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Research article

# The social effects of energy regulation: Energy-consuming rights trading system and corporate labor demand

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ABSTRACT

Although it is a key measure to control energy consumption and promote the improvement of industrial structure, energy market allocation reform has rarely been concerned with its impact on employment, an important livelihood issue. To fill this gap, this paper takes the Energy-Consumption Rights Trading System (ECRTS) enacted by China in 2016 as a research background and adopts the difference-in-difference approach to explore the effects and mechanisms of the ECRTS on enterprise labor demand. The results show that the ECRTS significantly reduces firms' labor demand, particularly for low-skilled workers, through both production scale effects and technological upgrading effects. Specifically, the ECRTS has led to a decrease in sales revenues and an increase in labor productivity, thereby reducing firms' labor demand. Heterogeneity tests indicate that the ECRTS has a greater impact on employment in firms with lower energy-consumption intensity, domestic capital injections, weaker innovation capacity, and lower market power. The paper also explores the welfare consequences of the policy, finding that while the ECRTS does not improve the environmental performance of firms it does not pass on the compliance costs of regulations to incumbent workers. The overall impact is neutral. This paper extends the study of the economic consequences of the ECRTS and has implications for other developing countries in reconciling energy regulation and employment.

## 1. Introduction

With a new era of rapid industrialization and urbanization, energy consumption and environmental pollution have become major challenges for China. As the largest developing country in the world, China is a leader in energy consumption and carbon emissions (Guo and Hu, 2023; Wang et al., 2021). In 2022, China's total primary energy consumption reached 5.44 billion tons of standard coal, and total carbon emissions reached 11.877 billion tons (carbon dioxide equivalent) (Statistical Review of World Energy, 2023). While China has implemented a variety of environmental policies in an effort to reduce pollution and improve air quality (Chen and Lin, 2021; Liu et al., 2021b; Wang et al., 2023c), measures to reduce energy consumption are needed to ensure energy security (Zhang et al., 2023b) and achieve sustainable development (Engel-Cox and Chapman, 2023). The concern is that while these policies improve environmental quality, they may also have a significant impact on the economy and people's livelihoods (Bezdek et al., 2008; Curtis, 2018; Haites, 2018; Sun et al., 2023; Walker, 2011; Wei et al., 2024; Zhang et al., 2020).

Employment is generally regarded as one of the most important livelihood issues (Jiang et al., 2023), and maintaining employment stability is key to reducing the negative impact of environmental regulation on economic growth and social stability (Huang and Lanz, 2018; Li et al., 2023). Employment is currently a top priority for the Chinese government as declining economic growth and increasing labor supply are making it increasingly difficult to achieve full employment in China (Chen et al., 2023). In China, where both environmental pollution and unemployment are very serious, understanding how environmental regulation affects employment is critical for the realization of high-quality development.

Solving the above problems is of great significance not only for China's development, but also for harmonizing environmental protection and employment issues in other developing countries. Unlike developed nations, most developing countries are experiencing rapid industrialization, which leads to serious environmental pollution problems (Zafar et al., 2020). Both increasing environmental pollution and

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energy insecurity generate significant public health risks (Anderson, 2020; Chen et al., 2013; Palma et al., 2022; Schlenker and Walker, 2016; Tang and Kim, 2023), forcing more and more developing countries to engage in global environmental governance, with far-reaching effects on the economy and employment (Greenstone, 2002; Hafstead and Williams, 2018; Yip, 2018).

Previous studies have primarily focused on the impact of environmental regulations on employment in the United States. For example, the National Association for Economic Research projects that the United States could lose nearly 2.7 million jobs by 2025 as a result of compliance with the requirements of the Paris Agreement and the pressure of onerous energy restrictions. Similarly, an environmental work poll revealed that one-third of respondents felt their jobs were somewhat threatened by environmental regulations (Morgenstern et al., 2002). However, there is a lack of research on whether environmental regulations affect employment in developing countries with a large number of low-income and low-skilled workers, where unemployment may lead further to social crises (Liu et al., 2021b). This paper takes China's Energy-Consumption Rights Trading System (ECRTS) policy as an example to examine the impact of environmental regulations on employment, focusing on source control. It fills a gap in the research on the relationship between energy policy and employment in developing countries, exploring the impact mechanism. Utilizing a Chinese case study provides practical insights for other developing countries striving to harmonize environmental governance and employment issues.

Existing studies have presented divergent views on the impact of environmental regulations on employment, with some suggesting that environmental regulations inhibit employment (Curtis, 2018; Liao et al., 2023; Liu et al., 2021b; Sheriff et al., 2019; Yip, 2018). For example, Greenstone (2002) discovered that nonattainment counties lost about 590,000 jobs relative to attainment counties in the first 15 years following the enactment of the Clean Air Act in the United States. Curtis (2018) noted that the nitrogen oxide (NOx) budget trading program led to a 1.3% decline in overall employment in manufacturing and a 4.8% decline in energy-intensive industries. Other studies have come to the opposite conclusion, arguing that environmental policies increase employment at the regional or firm level (Ren et al., 2020; Wang et al., 2023b; Yamazaki, 2017). Ren et al. (2020), for instance, found that market-based environmental regulations significantly increase labor demand in regulated firms.

Other studies in the literature are skeptical about whether environmental policies have any effect on employment (Berman and Bui, 2001; Gray et al., 2014; Martin et al., 2014; Morgenstern et al., 2002). Morgenstern et al. (2002) examined environmental regulation in the pulp and paper, plastics, oil, and steel industries and found that increases in environmental spending do not usually lead to significant changes in employment. Gray et al. (2014) argued that the U.S. Environmental Protection Agency's Cluster Rule had little impact on employment, and Martin et al. (2014) similarly pointed out that the imposition of a carbon tax does not significantly impact employment. Environmental policies lead to the allocation and transfer of labor between different industries or sectors, making the total effect on employment ambiguous (Bartik, 2015; Hafstead and Williams, 2018; Li and Jin, 2023).

As the world's largest developing nation, China has undertaken significant environmental governance efforts, actively attempting to utilize market mechanisms to address environmental pollution. The Carbon Emissions Trading System (CETS) and the ECRTS have played a key role in China's environmental governance and energy utilization (Wang et al., 2023c; Yang et al., 2020; Zhang et al., 2020). To date, some studies have explored the impact of environmental policies on employment, focusing on "end-pipe treatment" (Liu et al., 2017; Ren et al., 2020; Wang et al., 2023b). Wang et al. (2023b), for example, found that the CETS significantly increases the employment size of cities and firms while achieving emission reductions. In addition, several studies have explored the economic consequences of the ECRTS and its impact on the environment (Du et al., 2023; Guo and Hu, 2023; Wang et al., 2023a; Zhang et al., 2023a; Zhu and Liu, 2023). For example, Guo and Hu (2023) used the difference-in-differences (DID) approach to investigate the impact of the ECRTS on the quality of urban innovation. Zhu and Liu (2023) explored the key role of the ECRTS in promoting green innovation in industrial firms. Du et al. (2023) found that an energy quota trading policy significantly improved the carbon efficiency of the pilot city, exhibiting spatial spillover effects on emission reductions in neighboring regions. However, existing studies have neglected to discuss the impact of environmental policies that emphasize source control, such as the ECRTS, on firms' labor demand. Our paper attempts to fill this gap in the literature.

