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# Opportunity or Curse: Can Green Technology Innovation Stabilize Employment?

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**Abstract:** This study examines the influence of green technology innovation on employment in enterprises and explores the potential mechanisms behind this impact, which is critical to understanding the social impact of the green transition in the climate change scenario. This paper, based on detailed data from listed corporations in China between 2010 and 2020, discovers that the introduction of green technology innovation by corporations has a substantial positive impact on employment levels. The effects of green technology innovation on employment are both persistent and heterogeneous; they persist even two years later, with more significant effects observed in non-heavy-polluting industries, state-owned enterprises, and highly educated employees. This article also carries several policy implications. The findings presented in this paper provide useful insights into the potential employment consequences of the green transition as well as the reactions and adjustment behaviors that corporations exhibit in the low-carbon transition. Additionally, this development holds significant implications for other developing nations grappling with the challenges of switching to environmentally sustainable practices.

**Keywords:** green technology innovation; enterprise employment; green patent; scale expansion effect; factor complementarity effect



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## 1. Introduction

China's economy has witnessed unprecedented growth since reforming and opening up in 1978. Compared with the increased economic volume and people's income, significant environmental issues have arisen. The manufacturing-centric development paradigm has resulted in a substantial volume of greenhouse gas emissions, with a stunning 10,944,686 kilotons of carbon dioxide discharged into the atmosphere in 2020 alone (data source: https://data.worldbank.org/indicator/EN.ATM.CO2E.KT?locations=CN, accessed on 23 May 2024). China's green transition is of the utmost urgency due to the environmental challenges created by greenhouse gas emissions and concerns about long-term climate change. China's dedication to achieving the 'Dual Carbon' objectives, along with the execution of a range of action plans, is expediting the country's progress in green transition. Green technology innovation stands as a pivotal advancement in the realm of technological progress, encompassing the strategic deployment of technological solutions to minimize environmental pollution, optimize resource efficiency, and ultimately foster a more environmentally friendly and resource-conscious society. Enterprises' green technology innovation plays a crucial role in driving China's green transition, serving as the most significant factor in economic and social development and the primary contributor to the reduction of carbon emissions. As a result, several discussions have focused on the effects of green technology innovations on social development, such as employment, income, and skilled wage premiums.

Scholars have investigated the significant impact of green technology innovations on employment [1,2]. Employment is the largest livelihood project and the foundation of social stability, which is the 'barometer' of economic development and also an important support for the proper range of economic operations. Resolving the employment issue is crucial for promoting people's well-being, social harmony, and stability. Unfortunately, the COVID-19 pandemic, energy market volatility, and the green transition have posed major challenges to the development of the world economy. Currently, many countries are facing the dual pressures of low carbon transition risks and rising unemployment [3], while employment instability has the potential to have a pervasive impact on all levels of society [4]. Therefore, starting at the microenterprise level, this paper measures the impact of enterprise green technology innovation on employment, providing certain insights for comprehensive green transformation and enterprise climate adaptation.

The existing literature has discussed green technology innovation's impacts on employment in developed countries such as the United States, Japan, and various European countries, and the results suggest a significant positive relationship between green technology innovation and employment [5–7]. However, developing countries receive insufficient attention, with only a few studies demonstrating that green technology innovation enhances employment structures at the provincial level [8] and the industry level [9,10]. It is clear that talking about the link between green technology innovation and jobs at the micro-level has big policy and practical impacts. This is especially true in developing countries, where the industrial structure's high energy intensity will make the green transition and removal of old infrastructure even more pressing, which will further increase structural unemployment in the labor force.

This paper, concentrated on China, has the following considerations: First, China is the second-most populated country globally; its population will exceed 1.425 billion in 2024 (data source: https://www.worldometers.info/world-population/#google_vignette, accessed on 25 June 2024). Consequently, the issue of employment in China warrants significant attention. Furthermore, given China's significant efforts to reduce emissions, it is critical that the country undergo a green transition in order to successfully achieve the dual-carbon target. The potential displacement of jobs and the subsequent emergence of new employment opportunities resulting from economic structural transformation will exert a substantial influence on China's economic stability. In this context, studying the impact of green technology innovation is extremely important. Meanwhile, detecting the employment problem during China's green transition can provide valuable insights for other emerging countries, given that China is the world's largest developing nation. Therefore, this paper bases its analysis on the A-share listed companies in China from 2010 to 2020, along with the corresponding economic data, to measure the impact of green technology innovation on employment and its mechanisms. The research finds that green technology innovation can significantly enhance enterprises' employment levels, achieving the dual benefits of environmental protection and job promotion. The scale expansion effect and the factor complementarity effect are two paths by which green technology innovation promotes employment in enterprises.

Compared with existing research, this paper contributes in the following ways: First, it expands the study of the employment effects of green technology innovation to the micro-level of enterprises, contributing to the understanding of the micro-mechanisms and empirical evidence of the relationship between green technology innovation and employment, filling the research gap in this micro-field and the empirical evidence from developing countries. Second, this paper is the first to use a combination of text analysis and manual judgment to construct a tool variable for green technology innovation, which is innovative and attractive for future research. Third, this paper reveals two mechanisms of the impact of green technology innovation on employment in enterprises and finds that the employment effects of green technology innovation are persistent and heterogeneous. These explorations and verifications contribute to enriching the understanding of the impact of green technology innovation on employment in both theory and practice.

