，责任心强)	
600517	Building Energy Efficiency Development Engineer (建筑节能开发工程师)	<u>Job responsibilities</u>: 1. Conducting research and consulting services in the field of green building and building energy efficiency. (进行绿色建筑、建筑节能领域的研究、咨询服务) 2. Provision of EMC model building energy efficiency solutions, program design, and business model studies. (EMC 模式建筑节能方案的提供，方案设计，以及商业模式研究) 3. Tracking and integration of domestic and international building energy efficiency technology products. (国内外建筑节能科技产品的追踪集成) 4. Low-carbon, green building applications and building energy efficiency design. (低碳、绿色建筑应用及建筑节能设计) <u>Job requirements</u>: 1. Graduated in construction engineering, HVAC, thermal energy, construction equipment, environmental engineering, electrical, automation, refrigeration and other related majors. (建筑工程类、暖通空调、热能、建筑设备、环境工程、电气、自	Intelligent Building/Integrated Wiring/Security/Weak Power, Building Engineer (智能大厦/综合布线/安防/弱电，建筑工程师)

		动化、制冷等相关专业毕业) 2. More than 3 years working experience in building energy saving or green building, familiar with the products of various equipment manufacturers in building energy saving; working background in relevant energy saving research organizations is preferred. (具有 3 年以上建筑节能或绿色建筑相关工作经验，熟悉建筑节能各设备厂商产品；有相关节能研究机构工作背景优先) 3. Proficient in the use of computers, familiar with CAD and other design software. (熟练使用计算机，熟悉 CAD 等设计软件) 4. Strong presentation skills, able to take on projects individually and report back to the first party. (表达能力强，能够单独承担项目并向甲方汇报) 5. Strong research ability and love for green and ecological building career. (具有较强的研究能力，热爱绿色与生态建筑事业)	
688069	Environmental Operator (环保运行人员)	Skill requirements: Environmentally friendly operation, mechanically operated. (环保运行，机械操作) Job responsibilities: 1. Mainly responsible for the normal operation and maintenance of the company's equipment, etc. (主要负责公司设备的正常运行与维护等工作) 2. Participate in the company's project engineering. (参与公司项目工程建设) Job requirements: 1. Education: Bachelor's degree. (学历：本科) 2. Major: Unlimited, environment, machinery, construction and other related majors preferred. (专业：不限，环境、机械、建筑类等相关专业优先) 3. Experience: Unlimited, Fresh Graduates Acceptable. (工作经验：不限,可接受应届毕业生)	Environmental Engineer, Water Treatment Engineer (环保工程师，水处理工程师)

4. Good character, hard-working and obedient to the company's management. (品行端正、能吃苦耐劳，服从公司管理)
5. Able to adapt to work on a business trip. (能适应外派出差工作)
6. Work location: Kunming, Dali, Yuxi and other places. (工作地点：昆明、大理、玉溪等地)

Treatment and Benefits:
（1） Treatment: Income = Job Salary + Subsidies + Bonus. a. Job Salary: Starting from 2500RMB, finalized according to the interview. b. Subsidies: Expatriate subsidy (70RMB/day outside the province), party allowance (300RMB/month). c. Bonuses: Running assessment bonus, project award. (待遇:收入=岗位工资+补贴+奖金 a、岗位工资：2500 元起，根据面试情况最终确定。b、补贴：外派补贴（省外 70 元/天）、党员津贴（300 元/月）。c、奖金：运行考核奖金、项目奖。)
（2） Probationary period: One month, the probationary period in line with the company's employment conditions, for regularization procedures. (试用期：一个月，试用期满符合公司用人条件者，办理转正手续)
（3） Welfare a. Purchase of insurance and housing fund, regular physical examination, holiday gifts; b. The company provides food and accommodation; c. Overtime on national holidays, overtime pay in accordance with the provisions of the overtime. (福利：a、购买五险一金、定期体检、节日礼品；b、公司提供食宿；c、国家法定节假日加班，按规定发放加班工资)