In this paper, we take advantage of a recent environmental policy (i.e., the ECTRS) enacted by the Chinese government to assess the impact of energy regulation on firms' labor demand using a DID model. We find that environmental regulatory policies based on source control significantly reduce the employment size of firms, which is contrary to the employment effects of previous environmental policies that enforce end-of-pipe regulation. We suggest that the reason for such differences may lie in different environmental governance mechanisms. While end-of-pipe regulations can increase firms' labor demand through the need to install cleaning equipment (Berman and Bui, 2001; Morgenstern et al., 2002), environmental policies based on source control are more likely to force firms to reduce production or upgrade technology, which can have a substitution effect on labor. As suggested by Liu et al. (2021b), identifying polluting firms' emission reduction strategies and the possible differential impacts on employment will help explain the channels of influence. We thus explore the mechanisms through which the ECRTS reduces firms' labor demand in terms of the production scale effect and the technology upgrading effect. The impact of the ECRTS on labor demand shows obvious heterogeneity across firms. We also explore the welfare effects of the ECRTS and find that the program has a neutral impact on environmental performance and workers' wages. This suggests that the policy may place greater emphasis on energy regulation than environmental governance and that enterprises have not transferred the cost of energy savings to workers (despite a reduction in total employment).

The contributions of this paper are fourfold. First, it explores the impact of the ECRTS on firms' labor demand, expanding the research on the economic consequences of the ECRTS. The ECRTS is the first policy in China to include energy in the list of remunerated use of environmental resources, and only a small number of studies have meaningfully explored the economic consequences of this policy. While some studies have explored the impact of the ECRTS on energy consumption structure and intensity (Wang et al., 2021; Yang et al., 2020), carbon emissions (Du et al., 2023; Wang et al., 2023a; Zhang et al., 2023a), corporate green innovation (Zhu and Liu, 2023), urban innovation quality (Guo and Hu, 2023), and total factor productivity of the industrial sector (Wei et al., 2024), as of yet, no studies have focused on the relationship between this policy and employment. By exploring the impact of the ECRTS on firms' labor demand, this paper fills a notable gap in this field.

Second, our paper contributes to research on environmental regulation and employment by exploring the impact of market-incentivized environmental policies based on source control on employment in developing countries. Existing studies mainly discuss the relationship between environmental regulation and employment in developed countries (Curtis, 2018; Gray et al., 2014; Hafstead and Williams, 2018; Sheriff et al., 2019; Yamazaki, 2017; Yip, 2018), and there is a relative lack of studies on developing countries, such as China. At the same time, the small amount of literature on the impact of environmental policies on employment in China usually emphasizes end-of-pipe governance (Liu et al., 2017; Ren et al., 2020; Wang et al., 2023b). To the best of our knowledge, this paper is the first paper to discuss the causal effect between environmental regulation and employment from the perspective of source control, broadening the perspective of the field.

Third, this paper identifies and validates the mechanisms through which energy regulation policies affect employment, and categorizes labor demand under different skill levels, which helps enhance our understanding of the employment effects of different emission reduction strategies. We find that the ECRTS reduces the scale of enterprise employment through the production scale effect and the technology upgrading effect, especially for low-skilled labor. This suggests that source-control-based environmental policies focus more on changes in the production process than on treatment at the end of the pipeline, thus reducing firms' labor demand. Identifying polluters' emission reduction strategies and the impact of employment disparities can help explain the impact channels (Liu et al., 2021b). Our findings enrich the understanding of the relationship between energy regulation policies and employment.

Finally, our research also looks at the welfare consequences of the ECRTS, namely whether the policy improves the environmental performance of firms and reduces the wages of incumbent workers. Interestingly, we find no evidence that the ECRTS improves the environmental performance of businesses or that firms transfer compliance costs to workers. This suggests that the impact of energy regulation policies on the environment and worker welfare may be neutral, which is a novel and valuable finding. In addition, by analyzing heterogeneous effects across industries and firms, we also help policymakers gain more precise practical insights to minimize policy costs and improve efficiency.

The rest of the paper is structured as follows: Section 2 provides an overview of the institutional background of the ECRTS and outlines our research framework. Section 3 details the empirical specifications, encompassing model construction, variable selection, and description of data. Benchmark results and robustness tests are presented in Section 4. Section 5 delves into the mechanism through which the ECRTS influences enterprise labor demand. Heterogeneity analysis is conducted in Section 6. Section 7 comprises a welfare analysis, primarily focusing on the impact of the ECRTS on enterprise environmental performance and workers' wages. Finally, conclusions and recommendations are offered in Section 8.

## 2. Institutional background and research framework

### 2.1. China's ECRTS

Since the reform and opening up, China has achieved great success in its economic development. However, rapid industrialization and urbanization have also brought about formidable challenges, including excessive energy consumption and environmental pollution. In response to the escalating issue of environmental pollution, China has actively pursued effective environmental governance strategies that can be categorized into two types: command-and-control and market incentive. Command-and-control environmental regulation involves governmental efforts to regulate polluters' behavior through legal and administrative measures, while market-incentive environmental regulation employs policy measures to safeguard the environment via market mechanisms and economic incentives. Although China primarily relies on command-and-control environmental policies, efforts to explore market-incentive mechanisms date back to the 1990s. For instance, in 1994, several cities, including Taiyuan and Baotou, initiated a pilot atmospheric emissions trading scheme. To address global warming and promote a green transformation, the National Development and Reform Commission (NDRC) established a carbon emissions trading market in seven provinces and municipalities in 2011, including Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen. The initiative aimed to encourage enterprises to trade carbon emission permits to keep total emissions below specified limits. These pilot projects have yielded valuable insights for innovating and enhancing environmental resource utilization.

Given the significance of industrial pollution, primarily stemming from fossil fuels, the Chinese government has shifted its focus toward energy utilization. Industry consumed over two-thirds of China's total energy in 2021. The Made in China (2025) campaign outlined explicit targets, aiming to reduce energy consumption per unit of industrial value added by 18% and 34% by 2020 and 2025, respectively, and to reduce carbon dioxide emissions by 22% and 40% compared to 2015 levels. To bolster energy efficiency and curb greenhouse gas emissions, the NDRC introduced the Pilot Program for the Compensated Use and Trading System of Energy Consumption Rights in 2016, greenlighting its implementation in Zhejiang, Fujian, Henan, and Sichuan provinces. The ECRTS is the first time China has included energy in the list of environmental resources to be used for a fee and allowed energy use quotas to be traded on the market.

Similar to the European Union's white certificate trading system, the ECRTS sets energy use limits for energy users. Users have the option to purchase or sell energy use permits if their energy demand within the market if their actual energy demand exceeds or falls below designated limits. In brief, the ECRTS encompasses two distinct phases within separate trading realms. The government first establishes an energy allocation scheme to control total energy consumption levels. Energy quotas, derived from the energy consumption and production of energy-using entities, constitute the primary market, where the government acts as the supplier and energy users generate demand. Subsequently, energy users may engage in the trade of energy consumption permits within their allotted quota. In the secondary market, consumers with surplus energy units serve as the supply side, while those facing energy deficits represent the demand side. The program aims to achieve the dual control goal of controlling both total energy consumption and energy consumption intensity by promoting the complementarity of energy use rights among energy-using entities. Unlike environmental policies that focus on end-of-pipe treatments, the ECRTS primarily targets pollution reduction through energy use restrictions, embodying the concept of source control. The ECRTS program thus has the potential to reveal valuable insights on the employment impacts under this new emission reduction strategy.

### 2.2. Research framework

Existing theoretical frameworks suggest that firms' emission reduction strategies have a variable impact on labor demand. Firms typically address environmental regulatory pressures by reducing pollution emissions either through changes in production processes or end-of-pipe treatments (Liu et al., 2021b). Changes in production processes may decrease labor demand via downsizing and technology substitution, whereas end-of-the-pipe governance may require additional labor for the installation, operation, and maintenance of cleaning equipment, thus raising labor demand. Because the overall impact of environmental regulation on employment remains uncertain (Berman and Bui, 2001; Liu et al., 2017), a focused analysis of labor demand in the context of firms' emission reduction strategies is needed.