The rest of this paper is organized as follows: Section 2 provides the theoretical basis and develops the hypotheses. Section 3 outlines the research design employed in this work.

Section 4 shows the findings of this study. In Section 5, we conduct additional analyses. Section 6 summarizes the conclusions and offers policy implications.

## 2. Theoretical Analysis and Research Hypotheses

Although research on green technology innovation started relatively late, there is an increasing diversity in the perspectives of related studies. More and more of the literature focuses on the driving factors, environmental benefits, and economic effects of green technology innovation. Moreover, recent scholars have conducted rich research on the internal and external environments that promote green technology innovation [11,12], the relationship between green technology innovation and economic development [13], the link between green technology innovation and firm performance [14–16], and the connection between green technology innovation and digitization [17].

However, there are few studies on the impact of green technology innovation on corporate employment. One relevant category of the literature is the study of environmental regulations' employment effects, which has formed two opposing views. The first view holds that environmental regulations have a significant positive impact on labor employment and can achieve the dual dividend of environmental protection and employment. Carraro et al. [18] proposed the double dividend hypothesis, which suggests that the implementation of environmental taxes can reduce carbon emissions while increasing labor employment. The shift from end-of-pipe technologies to cleaner production technologies creates more job opportunities [19,20]. Berman and Bui [21], Walker [22], and Yip [23] found that environmental regulation policies can stimulate the reconfiguration of production factors and create more job opportunities, such as the significant growth of employment in the clean industry after the introduction of environmental regulation policies. Horbach and Rennings [13] found that green innovation can promote employment, especially for those who save on energy consumption. Kunapatarawong and Martínez-Ros [5] found a positive correlation between green technology innovation and employment, and this relationship is more apparent in 'dirty' firms. Zhong et al. [12] found that environmental regulation will have a heterogeneous impact on the employment of people with different skills. Zhang et al. [3] conducted an empirical analysis and found that implementing low-carbon city pilot policies significantly improves employment levels. Besides that, Pascucci et al. [24] point out that environmental awareness and personal norms for acting in a pro-environmental way have a positive influence on the sustainable entrepreneurial attitudes of college students.

The second viewpoint argues that environmental regulations can result in 'brown' job losses, leading to a dual paradox of incompatibility between environmental protection and employment. Orlitzky [25] found that under stricter environmental standards, the introduction of new green patents by enterprises can enhance production efficiency, potentially leading to the substitution of some labor, which may result in a reduction in employment opportunities. A significant number of green innovation initiatives have led to an increase in production costs for enterprises, prompting them to implement measures such as production reductions and work stoppages. These actions have subsequently diminished the scale of production within enterprises, ultimately resulting in a decrease in labor demand. Yamazaki et al. [26] and Hafstead and Williams [27] believe that the production costs of companies will continuously increase during the process of technological transformation, squeezing out productive investments and significantly reducing labor demand. Carrión-Flores [28] points out that a significant number of green innovation activities have increased the production costs of enterprises, forcing them to take measures such as reducing production and suspending operations. This has led to a decrease in the scale of production within enterprises, subsequently resulting in a reduction in the demand for labor. Under environmental regulation, the employment of different regulatory departments exhibits heterogeneity, and the implementation of environmental green transformation regulations significantly reduces the employment of heavily polluting industries [29]. Qin et al. [30], based on micro-data from Chinese listed companies, found that the improvement in environmental regulation levels prompts companies to reduce labor demand. Overall, there is no consensus on the impact of green technology innovation on corporate employment.

Based on the above analysis, the following hypotheses are proposed regarding the employment effects of green technology innovation:

**H1a:** *Green technology innovation may promote employment, resulting in a dual dividend of energy conservation and emissions reduction, as well as employment growth.*

**H1b:** *Green technology innovation may reduce employment, resulting in the dual paradox of environmental protection and employment reduction.*

According to the 'Porter Hypothesis' by Poter [31], environmental regulation drives enterprises to engage in technological innovation, actively introduce advanced clean production equipment, improve production efficiency, optimize production processes, generate 'innovation compensation', and obtain 'first mover advantage' to enhance enterprise competitiveness and make optimal decisions [32]. With the continuous strengthening of environmental protection measures in recent years, the high cost of environmental regulations encourages companies to engage in research and development of green technologies [33]. The improvement in green technology innovation creates new opportunities for corporation development [23], and it provides more vacancies for highly skilled laborers in enterprises [9,34]. Moreover, Harrison et al. [10] and Berman and Bui [21] also found that the application of new technologies leads to a reduction in overall production costs and an expansion of production scales, ultimately resulting in an increase in labor demand. This reflects the effects of the scale expansion of green technology innovation. More specifically, Kunapatarawong and Martínez-Ros [5] argue that the employment effects are more notable in heavy-pollution sectors. The findings above demonstrate that enterprise green technology innovation has the potential to generate new opportunities, reduce expenses, steer development in new directions, and offer additional job opportunities, thereby contributing to a scale expansion effect.