Appendix D: Validation of the measure of green hiring

This table demonstrates the validity of our indicator *Ln(Green posting)*. We regress on the following indicators instead of the dependent variable. *ESG* is defined as the firms' average ESG rating in year *t+1*. *Ln(Green patent)* is defined as the natural logarithm of the firms' number of green patents applied for in year *t+1* plus one. *Environmental honor & award* is a dummy variable that take the value of 1 if the firm receive honors or rewards for environmental protection in year *t+1*, and 0 otherwise. *Environmental protection activities* is a dummy variable that take the value of 1 if the firm participates in environmental protection activities in year *t+1*, and 0 otherwise. We control for industry-fixed effects and year-fixed effects in all columns. The *t*-values based on standard errors clustered at the firm level are reported in parentheses, and ***, **, and * represent estimated coefficients that are significant at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *ESG*	(2) *Ln(Green patent)*	(3) *Environmental honor & award*	(4) *Environmental protection activities*
Ln(Green posting)	0.329***	0.327***	0.024***	0.015*
	(4.520)	(20.339)	(2.741)	(1.710)
Size	0.573***	0.311***	0.050***	0.076***
	(6.885)	(18.880)	(5.225)	(8.003)
Leverage	-4.386***	0.229***	0.029	-0.055
	(-10.734)	(3.597)	(0.785)	(-1.473)
ROA	20.403***	0.567***	0.244***	0.042
	(24.939)	(5.099)	(3.596)	(0.674)
Growth	0.272***	0.023	-0.010	-0.007
	(2.739)	(1.413)	(-1.071)	(-0.710)
MTB	-0.160***	0.024***	0.004	0.009**
	(-3.762)	(3.293)	(0.908)	(2.190)
Largest	0.023***	0.001	0.001*	0.001
	(4.340)	(0.793)	(1.726)	(1.382)
INS	-0.007**	-0.001	0.000	0.001*
	(-2.004)	(-1.353)	(0.453)	(1.809)
Analyst Coverage	0.911***	-0.021	0.028	0.015
	(4.326)	(-0.570)	(1.143)	(0.687)
SGA/Sales	-2.491***	0.015	-0.047	0.010
	(-4.800)	(0.192)	(-0.972)	(0.197)
RD/Sales	8.848***	2.118***	0.101	-0.011
	(4.096)	(5.961)	(0.580)	(-0.061)
CAPX/TA	11.238***	0.188	0.327**	0.178

	(8.674)	(0.753)	(2.139)	(1.258)
CSR/ESG Report	4.411***	0.113***	0.327***	0.542***
	(27.076)	(3.504)	(13.779)	(22.043)
Intercept	59.185***	-6.477***	-1.030***	-1.601***
	(32.909)	(-17.972)	(-4.911)	(-7.808)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	17,760	18,183	18,175	18,175
Adj R^2	0.334	0.377	0.114	0.192

Appendix E: Variable definition

Variables	Definition
Dependent variables	
Green posting	We select 38 seed words with reference to the definitions of 134 "Green Occupations" added in the revised "Dictionary of Occupational Classification of the People's Republic of China". For each seed word, we use the word2vec method to search for and filter out the top 50 near-synonyms with the highest degree of similarity as a keyword thesaurus for identifying green recruitment, and then manually verify the keyword thesaurus with the *job description* in the postings, finally identifying 123 keywords for recognizing green job. Secondly, we search the *job description* of each corporate job posting, and identify the job posting as a green job posting if at least one green job keywords we defined in Appendix B appeared in the *job description*, otherwise identify it as a non-green job posting. After completing the match identification, we also use the information provided in the job postings, such as *job function*, for validation and exclusion to further minimize the impact of matching errors. *Green posting*, is defined as the original number of green job postings made by a firm in year *t+1*.
Ln(Green posting)	The natural logarithm of one plus the total number of green job postings made by a firm in year *t+1*.
Green dummy	A dummy variable that equals one if the firm made green job postings in year *t+1*, and zero otherwise.
Ln(Other posting)	The natural logarithm of one plus the total number of non-green job postings made by a firm in year *t+1*.
Green portion	The ratio of the number of green job postings made by a firm divided by the total number of job postings in year *t+1*.
Independent variables	
Punish	A dummy variable that equals one if the firm is subject to environmental punishment in year *t*, and zero otherwise.
Punish_High_Fines	We sum up the amount of environmental punishments received by firms each year, and calculated the median of the total annual fine amount for all firms in each year. *Punish_High_Fines* is a dummy variable that equals one if the firm's annual fine amount is higher than the median in year *t*, and zero otherwise.
Punish_Low_Fines	A dummy variable that equals one if the firm's annual fine amount is lower than the median in year *t*, and zero otherwise.
Control variables	