As an important reform that optimizes energy allocation and controls energy consumption intensity using market mechanisms, the ECRTS is generally regarded as a key environmental regulatory means of reducing pollution emissions at the source (Zhang et al., 2023a). While the literature has extensively examined the employment effects of end-of-pipe regulations, there is a notable gap in understanding how policy measures that focus on source control influence labor demand. Ren et al. (2020) observed a significant increase in labor demand among regulated companies under China's sulfur dioxide emissions trading scheme. In examining China's carbon emissions trading mechanism, Wang et al. (2023b) suggested that market-oriented environmental regulation has bolstered employment in cities and enterprises. If policies emphasizing end-of-pipe treatments can prompt firms to undertake corresponding pollution control activities, thereby enhancing employment (Morgenstern et al., 2002), it raises the question: how do environmental policies based on source control affect labor demand? We posit that, given specific institutional characteristics, policies aimed at reducing emissions at the source primarily influence firm employment through changes in the production process rather than end-of-pipe regulation. When constrained by energy use limitations, firms may react by downsizing production and upgrading technology, thereby diminishing labor demand. In the ensuing sections, we delve into these two mechanisms.

#### 2.2.1. Production scale effect

It is widely believed that the firms affected by environmental regulation make timely decisions to maximize profits (Acemoglu et al., 2012; Aghion et al., 2016). Stricter environmental regulations lead to higher production costs, leading firms to reduce output and shrink their labor force, thus leading to higher unemployment (Gollop and Roberts, 1983; Greenstone, 2002; Henderson, 1997). Under this traditional view, the ECRTS may influence labor demand through a *production scale effect.* Specifically, the program set energy use quotas for firms in the pilot areas, which then had to adjust their production schedules to comply with energy consumption regulations. Considering that one of the key tasks of the program is to eliminate outdated production capacity, some inefficient firms are forced to potentially reduce their production capacity as a compliance strategy (Wang et al., 2023c). There are several reasons firms undertake this reduction in production capacity as opposed to other measures of reducing energy use.

First, in terms of the policy environment, it is undeniable that China's ECRTS market is still imperfect (Pan and Dong, 2022), and the overall activity is low. This means that many enterprises may not have been able to successfully trade energy consumption rights, resulting in some inefficient enterprises having to instead reduce their production capacity to meet the energy use standards. Second, in terms of production costs, under the condition of constant technology, firms may reduce production to lower the cost of excess energy use as compared to purchasing additional energy use permits on the secondary market (i.e., a direct effect) (Che and Wang, 2022; Pan and Dong, 2022). On the other hand, when energy consumption indicators are insufficient, firms need to purchase energy use licenses from the market, increasing their marginal production costs (Che and Wang, 2022; Wang et al., 2023c). To ensure that profits are not lost, firms may then raise the price of their products, which will lead to a decline in market demand and force firms to reduce their production capacity and, ultimately, their labor force (i.e., an indirect effect) (Berman and Bui, 2001; Gray et al., 2014; Morgenstern et al., 2002).

In summary, when faced with constraints on energy use, firms may reduce capacity due to either the policy environment or production costs. Environmental regulations may also impact skilled and low-skilled employment differently (Zhong et al., 2021). Energy-intensive industries have a higher share of low-skilled labor (Yip, 2018) and high-skilled labor tends to be more adaptable than low-skilled labor (Mian and Sufi, 2014). We believe that low-skilled labor is likely to be more severely affected by reductions in production due to energy controls than high-skilled labor.

#### 2.2.2. Technology upgrading effect

By forcing firms to upgrade technology and increase labor productivity, the ECRTS has a substitution effect on labor. Besides adjusting production scale to comply with stricter environmental regulations, firms often resort to innovation and technological advancement. Unlike altering the production scale, innovation involves improving existing technological conditions to achieve emission reduction and productivity enhancement goals. So, how does the change in production processes based on technological upgrades affect enterprise labor demand? The dominant view in the literature is that technology is a potential cause of declining labor participation (Acemoglu and Restrepo, 2022; Virgillito, 2017) as the technological progress driven by environmental regulations enhances firms' labor productivity, thereby reducing labor requirements (Liu et al., 2021b; Sheriff et al., 2019). In imposing energy-use constraints on firms, the ECRTS compels them to adopt technological upgrades to improve energy efficiency and meet production targets within limited energy-use quotas. Some studies have indicated that the ECRTS fosters green technological innovation (Zhu and Liu, 2023), optimizes energy consumption, and enhances energy efficiency (Yang et al., 2020). Within the context of technological progress prompted by the ECRTS, increased labor productivity may displace some workers, shrinking overall employment. As with the production scale effect, these effects may vary among workers of different skill levels. Due to the inherent bias of technological change toward general skills, industrial technology adoption often displaces low-skilled labor (Autor and Dorn, 2013; Graetz and Michaels, 2018). Conversely, the adoption of new technologies may stimulate demand for a small number of technicians among high-skilled labor (Wang et al., 2023a), partially offsetting any negative impact on their employment. Compared to high-skilled labor, low-skilled labor may experience a greater reduction in employment due to the technology upgrading effect induced by energy regulation.

We posit that the ECRTS reduces the labor demand of enterprises—especially low-skilled labor—through the production scale effect and the technology upgrading effect. To provide a clearer depiction of the mechanism of ECRTS's influence on labor demand, we present a simple framework in Fig. 1.

## 3. Empirical strategy

### 3.1. Model specification

To establish the causal relationship between energy regulation and employment, we utilized China's 2016 implementation of the ECRTS as a quasi-natural experiment to assess the impact of energy use restrictions on corporate labor demand. Employing a DID setup enabled us to precisely estimate the employment effects of energy regulatory policies. The specific construction of the DID model is outlined below:

$$Ln(Labor_{ict}) = \alpha + \beta ECRT_i \times Post_t + \phi X_{it} + \theta Y_{ct} + \mu_i + \gamma_t + \varepsilon_{ict} \tag{1}$$

where $Ln(Labor_{ict})$ represents the labor demand of firm $i$ in city $c$ in year $t$. The dummy variable $ECRT_i$ is equal to 1 if the enterprise is located in the ECRTS pilot area and is equal to 0 otherwise. Similarly, $Post_t$ is a dummy variable that takes the value 1 if the year is greater than or equal to 2016 (the policy period) and 0 otherwise. $\beta$ captures the impact of the ECRTS on the firm's labor demand. $X_{it}$ and $Y_{ct}$ represent a series of firm-level and city-level control variables. $\mu_i$ is the firm fixed effect, which is used to control the influence of unobservable factors that vary with individual firms but not with time. $\gamma_t$ is a time fixed effect that captures any effects not observed in a particular year. $\varepsilon_{ict}$ is the random error term. To address potential heteroskedasticity and serial correlation, standard errors are clustered at the firm level.

### 3.2. Data

This paper constructs a panel dataset of Chinese A-share listed companies in Shanghai and Shenzhen for the period of 2011–2022, matching the city data for analysis. Typically, studies on Chinese enterprises rely on either listed company databases or industrial enterprise databases. We chose listed company data for two main reasons. First, listed firms provide comprehensive financial information, aiding in controlling specific enterprise-level factors. Second, listed companies offer faster data updates and longer sample periods, allowing us to include policy pilot years within our analysis period, facilitating policy effect evaluation. Additionally, we utilized a city-level dataset to capture urban economic development and wages. Firm-level data was sourced from the China Stock Market and Accounting Research (CSMAR) database, while city-level data was obtained from the China City Statistical Yearbook.

To align the data with the goals of the study, we conducted several filtering steps. First, we excluded samples with risk warnings (ST or *ST companies) due to their prolonged financial distress and delisting risk.