However, during the research and application of green technologies in the production process, enterprises need to invest a magnificent amount of R&D funds and import internationally advanced production equipment. This internalizes some external costs for the corporations, increases their production costs [35], raises product prices, reduces product demand, causes a decline in corporation scale, and subsequently decreases the demand for labor [36], resulting in an adverse impact on overall employment levels, known as scale reduction effects. Meanwhile, Mondolo [37] holds the point that technological innovation will optimize the allocation of labor force, which may eliminate low-skilled workers in corporations, and it also leads to scale reduction effects. Besides that, existing studies agree that the relationship between green technology innovation and employment is complex and heterogeneous in terms of different goals. If enterprises aim to reduce costs by introducing green technology, the employment effects are negative [19,38], which also proves the scale reduction effects.

Whether corporations choose to apply green technologies in the production process or at the end of production, they need to increase fixed assets and intangible assets for green patent research and development, prompting corporations to increase labor input that matches green technology research and development [35]. This may lead some companies to prefer using labor as a substitute for expensive production factors that create pollution [39]. The application of green technologies also increases the production process, necessitating the employment of more employees to produce a given output [40]. This complementary relationship between green technology innovation and labor demand is known as factor complementarity. However, increasing environmental investments may crowd out some productive investments and labor expenses, resulting in a 'crowding-out effect' [30]. This leads to a decline in the demand for labor per unit of output [41]. This indicates that there is a substitution relationship between green technology innovation and labor demand.

In summary, the relationship between green technology innovation and enterprise employment levels, as shown in Figure 1, depends on the scale and factor effects. Based on the upper analysis, this paper proposes the following hypotheses about the impact of green technology innovation on corporate employment:

**H2a:** *Green technology innovation will increase corporation employment levels through scale expansion effects and factor complementarity effects.*

**H2b:** *Green technology innovation will reduce corporation employment levels through scale reduction and factor substitution.*

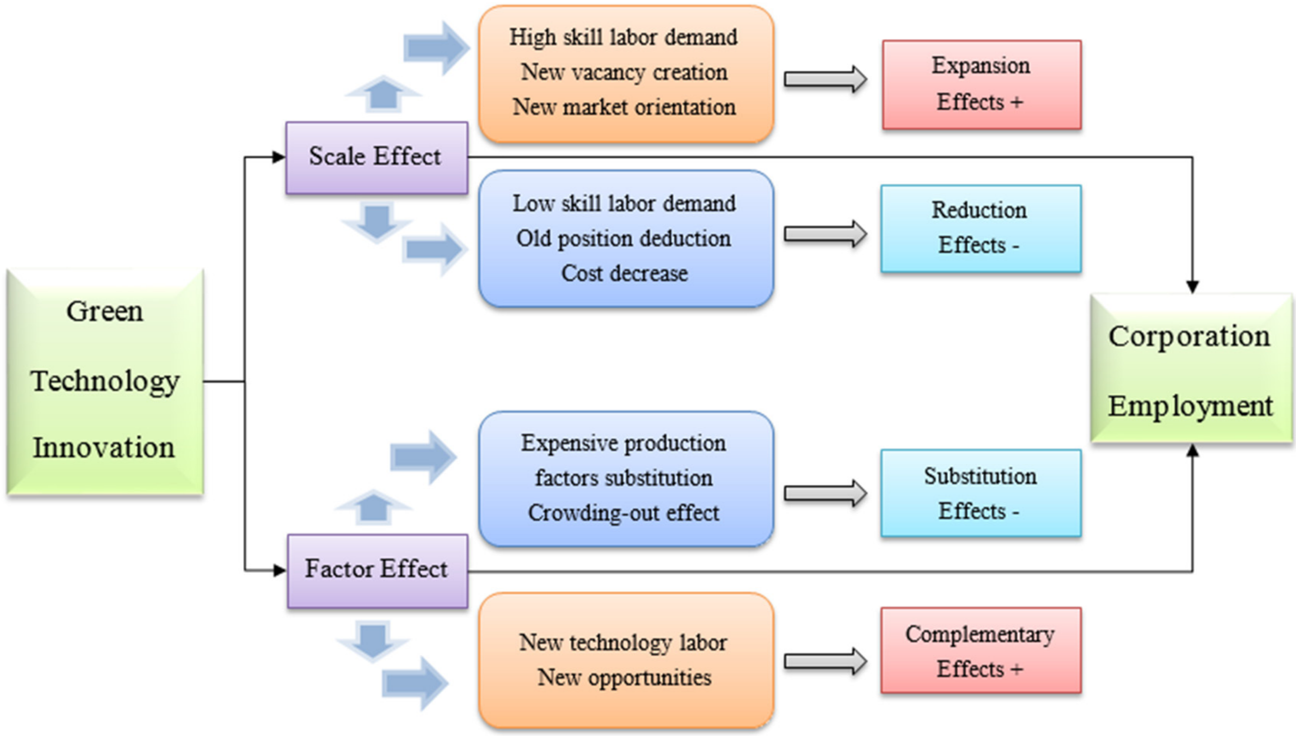


**Figure 1.** The impact mechanism of green technology innovation on the employment level of enterprises. Note: The content in Figure 1 is based on previous literature analysis.

## 3. Research Design

### *3.1. Data*

This section outlines the data sources and selection process for Chinese A-share listed corporations' green technology innovation data from 2010 to 2020, as well as the corresponding economic data at the enterprise and city levels. Two main steps are involved in selecting green technology innovation data from listed companies: first, we obtain the patent data of listed companies for each year from the National Intellectual Property Administration, and then we use the World Intellectual Property Organization's Green Inventory tool, launched in 2010, to identify and extract the green patent data of listed companies based on the International Patent Classification (IPC) codes. The CSMAR database provides the economic data at the listed company level, and the China City Statistical Yearbook for each year provides the city-level economic data.