Size	The natural logarithm of total assets.
Leverage	Total liabilities divided by the total assets.
ROA	Net income divided by total assets.
Growth	Annual change in sales scaled by lagged total sales.
MTB	The market value at the end of the fiscal year over book value of the equity.
CAPX/TA	The capital expenditure divided by total assets.
R&D/Sales	The R&D expense divided by total assets.
SG&A/Sales	The selling and administrative expense divided by total assets.
Largest(%)	Percentage of shares owned by the largest shareholder.
INS(%)	Percentage of shares owned by institutional investors.
Analyst Coverage	A dummy variable that equals one if the firm is followed by at least one analyst, and zero otherwise.
CSR/ESG Report	A dummy variable that equals one if the firm releases CSR report or ESG report in a given year, and zero otherwise.
Other variables	
Improvement	A dummy variable that equals one if the firm is subject to environmental punishment in year *t+1* but not in year *t+2*, and zero otherwise.
Fines_reduction	A dummy variable that equals one if the amount of fines imposed on the firm in year *t+2* is less than the amount in year *t+1*, and zero otherwise.
Ln(Green patent)	Natural logarithm of the total number of green patent applications by firms plus one in year *t+1*.
L1_Punish_city	The total number of punished firms in the city in which the focal firm is located in year *t-1*.
Reform	A dummy variable that equals one if the province where the firm is located has implemented the verticalization reform, and zero otherwise.
High Legal Score	A dummy variable that equals one if the rule-of-law level scores from Fan et al. (2019) are above the median value of scores based on the scores in 2013, and zero otherwise.
Peer Punish	First, we exclude the sample of firms that received environmental punishments in year *t*. Then *Peer Punish* is defined as a dummy variable that equals one if there are firms in the focal firm's industry that receive environmental punishments in year *t*, and zero otherwise.
Government concern	The ratio of the number of environment-related keywords in provincial government work reports to the total number of words.
Public concern	The number of environmental letters at the province level.
Environmental court	A dummy variable that takes the value of one if the city where the

	firm is located has set up a specialized environmental court, and zero otherwise.
Legal score	The province-level rule of law level scores from Fan et al. (2019).
SOE	A dummy variable that takes the value of one if the firm is a State-owned enterprise, and zero otherwise.
KZ	KZ index, referring to Kaplan and Zingales (1997).
Punish_High_Fines	A dummy variable that takes value of one if the firm's total amount of fines is above the median in given year, and zero otherwise.
Punish_Low_Fines	A dummy variable that takes value of one if the firm's total amount of fines is below the median in given year, and zero otherwise.
Polluter	A dummy variable that takes value of one if the firm belongs to a highly polluting industry, and zero otherwise.
Taxation	A dummy variable that takes value of one in years after the implementation of environmental protection tax law in 2018, and zero otherwise.

Appendix F: Balancing test

Panel A: Nearest neighbor 1:1 propensity score matching

	Control		Treat		
Variable	N	Mean	N	Mean	MeanDiff
Size	967	22.362	967	22.393	-0.031
Leverage	967	0.465	967	0.463	0.002
ROA	967	0.024	967	0.027	-0.003
Growth	967	0.150	967	0.173	-0.023
MTB	967	2.121	967	2.129	-0.009
Largest	967	34.783	967	34.595	0.189
INS	967	45.254	967	45.249	-0.005
Analyst Coverage	967	0.160	967	0.172	-0.011
SGA/Sales	967	0.163	967	0.160	0.002
RD/Sales	967	0.007	967	0.006	0.000
CAPX/TA	967	0.045	967	0.045	-0.000
CSR/ESG Report	967	0.297	967	0.284	0.013

Panel B: Overall entropy balance matching

		Control			Treat	
Variable	N	Mean	SD	N	Mean	SD
Size	11124	22.491	1.192	7085	22.492	1.192
Leverage	11124	0.466	0.202	7085	0.467	0.202
ROA	11124	0.027	0.074	7085	0.027	0.074
Growth	11124	0.155	0.438	7085	0.155	0.437
MTB	11124	1.981	1.346	7085	1.981	1.346
Largest	11124	33.736	14.472	7085	33.713	14.477
INS	11124	44.797	23.562	7085	44.797	23.553
Analyst Coverage	11124	0.120	0.325	7085	0.119	0.324
SGA/Sales	11124	0.152	0.123	7085	0.152	0.123
RD/Sales	11124	0.015	0.026	7085	0.015	0.026
CAPX/TA	11124	0.044	0.042	7085	0.044	0.042
CSR/ESG Report	11124	0.283	0.451	7085	0.283	0.451