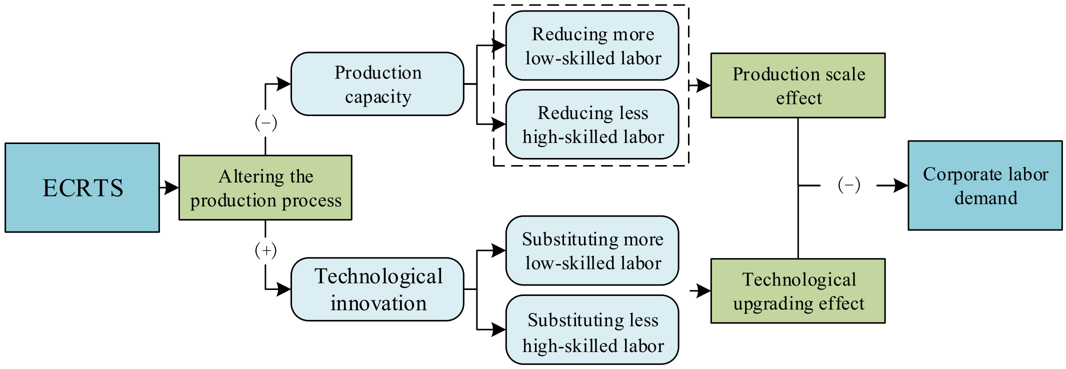


**Fig. 1.** Framework of the influence mechanism.

Second, in recognition of the unique characteristics of the financial industry, we omitted financial sector samples from the analysis. Third, we removed samples with significant missing values. Lastly, to mitigate potential bias from extreme values, we winsorized all continuous variables at the 1% and 99% levels.

### 3.3. Variable description

#### 3.3.1. Dependent variables

The outcome variable of interest in this paper, $Ln(Labor_{ict})$, represents firm labor demand, quantified by the logarithm of the firm's employee count (Gray et al., 2014; Liu et al., 2017; Ren et al., 2020). To explore the impact of the ECRTS on the demand for labor across skill levels, we differentiated between high-skilled (*High-Skill*) and low-skilled (*Low-Skill*) labor based on workers' educational attainment. Specifically, high-skilled labor demand is defined as the logarithm of employees holding a college degree or higher, while low-skilled labor demand refers to the logarithm of employees with a high school diploma or below.

#### 3.3.2. Independent variable

The primary independent variable in this study is a binary indicator for the ECRTS. In Model (1), the interaction term $ECRT_i \times Post_t$ indicates whether the firm operates within the ECRTS pilot region and whether the observation year is 2016 or later. The coefficient on this interaction term captures the average difference between the labor demand of firms in pilot areas and firms in non-pilot areas before and after the implementation of the policy, which is the parameter that we are most interested in.

#### 3.3.3. Control variables

Informed by prior related studies (Liu et al., 2021a; Ren et al., 2020; Wang et al., 2023b), we included a series of control variables in Model (1) to exclude the influence of some firm-level and city-level factors on the conclusion. The control variables at the firm level include capital intensity (*Capital*), selling expense ratio (*SER*), income tax (*Tax*), profitability (*ROA*), corporate growth (*Growth*), firm size (*Size*), firm age (*Age*), and the nature of ownership (*SOE*). At the city level, the control variables include the level of economic development (*GDP*) and city workers' wages (*Wage*). For specific definitions of these variables, see Table A1 in the appendix.

Table 1 reports descriptive statistics for the key variables. *Ln* (*Labor*) exhibits substantial variation between its maximum and minimum values, with a standard deviation exceeding 1, suggesting considerable dispersion in firms' workforces. Moreover, the mean value of the variable *ECRT* is 0.195, indicating that the majority of firms in the sample operate outside the pilot areas, with only a small proportion situated in the experimental group.

**Table 1**
Descriptive statistics of variables.

| Variables | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| *Ln* (*Labor*) | 30,152 | 7.638 | 1.281 | 4.673 | 11.229 |
| *ECRT* | 30,152 | 0.195 | 0.396 | 0 | 1 |
| *Capital* | 30,152 | 0.197 | 0.156 | 0.002 | 0.686 |
| *SER* | 30,152 | 0.073 | 0.090 | 0 | 0.480 |
| *Tax* | 30,152 | 17.175 | 1.769 | 11.623 | 21.759 |
| *ROA* | 30,152 | 0.043 | 0.058 | −0.228 | 0.198 |
| *Growth* | 30,152 | 2.016 | 1.307 | 0.842 | 8.612 |
| *Size* | 30,152 | 22.228 | 1.335 | 19.863 | 26.405 |
| *Age* | 30,152 | 2.912 | 0.337 | 1.792 | 3.526 |
| *SOE* | 30,152 | 0.351 | 0.477 | 0 | 1 |
| *GDP* | 30,152 | 11.493 | 0.502 | 10.062 | 12.223 |
| *Wage* | 30,152 | 11.377 | 0.425 | 10.398 | 12.279 |

## 4. Empirical analysis

### 4.1. Baseline results

Table 2 presents the outcomes of the benchmark regression. In

**Table 2**
The impact of the ECRTS on firm labor demand.

| | (1) | (2) | (3) |
|---|---|---|---|
| | *Ln* (*Labor*) | High-Skill | Low-Skill |
| *ECRT* × *Post* | −0.080*** | −0.046* | −0.082** |
| | (0.025) | (0.026) | (0.036) |
| *Capital* | 0.843*** | 0.180** | 0.969*** |
| | (0.090) | (0.081) | (0.114) |
| *Ser* | 0.678*** | 0.881*** | 0.525*** |
| | (0.143) | (0.164) | (0.187) |
| *Tax* | 0.013** | 0.015*** | 0.016** |
| | (0.005) | (0.005) | (0.007) |
| *ROA* | −0.024 | 0.080 | −0.071 |
| | (0.098) | (0.094) | (0.147) |
| *Growth* | 0.013*** | 0.021*** | 0.016*** |
| | (0.004) | (0.005) | (0.006) |
| *Size* | 0.677*** | 0.657*** | 0.648*** |
| | (0.017) | (0.018) | (0.023) |
| *Age* | 0.230** | 0.012 | 0.160 |
| | (0.091) | (0.116) | (0.149) |
| *SOE* | 0.065* | 0.003 | 0.129 |
| | (0.038) | (0.035) | (0.096) |
| *GDP* | −0.015 | 0.105*** | −0.016 |
| | (0.029) | (0.035) | (0.042) |
| *Wage* | −0.081 | −0.059 | −0.106* |
| | (0.051) | (0.057) | (0.063) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| N | 30,152 | 27,050 | 28,434 |
| Adj-$R^2$ | 0.934 | 0.931 | 0.888 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level.

Column (1), which includes all control variables and each fixed effect, the coefficient of $ECRT \times Post$ is significantly negative at the 1% level, indicating a notable reduction in enterprise labor demand due to the ECRTS. Following the implementation of the ECRTS policy, firms within the pilot areas experienced an average 8% decrease in employment size compared to those outside the pilot areas. To further explore variations in policy effects among different worker groups, we categorized workers into high-skilled and low-skilled labor based on educational qualifications (see Section 3.3.1 for a specific definition). Columns (2) and (3) demonstrate that the absolute value of the regression coefficient for the core independent variable is larger in the low-skill group, with a higher level of statistical significance. This suggests a more pronounced reduction in demand for low-skilled labor due to the ECRTS, compared to relatively minor effects on high-skilled labor employment.

### 4.2. Robustness checks

#### 4.2.1. Parallel trend test

The parallel trend hypothesis is a crucial prerequisite for policy evaluation using the DID model. Accurate estimation of the policy's average treatment effect relies on both the treatment and control groups exhibiting similar trends prior to policy implementation. Referring to Beck et al. (2010), we employed the event study approach to test this hypothesis. The model is set up as follows:

$$Ln(Labor_{ict}) = \alpha + \sum_{t}^{2022} \beta_t ECRT_i \times Year_t^s + \phi \vec{X}_{it} + \mu_i + \gamma_t + \varepsilon_{ict} \tag{2}$$

where $Year_t^s$ is a year dummy variable, $t$ denotes the year, and the value of $s$ ranges from 2011 to 2022. If $t = s$, $Year_t^s$ equals 1; otherwise it equals 0. $\vec{X}_{it}$ denotes the set of control variables. All remaining variables have the same meaning as in Model (1).