This paper then explains the steps taken to select and process the research sample: (1) It excluded listed companies in the financial, real estate, wholesale and retail, accommodation, and catering sectors, as well as the agricultural, forestry, animal husbandry, and fishery sectors, and only retained listed companies in the manufacturing sector. (2) The sample excludes ST stocks, which are stocks under special treatment due to financial difficulties or other issues, as well as *ST stocks, which indicate a more terrible financial situation than ST stocks and are under heightened supervision, as well as delisted companies. (3) It also excluded listed companies with negative total asset return on investment and abnormal asset–liability ratios. (4) Listed companies with severe missing key data are also excluded. And (5) it manually selected partial missing data for individual listed companies from their annual reports. Applying these five steps yields a panel dataset of 16,756 valid samples from a total of 2410 listed companies. All continuous variables are winsorized at the 1% level to eliminate the influence of extreme outliers on the research results.

### *3.2. Model Settings*

To analyze the impact of green technology innovation on employment in enterprises, we construct the fixed effects model to realize it. Compared with the Ordinary Least Squares (OLS) regression, this model assumes that differences between individuals can be accommodated from different intercepts, which perfectly resolves the problems caused by cross-section and time difference and provides more exact results. Therefore, it has frequently been applied in recent research [42,43]. In this paper, empirical model encompasses both enterprises and years in the baseline regression and has further mitigated potential biases by controlling for the interactive fixed effects of cities and years in the robustness checks. The specific details are as follows:

$$labor_{it} = \beta_0 + \beta_1 GrePatNum_{it} + \rho X_{ict} + \alpha_i + \delta_t + \varepsilon_{it} \tag{1}$$

where the subscripts $i$, $c$, and $t$ represent the variables for firm, city, and year, respectively. The dependent variable $labor_{it}$ represents the employment level of firm $i$ in year $t$. The primary explanatory variable $GrePatNum_{it}$ represents the number of green patents applied by firm $i$ in year $t$. $X_{ict}$ represents a series of control variables at the firm level and city level that may affect employment. Additionally, the model controls for firm fixed effects $\alpha_i$ and year fixed effects $\delta_t$, and $\varepsilon_{it}$ represents the random disturbance term. The coefficient of $\beta_1$ in this study is the core focus, which represents the employment effect of green technology innovation. If this coefficient is significantly greater than 0, it indicates that green technology innovation increases the employment level of firms. Conversely, if the coefficient is negative, it suggests that green technology innovation decreases the employment level of enterprises.

While this paper has adopted a two-way fixed-effects model, there remains a potential endogeneity issue due to a possible reverse causality between green technology innovation and corporate employment. Specifically, an increase in the scale of corporate employment might motivate enterprises to prioritize the use of green patents for environmental protection. To address the endogeneity issue that may exist between green technology innovation and enterprise employment, this paper employs the instrumental variable (IV) approach. First, we use a combination of text analysis and manual judgment to scrutinize the texts pertaining to green, environmental protection, innovation, and research and development (R&D) in the State Council's government work reports from 2010 to 2020. We judge each term individually to determine its alignment with the concept of green technology innovation, and after aggregation, we calculate the proportion of relevant vocabulary. Next, the instrumental variable for green technology innovation ($Keyword_t \times lnR\&D_{t-1}$) is made by multiplying the percentage of words used to describe green technology innovation by the value of R&D spending by businesses over a period of time (logarithmically transformed).

The instrumental variables constructed in this way have good externality. First, the government's attention to green technology innovation will stimulate enterprises to carry out green technology innovation through the policy transmission effect and green policy tools. Secondly, the implementation of green technology innovation policies at the government level will not have a direct impact on employment at the enterprise level. Therefore, using it as an instrumental variable can effectively solve potential endogenous issues.

### 3.3. Variables

Dependent variable: firm employment. Referring to the studies of Wang and Ge [35], this paper uses two methods to measure firm employment. The first method measures firm employment in terms of the absolute scale of the number of employees (labor) by taking the logarithm of the total number of employees in the firm in a given year. The second method measures firm employment in terms of the employment growth rate (labor growth) by dividing the total number of employees in the firm in a given year by the total number of employees in the previous year and then subtracting 1. Baseline regression primarily uses the former, while robustness tests use the latter.

Explanatory variable: green technology innovation. Effectively measuring a firm's green technology innovation is a key issue in this paper. Drawing on the mature practices of Xu and Cui [44], the core measure of green technology innovation is the number of green patents applied by the firm. (A green patent is one that uses green technology as the invention's subject matter. It should have a direct and obvious technical effect of reducing or stopping the consumption of natural resources, as well as being environmentally friendly in comparison to prior art). There are two main reasons for selecting this indicator: Firstly, compared to research and development investment and green total factor productivity, green patents are more intuitive and quantifiable. Secondly, due to the lengthy process from patent application to authorization, the performance of the enterprise may be affected during the patent technology application process. Therefore, patent application data can better reflect the firm's innovation level and have more timeliness compared to patent authorization data. We can further divide green patents into green invention patents and green utility model patents, with the former being more innovative and valuable than the latter.

Mechanism variables: To assess the impact of scale, the logarithm of total assets listed in the balance sheet is utilized as an indicator of the scale factor. Furthermore, in order to examine the factor effect, the proportion of corporate environmental investment is represented by the percentage of cash expended on fixed assets, intangible assets, and other long-term assets, as outlined in the cash flow statement.

Control variables. Drawing on the existing literature from domestic and international sources, this study selects the following eight variables as control variables: First, firm-level controls, the size, revenue capacity of the business, and other aspects are company-level features that might influence company performance, as discussed in several studies [45,46]. (1) Firm size (size). Generally, larger firms tend to have more employment [35]. This paper measures firm size using the logarithm of total assets. (2) Capital structure (lev). Entrepreneurs make full use of borrowed funds to hire labor and develop patents. This paper measures capital structure using the ratio of total liabilities to total assets at the end of the period. (3) Profitability (roa). Firm profitability is an important factor influencing the number of employees [47]. A higher ratio indicates better control of labor input. This paper measures profitability using the ratio of net profit to total assets. (4) Growth ability (growth). The faster the growth rate of a company's revenue, the greater its growth potential and the better the market prospects, which will increase the demand for more labor. It measures firm growth using the growth rate of operating income. (5) Capital intensity (ci). Compared to labor-intensive industries, companies in capital-intensive industries tend to employ relatively fewer laborers. In this article, capital intensity is measured by the ratio of total assets to operating revenue of the company. (6) Ownership nature (soe). Different ownership types of firms, such as state-owned enterprises, have significant differences in size and policy support, which lead to significant differences in employment levels. This paper sets a virtual variable for state-owned enterprises based on the different categories of actual controllers. If the actual controller is state-owned, the value is 1; otherwise, it is 0.

Additionally, this paper controls several macro variables. (1) City economic development level (pgdp). Labor demand closely relates to the level of economic development in the city where the firm is located. This paper uses the logarithm of per capita GDP. (2) City wage level (pwage). Employment closely correlates with the wage level of employees in the city where the firm is located. This paper measures the wage level using the logarithm of the per capita wage in the city.

Table A1 in Appendix A reports the descriptive statistics of the main variables. During the sample period, Chinese listed companies averaged 7.6972 employees, ranging from a minimum of 5.4424 to a maximum of 10.8415. This indicates an increasing trend in the total number of employees in these companies. The average number of green patent applications is 0.9883, with a standard deviation of 1.1867. The minimum value is 0, and the maximum value is 4.7274. This suggests that the level of green technology innovation in the sampled listed companies is relatively low, and there is a significant difference in green technology innovation levels among different companies. Furthermore, most of the control variables selected for this study have standard deviations smaller than their means at the firm and city levels, indicating reasonable data distribution and sample stability.

## 4. Results

### *4.1. Benchmark Regression Results*

This article uses Equation (1) to examine the impact of green technology innovation on company employment. Table 1 displays the baseline regression results, which show a significant increase in firm employment levels due to green technology innovation, resulting in both energy conservation and job creation, thereby supporting hypothesis H1a. This study accounts for firm fixed effects and year fixed effects in columns (1) to (6) of Table 1, clustering robust standard errors at the firm level. Specifically, the core explanatory variable in the first two columns is the total number of green patent applications. In column (1), which does not consider firm- and city-level control variables, *GrePatNum's* coefficient estimate is 0.1120 and significantly positive at the 1% level. Column (2) represents the estimation results when considering the control variables. The coefficient estimate for *GrePatNum* is 0.0228; although it has decreased, it still remains significantly positive at the 1% level.

**Table 1.** The impact of green technology innovation on employment.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *GrePatNum* | 0.1120 ***<br>(0.0086) | 0.0228 ***<br>(0.0040) | | | | |
| *GreInvPatNum* | | | 0.1182 ***<br>(0.0102) | 0.0176 ***<br>(0.0048) | | |
| *GreUtyPatNum* | | | | | 0.1095 ***<br>(0.0095) | 0.0143 ***<br>(0.0044) |
| Controls | No | Yes | No | Yes | No | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 16,756 | 16,756 | 16,756 | 16,756 | 16,756 | 16,756 |
| Adjusted $R^2$ | 0.9042 | 0.9624 | 0.9034 | 0.9623 | 0.9030 | 0.9623 |

Note: (1) *** represents statistical significance at the 1% level. (2) The numbers in parentheses indicate robust standard errors clustered at the firm level, which apply to all the tables below. (3) Due to space limitations, regression results for company-level and city-level control variables, company dummy variables, and yearly dummy variables were not reported. The same applies to the following tables. (4) The data presented in this table were attained through our own calculations.

Furthermore, when distinguishing between different types of green patents, the core explanatory variables in columns (3) and (4) are the number of green invention patents. Without including firm- and city-level control variables, the coefficient estimate of *GreInvPatNum* is significantly positive at the 1% level. After including control variables, *GreInvPatNum's* coefficient estimate decreases but remains significantly positive at the 1% level. The economic implication is that an increase of 1% in green patents drives a 1.76% increase in employment within the enterprise. The last two columns show the number of green utility model patents. Like the first four columns, the main variables that explain the data are significantly positive at the 1% level, even when firm- and city-level control variables are taken into account. Comparing the coefficients in columns (4) and (6) reveals that green invention patents, exhibiting higher levels of novelty and value, exhibit more pronounced employment effects of green technology innovation. In summary, green technology innovation has a significant positive impact on corporate employment, which can achieve the dual dividend of environmental protection and employment. The conclusion is also relatively consistent with the literature by Kunapatarawong and Martínez-Ros [5], Horbach and Rennings [13], and Yip [23].