To avoid complete collinearity, we used the first period of the sample as the base year, so the value of $s$ does not include 2011. The $\beta_t$ coefficient, which captures the difference in labor demand between the treatment group and the control group in each period, is of primary interest. Fig. 2 depicts the results of the parallel trend test. As expected, the $\beta_t$ none of the coefficients are significantly different from 0 before the policy implementation. This means that the enterprises in the treatment group and the control group meet the common trend hypothesis, and there is no significant systematic difference between them. After 2016, the $\beta_t$ coefficients are significantly negative. In other words, compared with enterprises in non-pilot areas, enterprises in pilot areas significantly reduced their labor demand due to the influence of the ECRTS. These results strongly verify the common trend hypothesis and confirm the conclusion of our benchmark regression.

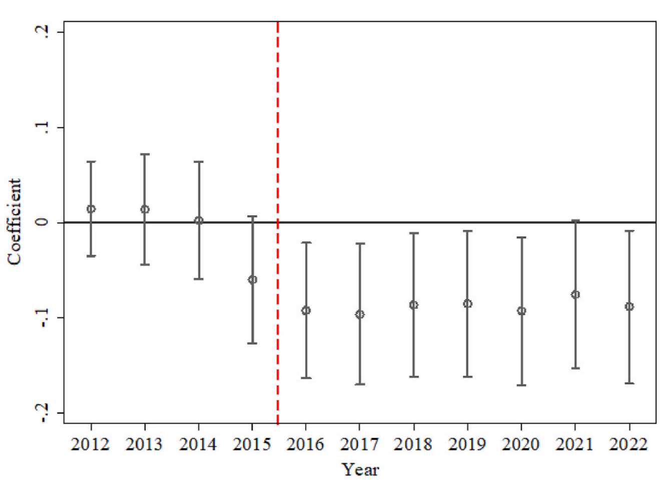


**Fig. 2.** Parallel trend test. Notes: The vertical solid black lines in the figure represent the 95% confidence interval, and the circles represent the estimated coefficients.

**Table 3**
PSM-DID results.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Firm-level | | City-level | |
| | 1:1 nearest neighbor matching | 1:2 nearest neighbor matching | 1:1 nearest neighbor matching | 1:2 nearest neighbor matching |
| *ECRT × Post* | −0.082*** | −0.087*** | −0.082** | −0.089** |
| | (0.030) | (0.026) | (0.037) | (0.035) |
| *Controls* | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 10,757 | 14,565 | 10,146 | 10,241 |
| Adj-$R^2$ | 0.933 | 0.929 | 0.946 | 0.946 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1). There are fewer observations in Table 3 than in the baseline regression due to the loss of a portion of the sample for estimation by the propensity score matching method.

#### 4.2.2. Propensity score matching

To mitigate systemic differences between the treatment and control groups, we employed the propensity score matching (PSM) method to re-estimate policy effects. Using the control variables from Model (1) as matching factors, we conducted nearest neighbor matching in both 1:1 and 1:2 modes to select control group firms with similar characteristics for comparison, reducing sample selection bias. Given that Model (1) includes control variables at both firm and city levels, we conducted PSM separately at these levels to minimize differences among enterprises and cities. Table 3 presents the estimation results based on the PSM method. Columns (1) and (2) utilize firm-level control variables for matching, while Columns (3) and (4) employ city-level control variables. Additionally, Columns (1) and (3) utilize a 1:1 nearest neighbor matching pattern, whereas Columns (2) and (4) utilize a 1:2 nearest neighbor matching pattern. We consistently found a significant negative impact of the ECRTS on enterprise labor demand across different matching levels and modes, reaffirming the robustness of our benchmark conclusion.

#### 4.2.3. Non-randomness in the selection of pilot areas

Considering that the selection of pilot areas for the ECRTS may have been related to economic, environmental, and demographic factors, these factors may have differential impacts on employment over time. To overcome the potential non-randomness of pilot area selection, we added interaction terms between variables of regional characteristics and time trends to the model, following Edmonds et al. (2010) and Lu et al. (2017). The resulting model is as follows:

$$Ln(Labor_{ict}) = \alpha + \beta ECRT_i \times Post_t + \phi X_{it} + \theta Y_{ct} + Z_c' \times Trend_t + \mu_i + \gamma_t + \varepsilon_{ict} \tag{3}$$

where $Z_c'$ denotes the set of regional characteristic variables, including dummy variables indicating whether the region is a special economic zone (*SEZ*), a Two Control Zone (*TCZ*),[1] or on the eastern side of the Hu Huanyong line (*HHYL*).[2] $Trend_t$ denotes the linear time trend. The interaction term $Z_c' \times Trend_t$ controls the impact of characteristic differences between regions on dependent variables from a linear

[1] A Two Control Zone refers to an acid rain control area or a sulfur dioxide pollution control area.

[2] The population and GDP of the area east of the Hu Huanyong Line account for more than 90% of the country.

**Table 4**
Non-randomness of pilot area selection.

| | (1) | (2) | (3) |
|---|---|---|---|
| *ECRT* × *Post* | −0.0798*** | −0.0808*** | −0.0807*** |
| | (0.0249) | (0.0248) | (0.0248) |
| *SEZ* × *Trend* | Yes | Yes | Yes |
| *TCZ* × *Trend* | No | Yes | Yes |
| *HHYL* × *Trend* | No | No | Yes |
| *Controls* | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| N | 30,152 | 30,152 | 30,152 |
| Adj-$R^2$ | 0.934 | 0.934 | 0.934 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1).

perspective, alleviating the estimation bias caused by the non-random selection of pilot areas to a certain extent.

Table 4 reports the estimated results of Model (3). The results in Column (3) show that the estimates of our baseline model remain robust to the inclusion of interactions between all characteristic variables and temporal trends in the model.

#### 4.2.4. Placebo test

Despite controlling for various firm characteristics and fixed effects in our baseline regressions, it is possible that we may have overlooked some crucial variables related to the interaction term (*ECRT* × *Post*). In other words, our conclusion may be driven by unobserved random factors rather than the impact of the ECRTS. To address this concern, we randomly assigned the treatment variable and policy period to each enterprise, following Chetty et al. (2009) and La Ferrara et al. (2012). This process involved creating a pseudo-treatment group (*Treat*) and an associated interaction term (*Treat*×*Year*). To maintain consistency, we ensured an equal sample size to that of the pilot enterprises for random allocation. As this allocation process is stochastic, we anticipated that the resulting interaction term (*Treat*×*Year*) would not significantly affect firm labor demand. To enhance the validity of our test, we repeated this random assignment process 500 times.

Fig. 3 illustrates the estimated coefficients and corresponding p-values from the 500 regressions. Notably, the coefficients from these regressions generally exhibit a normal distribution with a mean of 0, and most estimates possess p-values exceeding 0.1. Conversely, the coefficient estimate from the baseline regression (−0.080) falls outside this distribution and stands out as an outlier in Fig. 3. These findings indicate that the baseline results obtained from Model (1) are less susceptible to the influence of unobserved omitted variables, thereby affirming the robustness and credibility of our conclusions.