### 4.2. Robustness Tests

Replacement of the dependent variable. Considering the potential bias in using the absolute scale measure of the number of employees, this study replaces the original dependent variable with the growth rate of the number of employees for robustness testing. Column (1) of Table A2 (in Appendix A) presents the estimation results, showing a significantly positive coefficient estimate of *GrePatNum* at the 10% significant level. Although the significance level decreases compared to the baseline regression, it still indicates that green technology innovation improves employment, supporting the robustness of the baseline analysis.

Replace the core explanatory variable. This study employs the proportion of green patents a firm applies to its total patent applications in a year as a robustness indicator to mitigate the potential bias resulting from unobservable motivations for patent applications. As shown in column (2) in Table A2 (see Appendix A), the regression results show that the coefficient estimate of *GrePatRatio* is significantly positive at the 5% level. This backs up the research findings from the baseline regression.

Some firms have never applied for green patents during the sample period, which may introduce bias in the regression results. Therefore, we have excluded corporations that have never applied for green patents. The results reported in column (3) of Table A2 suggest that the coefficient estimate of *GrePatNum* remains significantly positive at the 1% level, indicating no significant change in the empirical results and confirming the research findings' reliability.

The regression method was replaced. Descriptive statistics indicate that the dependent variable *GrePatNum* has a left truncation of zero. Therefore, using the panel Tobit regression method may provide a better fit to the sample data. The regression results in column (4) in Table A2 demonstrate that even after replacing the regression method, green technology innovation still significantly enhances the level of employment, confirming the research conclusions of this study.

Interactive fixed effects were introduced. This study considers the Bai [48] approach, introducing interactive fixed effects of city and year to better capture time-varying characteristics and control for omitted variables. Even when interactive fixed effects are taken into account, the estimation results in column (5) of Table A2 show that green technology innovation still significantly increases firm employment. This is more evidence that the research findings in this study are robust.

### 4.3. Endogeneity Issues

To address the endogeneity issue, this paper employs the instrumental variable (IV) approach. Table 2 presents the results of the two-stage least-squares estimation. Column (1) reports the regression results of the first stage using the instrumental variable. The calculated coefficient of the instrumental variable $Keyword_t \times lnR\&D_{t-1}$ is significantly positive at the 1% level. This means that there is a correlation between the instrumental variable and the endogenous explanatory variable, which meets the relevance requirement. Column (2) displays the results of the second-stage regression using the instrumental variable, demonstrating a significant increase in enterprise employment levels through green technology innovation. In addition, the *F*-statistic value of the first-stage regression is 343.67, which is significantly larger than the critical value of 10, indicating no weak instrument problem. The *p*-value in the under-identification test is less than 0.01, indicating a significant rejection of the null hypothesis of inadequate instrument identification at the 1% level, suggesting no under-identification problem in this paper. Therefore, using the instrumental variable approach to address the endogeneity issue further enhances the credibility of the research findings in this paper.

**Table 2.** Test results using instrumental variable method.

| Variables | (1) | (2) |
|---|---|---|
| | ***GrePatNum*** | ***Labor*** |
| *GrePatNum* | | 0.1183 *** (0.0185) |
| $Keyword_t \times lnR\&D_{t-1}$ | 0.1677 *** (0.0130) | |
| Controls | Yes | Yes |
| Firm fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| First stage *F*-statistic | 343.67 (0.0000) | |
| Incomprehensible test | | 388.954 *** (0.0000) |
| Observations | 16,756 | 16,756 |
| Adjusted $R^2$ | 0.4253 | 0.5857 |

Note: (1) The values in the parentheses for the first stage *F*-statistic and the values for the *p*-value corresponding to the statistic for the test of insignificance. (2) The data presented in this table were calculated in this paper. (3) *** represents statistical significance at the 1% level.

## 5. Further Discussion

### *5.1. Potential Mechanisms*

The theoretical analysis from the previous discussion suggests that green technology innovation impacts employment in corporations through two main mechanisms. First, the increase or decrease in production scale due to green technology innovation activities could lead to a corresponding increase or decrease in labor demand, thereby creating a scale effect. Second, green technology innovation activities may lead to an increase in fixed assets and intangible assets used for green patent research and development. The corresponding increase in environmental protection investment could potentially substitute or complement labor factors, thereby creating a factor effect.

Table 3, column (1), presents the estimated results of the impact of green technology innovation on firm size. The coefficient estimate is significantly positive, suggesting that green technology innovation can significantly increase firm size. In column (2), this article further examines the relationship between enterprise size and employment, and the results show that the coefficient of size is significantly positive at the 1% level. The results of these two columns indicate that green technology innovation significantly promotes employment in enterprises through the scale expansion effect. This conclusion is also in line with the findings of Harrison et al. [10], Carrión-Flores et al. [28], and Wang and Ge [35].

The estimation results of the impact of green technology innovation on the proportion of environmental protection investment by enterprises are shown in Table 3, column (3). The estimated coefficient of *GrePatNum* is significantly positive at the 1% level, indicating that an increase in green technology innovation will increase enterprises' environmental protection investment. This article further explores the relationship between the proportion of environmental protection investment and employment in column (4), revealing a significant positive investment at the 1% level. This indicates that investment in green patent research and development for environmental protection is complementary to labor factors. The results of these two columns indicate that green technology innovation significantly improves enterprise employment levels through the factor complementarity effect.

**Table 3.** Mechanism testing results.

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *GrePatNum* | 0.1066 ***<br>(0.0078) | | 0.0019 ***<br>(0.0005) | |
| *size* | | 0.7623 ***<br>(0.0184) | | |
| *investratio* | | | | 0.3521 ***<br>(0.1241) |
| Controls | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 16,756 | 16,756 | 16,756 | 16,756 |
| Adjusted $R^2$ | 0.9306 | 0.9622 | 0.4530 | 0.9179 |

Note: The data presented in this table were calculated in this paper. Columns (1) and (2) represent the scale effect results, and columns (3) and (4) are the factor effect results. *** represents statistical significance at the 1% level.

To sum up, the scale expansion effect and the factor complementarity effect are two ways that green technology innovation helps businesses hire more people, which supports hypothesis H2a.

### 5.2. Duration of Effects

According to previous research findings, green technology innovation can significantly increase employment in enterprises. Is this promotion effect persistent? How long is the duration? To further explore the above issues, this article uses the next 1–4 periods of enterprise employment as the dependent variable. The remaining variable symbols carry the same meaning as Equation (1).

Table 4 displays the results of the persistence test. The coefficient estimates for *GrePatNum* show a decreasing trend. At year t + 1 and t + 2, green technology innovation and firm employment are significantly positive at the 1% and 10% levels, respectively. However, at year t + 3 and t + 4, the relationship is no longer significant. This result indicates that the positive effect of green technology innovation on employment persists even two years later. This result undoubtedly reaffirms the positive impact of green technology innovation on employment, and it is indeed exciting in the long term, as it confirms the sustainability of this positive effect on green transformation.

**Table 4.** Impact sustainability test results.

| Variables | $Labor_{i,t+1}$ | $Labor_{i,t+2}$ | $Labor_{i,t+3}$ | $Labor_{i,t+4}$ |
|---|---|---|---|---|
| | (1) | (2) | (4) | (5) |
| $GrePatNum_{i,t}$ | 0.0228 ***<br>(0.0040) | 0.0121 *<br>(0.0063) | 0.0086<br>(0.0072) | 0.0031<br>(0.0028) |
| Controls | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 16,756 | 12,056 | 8411 | 4635 |
| Adjusted $R^2$ | 0.8524 | 0.6406 | 0.3643 | 0.2271 |

Note: The data presented in this table were calculated in this paper. * and *** represent statistical significance at the 10% and 1% levels, respectively.

### 5.3. Heterogeneity Discussion

Furthermore, a thought-provoking question arises: Does the heterogeneity in industries and ownership structures, as well as variations in employees' educational levels, affect the relationship between green technology innovation and employment in companies? To delve deeper into this question, the following sections of this article will examine the heterogeneity of the impact of green technology innovation on employment from three perspectives: industry type, ownership type, and employee education.

This study regroups all firms based on whether they belong to heavily polluting industries. Comparing columns (1) and (2) of Table 5, it is evident that green technology innovation has a greater impact on employment in non-heavily polluting industries. The lower effect of green technology innovation on employment in heavily polluting industries, which often comprise capital-intensive corporations, could explain this result.

**Table 5.** Heterogeneity test results.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Heavy Pollution Industries** | **Non-Heavy Pollution Industries** | **State-Owned Enterprises** | **Non-State-Owned Enterprises** | **High Educational Level** | **Low Educational Level** |
| *GrePatNum* | 0.0174 ***<br>(0.0065) | 0.0238 ***<br>(0.0050) | 0.0266 ***<br>(0.0066) | 0.0204 ***<br>(0.0046) | 0.0215 ***<br>(0.0042) | 0.0186 ***<br>(0.0058) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Yearly fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5994 | 10,762 | 5436 | 11,320 | 22,581 | 13,634 |
| Adjusted $R^2$ | 0.9666 | 0.9624 | 0.9664 | 0.9567 | 0.9553 | 0.9512 |

Note: The data presented in this table were calculated in this paper. *** represents statistical significance at the 1% level.

We conduct the regression analysis separately for state-owned and non-state-owned enterprises, taking into account the distinct objectives of different ownership types in terms of job creation and environmental protection. In columns (3) and (4) of Table 5, we can see that green technology innovation has a significant positive impact on employment in state-owned enterprises. One possible explanation for this result is that state-owned enterprises, with larger overall scales, have more resources to engage in green technology innovation activities and thus can employ a greater number of workers in the transition to a greener economy.

This paper divides all employees into two groups: those with higher education (bachelor's degree and above) and those with lower education (associate degree and below). We conducted regression analyses separately for each group. According to the results in columns (5) and (6) of Table 5, it is evident that as the level of green technology innovation increases, the demand for highly educated employees also rises. We can attribute this result to firms recruiting more R&D personnel, which in turn leads to a greater increase in the employment of highly educated individuals.