#### 4.2.5. Instrumental variable tests

Although the DID approach mitigates the endogeneity problem to a certain extent, potential biases due to factors such as non-random pilot district selection and omitted variables may still be present in our model. To overcome this problem, we used the instrumental variable method for robustness testing. Aligning with Guo and Hu (2023), we selected urban topographic relief as the instrumental variable of ECRTS policy because it is an important factor influencing firms' location choice. A city with more firms consumes more energy, which increases the likelihood that the city will be selected as an ECRTS pilot area, satisfying the correlation hypothesis. Urban topography is also naturally shaped by geographic conditions and is largely unaffected by unobserved variables in the model, satisfying the exogeneity assumption. Since topographic relief remains constant over time, we constructed an instrumental variable (*IV_Post*) through the interaction of topographic relief with a time dummy variable and performed a two-stage least squares (2SLS)

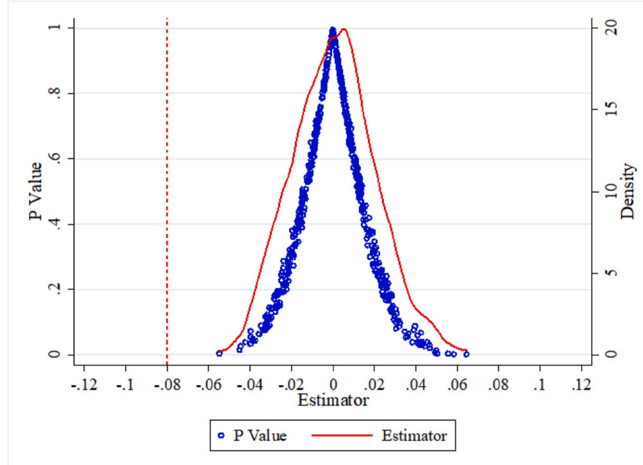


**Fig. 3.** Placebo test.

estimation, following Duflo and Pande (2007). The results of the estimation are shown in Table 5. Columns (1) and (2) do not include any control variables in the model, while Columns (3) and (4) control for all covariables. The results in Column (3) indicate that urban topography has a significant effect on the selection of pilot areas (Guo and Hu, 2023), and pass the unidentifiable test and the weak instrumental variable test. The results in Column (4) imply that our conclusions remain robust after the instrumental variable approach is used to solve the endogeneity problem.

#### 4.2.6. Spillover effect tests

One of the key assumptions of the DID methodology is the stable unit treatment value assumption (SUTVA), which assumes there are no spillovers of policies. It is possible that environmental policies may have spillover effects on neighboring regions through resource allocation and industrial transfer (Du et al., 2022a, 2022b). To determine whether spillover effects exist, we changed the identification strategy. Specifically, we re-ran regressions with firms in provinces adjacent to the pilot regions as the treatment group and firms in other non-pilot regions (not adjacent to the pilot region) as the control group. The results in Column (1) of Table 6 show that the ECRTS has no significant effect on the labor demand of enterprises in pilot-adjacent areas, indicating that there is no significant spillover effect. In addition, referring to Lu et al. (2019), we also removed the control group samples that may be affected by the policy to eliminate the potential error of spillover effect as much as possible. In other words, the sample of firms in provinces near the pilot

**Table 5**
Instrumental variable tests.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ECRT × Post | *Ln* (*Labor*) | ECRT × Post | *Ln* (*Labor*) |
| *IV_Post* | 0.074*** | | 0.071*** | |
| | (0.014) | | (0.013) | |
| *ECRT* × *Post* | | −1.016*** | | −0.797*** |
| | | (0.320) | | (0.268) |
| *Controls* | No | No | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| K–P rk LM statistic | 54.24*** | | 52.18*** | |
| K–P Wald rk F statistic | 28.67 | | 28.01 | |
| N | 30,152 | 30,152 | 30,152 | 30,152 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1).

area was excluded for re-estimation. The results in Column (2) suggest that the baseline estimates remain robust after excluding possible policy spillover effects.

*4.2.7. Excluding other possible explanations*

It is possible that other policies might impact firms' labor demand throughout the study period, potentially undermining the robustness of our findings. Based on a review of the existing literature, we focused on three programs: the Carbon Emission Trading System (CETS), the Low-Carbon City Pilot Policy (LCCPP), and the Broadband China Strategy (BCS). In this section, we will individually exclude the impact of each of these key policies from the conclusions of this paper.

*4.2.7.1. Carbon Emission Trading System.* To realize the strategic objectives of carbon neutrality and carbon peak, the Chinese government initiated two phases of CETS pilots across seven provinces—Beijing, Tianjin, Shanghai, Hubei, Guangdong, Chongqing, and Fujian—in 2013, 2017. Serving as a pivotal component of the market-driven environmental regulatory framework, the CETS has been instrumental in China's environmental governance. Unlike the source control concept within ECRTS, CETS prioritizes end-of-pipe regulation, which stimulates corporate pollution control endeavors and consequently impacts labor demand (Morgenstern et al., 2002). Studies have indicated that, alongside emission reductions, the CETS notably boosts employment in enterprises through robotic applications (Wang et al., 2023b). To mitigate the influence of the CETS on the findings of our paper's findings, we introduced the dummy variable *CETS* into our model. Specifically, *CETS* equals 1 if the firm operates within a CETS pilot area post-policy implementation and 0 otherwise. The regression results in Column (1) of Table 7 demonstrate that our conclusions remain robust even after eliminating any effects of the CETS.

*4.2.7.2. Low-Carbon City Pilot Policy.* In addition to pollution control at the corporate level, the Chinese government has endeavored to control carbon emissions on a macro scale at the city level. Since 2010, the NDRC has initiated three rounds of LCCPP in dozens of cities—including Beijing, Tianjin, and Shenzhen—aiming to reduce greenhouse gas emissions and explore models for green and low-carbon development. The program seeks to foster sustainable economic growth by nurturing low-carbon industries and fostering green and low-carbon lifestyles within urban areas. As a macro-level environmental regulation policy, the LCCPP inevitably influences corporate hiring decisions (Wang et al., 2023a). To mitigate the influence of the LCCPP on firm employment size, we introduced the dummy variable *LCCPP* to our model. Specifically, *LCCPP* takes a value of 1 if the sample of firms is located in an LCCPP region after the policy year, and 0 otherwise. As demonstrated in Column (2) of Table 7, our conclusions remain robust even after accounting for the impact of the LCCPP.

*4.2.7.3. Broadband China strategy.* Because the existing literature suggests that increasing internet penetration promotes employment (Jin et al., 2023; Wang et al., 2022), we also considered the effects of the BCS. Beginning in 2014, the Chinese government rolled out the Broadband China policy in three phases across numerous cities—including Beijing, Tianjin, and Shanghai—aiming to boost economic and social development by enhancing the application of network information technology. As a pivotal digital infrastructure initiative, the BCS has significantly influenced China's labor market (Zhou et al., 2022). To mitigate the potential influence of the BCS on study conclusions, we constructed a dummy variable for BCS and integrated it into the baseline model. The variable *BCS* equals 1 if the firm is situated in the pilot area and the year is a post-policy period; otherwise, it equals 0. Column (3) of Table 7 reveals that after removing the interference of the BCS, our conclusions remain largely unchanged. Lastly, Column (4) includes all three policies, further strengthening our test. The findings continue to demonstrate the robustness of our conclusions, despite the imposition of stricter control measures.

**Table 6**
Spillover effect tests.

| | (1) | (2) |
|---|---|---|
| *ECRT* × *Post* | 0.0276 | −0.0586** |
| | (0.0238) | (0.0297) |
| *Controls* | Yes | Yes |
| Firm FE | Yes | Yes |
| Year FE | Yes | Yes |
| N | 24,276 | 12,753 |
| Adj-$R^2$ | 0.936 | 0.939 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1).

**Table 7**
Excluding the impact of other policies.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Carbon Emission Trading System | Low-Carbon City Pilot Policy | Broadband China Strategy | All Policies |
| *ECRT* × *Post* | −0.076*** | −0.081*** | −0.080*** | −0.076*** |
| | (0.025) | (0.025) | (0.025) | (0.025) |
| *CETS* | 0.075*** | | | 0.074*** |
| | (0.022) | | | (0.023) |
| *LCCPP* | | −0.006 | | −0.012 |
| | | (0.018) | | (0.018) |
| *BCS* | | | 0.018 | 0.006 |
| | | | (0.018) | (0.019) |
| *Controls* | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 30,152 | 30,152 | 30,152 | 30,152 |
| Adj-$R^2$ | 0.934 | 0.934 | 0.934 | 0.934 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1).