## 6. Conclusions and Policy Implications

Green technology innovation is an important driving force for transforming the development mode into a greener one. Studying green technology innovation's employment effects has significant theoretical and practical value in achieving both energy conservation and emission reduction, as well as promoting employment. Based on Chinese A-share listed corporations' data, this paper innovatively explores the impact mechanism of green technology innovation on employment from a theoretical perspective and then empirically examines the impact of the improvement in green technology innovation level on enterprise employment. This paper primarily draws the following conclusions: First, green technology innovation significantly enhances enterprise employment levels and can achieve the dual dividend of energy conservation and employment growth, with its employment effects more reflected in green invention patent applications. An increase of 1% in green patents leads to a 1.76% increase in employment within the enterprise. A series of robustness and endogeneity tests confirm this conclusion. Second, the scale expansion effect and the factor complementarity effect are two mechanisms that significantly promote enterprise employment through green technology innovation. Third, the employment effects of green technology innovation are sustainable and heterogeneous and still have a significant positive effect on enterprise employment levels two years later, with a greater promotion effect on non-heavy-polluting industry corporations, state-owned enterprises, and highly educated employees.

Therefore, this article proposes three policy implications that aim to guide the employment effects of green technology innovation, promote corporate green transformation, and achieve high-quality full employment.

First, green technology innovation significantly enhances enterprise employment levels, and its employment promotion effect is sustainable. Therefore, enterprises should continuously improve their green technological innovation level and continue to carry out research and application of green patents, especially green invention patents. In the initial stage of green technology innovation, enterprises may face significant capital investment, so the government should increase its support for green credit to these enterprises and encourage them to participate in government-funded green technology innovation projects to guide businesses to actively engage in green technology innovation activities.

Second, the improvement of green technology innovation levels will influence enterprise employment through its impact on enterprise scale and environmental investment. As a result, enterprises should continuously introduce advanced green production equipment and increase environmental governance investment in order to achieve a full green production chain. Meanwhile, the government should increase tax incentives for businesses that purchase and actually use green environmental protection equipment, fully leverage tax as an economic lever, and take multiple measures to encourage enterprises to invest in environmental governance.

Finally, when formulating policies, it is important to consider heterogeneity due to the varying employment impacts of green technology innovation on different enterprises. The government should further stimulate the vitality of green technology innovation in heavy-polluting industry enterprises and non-state-owned enterprises, help broaden their financing channels, and vigorously promote the research and application of green patents in these enterprises. At the same time, enterprises should increase the training and recruitment of environmental protection technical talents, focus on the important role of highly educated talents in green technology innovation, and strengthen the skill training of low-educated employees.

Although the findings presented in this paper provide useful insights into the potential employment consequences of the green transition as well as the reactions and adjustment behaviors that corporations exhibit to the low-carbon transition, as this paper primarily focuses on listed corporations in China, the findings may not accurately represent the circumstances of most global enterprises, particularly small and medium-sized ones. We anticipate that future research will expand the sample to include more small and medium-sized enterprises, thereby ensuring a more comprehensive understanding of the impact of green technology innovation on employment across different enterprise types.

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## Appendix A

**Table A1.** Descriptive statistical results of main variables.

| Variable | Variables Definition | Sample | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| *labor* | the total number of employees in the enterprise | 16,756 | 7.6972 | 1.1241 | 5.4424 | 10.8415 |
| *GrePatNum* | total number of green patent applications | 16,756 | 0.9883 | 1.1867 | 0.0000 | 4.7274 |
| *GreInvPatNum* | number of green invention patent applications | 16,756 | 0.6665 | 0.9896 | 0.0000 | 4.2485 |
| *GreUtyPatNum* | number of green utility model patent applications | 16,756 | 0.6608 | 0.9419 | 0.0000 | 3.8067 |
| *size* | Enterprise scale | 16,756 | 21.9515 | 1.1430 | 20.0088 | 25.4792 |
| *lev* | capital structure | 16,756 | 0.3768 | 0.1895 | 0.0502 | 0.8329 |
| *roa* | profitability | 16,756 | 0.0463 | 0.0538 | −0.1665 | 0.1978 |
| *growth* | growth ability | 16,756 | 0.1464 | 0.2685 | −0.4091 | 1.2925 |
| *ci* | property rights | 16,756 | 2.0602 | 1.1539 | −0.4642 | 7.0410 |
| *soe* | ownership nature | 16,756 | 0.3077 | 0.4615 | 0.0000 | 1.0000 |
| *pgdp* | urban economic development level | 16,756 | 11.3640 | 0.5245 | 9.9332 | 12.2234 |
| *pwage* | urban salary level | 16,756 | 11.4637 | 0.4583 | 10.3683 | 12.7341 |

Note: The data presented in this table were calculated in this paper.

**Table A2.** Robustness test results.

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *GrePatNum* | 0.0061 * (0.0036) | | 0.0186 *** (0.0053) | 0.0274 *** (0.0027) | 0.0223 *** (0.0028) |
| *GrePatRatio* (This article also uses two additional indicators, namely the ratio of green invention patent applications (*GreInvPatRatio*) and the ratio of green utility patent applications (*GreUtyPatRatio*), to conduct robustness tests. The results are similar to those in column (2) of Table 3 and are also statistically significant. Due to space limitations, the results are not shown) | | 0.0454 ** (0.0197) | | | |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| City fixed effects and city year interaction | | | | | Yes |
| Observations | 16,756 | 16,756 | 16,756 | 16,756 | 16,756 |
| Adjusted $R^2$ | 0.1700 | 0.3905 | 0.9677 | 0.5381 | 0.4513 |

Note: The data presented in this table were calculated in this paper. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

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