*4.2.8. Other robustness tests*

*4.2.8.1. Variable substitution.* Given that managers typically wield more bargaining power than ordinary employees, they may be less susceptible to corporate layoffs. Hence, we redefined labor demand as the logarithm of the ordinary employee count and employed Model (1) for estimation. The findings, presented in Column (1) of Table 8, indicate that our conclusions persist even after mitigating the influence of manager numbers.

*4.2.8.2. Multi-dimensional fixed effect.* While we controlled for the influence of individual-varying and time-varying factors in our baseline estimate, unobservable industry and city factors, such as industrial policies or market conditions, may still affect the results. To address this, we introduced industry fixed effects and city fixed effects, presenting the results in Columns (2) and (3) of Table 8, respectively. The estimation results reveal that the coefficients of the interaction terms are all significant at the 1% level, affirming the robustness of our findings.

*4.2.8.3. Removing biased samples.* In the benchmark model, we used the ECRTS implemented in 2016 as an exogenous shock to investigate the impact of environmental regulations on firm labor demand, defining the policy period as 2016 and beyond. However, given the potential time lag of the policy, the sample in the policy year may generate some noise. To mitigate this potential noise, we removed the year 2016 from our sample. The results in Column (4) of Table 8 affirm the validity of our conclusions.

**Table 8**
Other robustness tests.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *ECRT* × *Post* | −0.081*** | −0.068*** | −0.066*** | −0.082*** | −0.080*** | −0.081*** |
| | (0.029) | (0.022) | (0.022) | (0.027) | (0.024) | (0.025) |
| *Controls* | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | Yes | No | No | No |
| City FE | No | No | Yes | No | No | No |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 30,152 | 30,152 | 30,152 | 27,784 | 20,352 | 23,960 |
| Adj-$R^2$ | 0.927 | 0.940 | 0.940 | 0.932 | 0.932 | 0.927 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1). Columns (4)–(6) omit a small number of data points, resulting in fewer observations than the baseline regression.

*4.2.8.4. Eliminating impacts of the COVID-19 pandemic.* In 2020, the global COVID-19 pandemic significantly impacted economies and livelihoods worldwide. In China, stringent quarantine measures notably diminished consumption and commodity production, leading to pronounced unemployment. According to the National Bureau of Statistics (NBS), China experienced declines in total employment of 3.83 million and 4.12 million during 2020 and 2021, respectively, particularly in the tertiary sector. To mitigate the effect of the COVID-19 pandemic on firm labor demand, we excluded data from 2020 and beyond. The results presented in Column (5) of Table 8 demonstrate that the coefficient on the interaction term remains statistically significant at the 1% level, affirming the robustness of our conclusions.

*4.2.8.5. Enterprise entry and exit.* It is widely acknowledged that effective DID estimators rely on observing changes in individuals before and after policy implementation. Analysis of our data revealed that some firms exited the market before the ECRTS was implemented or did not go public until after policy implementation. Considering the normative nature of policy evaluation, these firms should be considered invalid samples, as their inclusion could introduce errors in the results. To obtain a cleaner policy effect, we thus removed firms that exited the market before 2016 as well as those that went public after 2016 from our sample. Column (6) of Table 8 confirms that our conclusions remain unaffected after removing invalid samples.

## 5. Mechanism analysis

The preceding findings confirm that the ECRTS notably diminishes enterprise labor demand. But how does the program influence firm labor demand? In our earlier theoretical analysis, we posited that firms, constrained by energy usage, might curtail production or enhance technology to align with total energy consumption standards, consequently decreasing employment. We next examine how the ECRTS impacts firms' labor demand through the production scale effect and the technology upgrading effect.

### 5.1. Production scale effect

The influence of the ECRTS on enterprises' production scale manifests in two primary ways. First, by allocating energy use quotas, the policy prompts firms to curtail energy consumption when used quotas are insufficient by reducing production. Second, firms may opt to augment their energy use quota by purchasing licenses in the secondary market, elevating production costs. To offset regulatory compliance expenses, enterprises might increase product prices, thereby dampening market demand. By constraining production scale, the ECRTS consequently diminishes labor demand.

To examine this hypothesis, we analyzed the impact of the ECRTS on firm production size. Column (1) of Table 9 utilizes the logarithm of sales revenue to gauge enterprise production scale. The findings reveal a significantly negative coefficient for the interaction term, indicating that firms reduce their production scale in response to the ECRTS. Column (2) assesses the production scale effect by estimating the impact of sales revenue on firm labor demand, revealing a significant positive relationship. The impact of the ECRTS on labor demand can thus be attributed to the reduction in production scale, as evidenced by the results in Columns (1) and (2).

In the baseline estimation, we found that the ECRTS has a greater impact on low-skilled labor. We further explored the impact of enterprise production scale on the labor demand for different skill levels. The findings in Columns (3) and (4) of Table 9 indicate that firm production size has a more pronounced effect on low-skilled labor than high-skilled labor, implying that reductions in production scale correspond to larger decreases in low-skilled labor. In other words, the decrease in production scale prompted by the ECRTS predominantly impacts the employment of low-skilled workers. As described in the theoretical analysis, energy-intensive companies have a higher proportion of low-skilled workers and relatively weak bargaining power, which makes them more likely to suffer from policy shocks.

### 5.2. Technology upgrading effect

Environmental regulations often spur technological upgrades, enhancing enterprise labor productivity and potentially displacing labor. Technological progress serves as an alternative production strategy for firms facing energy constraints, along with maintaining established production plans. When companies seek to avoid scaling down production to reduce energy consumption, their recourse lies in upgrading existing production technologies to enhance energy efficiency and meet production goals within allocated energy quotas. Past research has indicated that technological advancements typically lower labor market participation rates (Acemoglu and Restrepo, 2022). Thus, we posit that the ECRTS forces enterprises to upgrade technology to

**Table 9**
Mechanism test I: Production scale effect.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Ln* (*Sales*) | *Ln* (*Labor*) | High-Skill | Low-Skill |
| *ECRT* × *Post* | −0.047** | | | |
| | (0.021) | | | |
| *Ln* (*Sales*) | | 0.336*** | 0.228*** | 0.370*** |
| | | (0.021) | (0.021) | (0.030) |
| *Controls* | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 30,152 | 30,152 | 27,050 | 28,434 |
| Adj-$R^2$ | 0.956 | 0.939 | 0.933 | 0.893 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1).

improve energy efficiency, and the associated changes in production processes improve labor productivity, thereby reducing the demand for labor. To evaluate this hypothesis, we followed Vittori et al. (2024) and employed the logarithm of value added per employee to gauge firm labor productivity (*LP*) and assess the impact of the ECRTS on firm labor productivity. Column (1) of Table 10 reveals a significantly positive coefficient for the interaction term, signifying that the ECRTS enhances firms' production technology and boosts labor productivity. Column (2) explores the technology upgrading effect by estimating the impact of labor productivity impact on labor demand, demonstrating a significant reduction in labor demand with increased labor productivity. Synthesizing the findings from Columns (1) and (2), we can conclude that the ECRTS induces a substitution effect on labor by driving technological progress in firms.

To investigate the influence of employee skills, we assessed the impact of labor productivity on the demand for labor of varying skill levels. The findings presented in Columns (3) and (4) indicate a stronger substitution effect of labor productivity on low-skilled labor. This may be because highly skilled labor is needed to operate and maintain new technologies and equipment that firms introduce to comply with stringent environmental regulations, partially offsetting the adverse effects of technological advancements on highly skilled labor. Consequently, policy-driven technological upgrades exert a lesser impact on high-skilled workers compared to their low-skilled counterparts.

## 6. Heterogeneity analysis

Considering that various firm characteristics may impact the conclusions, in this section, we aim to provide additional support for the findings of this study by exploring heterogeneity in terms of energy consumption intensity, type of capital, innovation capability, and market power.

### 6.1. Energy consumption intensity

Given that the ECRTS allocates energy quotas to enterprises based on their energy usage, the scheme's binding effect may vary among enterprises with different energy consumption intensities. According to regulations, companies with higher energy intensity typically receive a larger quota, often leveraging advanced technology and equipment to enhance energy efficiency, thereby reducing their reliance on quotas. Conversely, enterprises with lower energy intensity may face more significant policy constraints due to receiving a lower quota and failing to upgrade their energy-using equipment. These enterprises, facing quota shortages, may respond by reducing production or purchasing energy-use licenses, leading to increased production costs and reduced labor demand. Consequently, we anticipate that the ECRTS exerts a more pronounced impact on the labor demand of firms with lower energy intensity.

**Table 10**
Mechanism test II: Technology upgrading effect.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | LP | *Ln* (*Labor*) | High-Skill | Low-Skill |
| *ECRT* × *Post* | 0.048** | | | |
| | (0.024) | | | |
| *LP* | | −0.444*** | −0.206*** | −0.445*** |
| | | (0.029) | (0.017) | (0.030) |
| *Controls* | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 30,152 | 30,152 | 27,050 | 28,434 |
| Adj-$R^2$ | 0.799 | 0.954 | 0.935 | 0.903 |

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are presented in parentheses and are clustered at the firm level. The variable *Controls* contains all the control variables in Model (1).

To test this hypothesis, we conducted a heterogeneity analysis of firms with different energy consumption intensities. According to the 2010 Statistical Report on National Economic and Social Development, industries with high energy consumption include chemical raw materials and chemical products manufacturing, ferrous metal smelting and rolling processing, non-ferrous metal smelting and rolling processing, non-metallic mineral products, petroleum processing and coking and nuclear fuel processing, and electricity and heat production and supply. We defined firms belonging to these six industries as high energy consumption firms and all other firms as low energy consumption firms. Fig. 4(a) presents estimates for firms with varying energy consumption intensities. The results indicate a more pronounced impact of the ECRTS on the labor demand of low-energy-consumption enterprises and a statistically insignificant effect on high-energy-consumption enterprises, aligning with theoretical expectations.

### 6.2. Type of capital

An increasing number of foreign enterprises are entering China's capital and commodity markets, where they are subject to compliance with local regulations, including environmental standards. Typically, foreign companies exhibit superior environmental performance compared to domestic counterparts (Liu et al., 2021b), possibly because they require fewer operational adjustments to meet new environmental regulations (Dean et al., 2009). The ECRTS, which primarily emphasizes source control, may affect foreign and domestic enterprises differently. Foreign-owned enterprises, which mainly operate in construction, financial, and technical services sectors, typically have lower energy demands and are often excluded from the ECRTS pilot, resulting in a minimal impact on their labor demand. In addition, the lower environmental pollution generated by foreign-owned enterprises suggests that they consume less energy or have high energy efficiency, thus achieving better environmental performance. Consequently, foreign-owned firms are less likely to alter their production processes due to energy constraints, reducing the effect on labor demand. To assess this hypothesis, we conducted separate estimations for firms with foreign and domestic ownership structures. The results in Fig. 4(b) indicate the ECRTS has a more pronounced effect on the labor demand of domestic enterprises compared to their foreign-owned counterparts, aligning with theoretical expectations.

### 6.3. Innovation capability

In our analysis of mechanisms, we examined technological progress as a crucial pathway through which the ECRTS impacts firm labor demand. When energy quotas are insufficient, firms can reduce energy usage by upgrading technology, often leading to labor displacement. Notably, firms with advanced technologies typically experience diminished marginal benefits from such upgrades in environmental governance. Consequently, they have a lower incentive to pursue additional technological innovations driven by environmental policy. Conversely, less innovative firms stand to gain more from technological upgrades due to their greater potential for progress. Upgrading technology is thus a pivotal strategy for less innovative firms to mitigate environmental pollution. We posit that the technology upgrading effect of the ECRTS is more pronounced in firms with lower technological capacity. In other words, when confronted with energy regulation shocks, less innovative firms may substitute more labor through technological progress.

To investigate the hypotheses, we examined differences in innovation capabilities among firms. Following relevant literature (Gross and Sampat, 2023; Jin et al., 2019), we utilized the number of inventions by enterprises as a measure of innovation capability. We assess the median value of this metric for each industry year, categorizing firms above the median as having strong innovation ability and those below the median as having weak innovation ability. Fig. 4(c) presents the findings of the

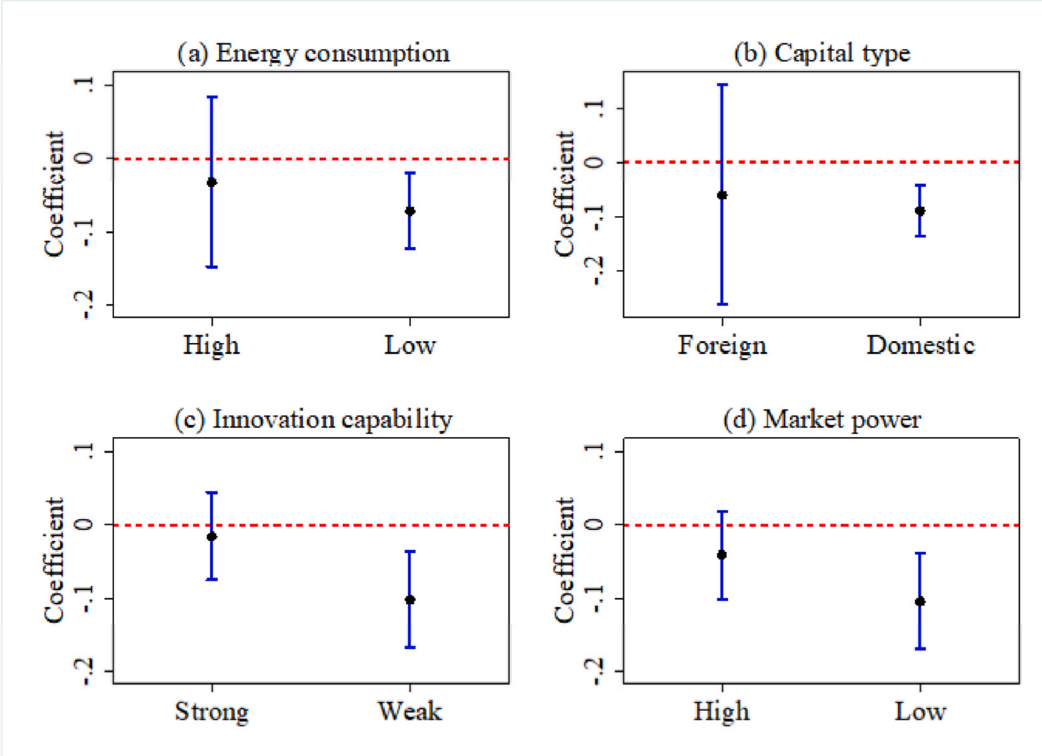


**Fig. 4.** Heterogeneity tests.

subgroup analysis. As anticipated, the ECRTS exhibits a more pronounced effect on the labor demand of less innovative firms.

### *6.4. Market power*

The market power of an enterprise determines its ability to dominate and access various resources in the market; firms with greater market power are usually the leaders in their industry. So, how does the ECRTS influence firms with varying market power? As detailed in Section 2.1, the program seeks to enhance energy efficiency by allocating different energy-use quotas to enterprises. Despite potentially encountering energy quota shortages, enterprises with high market power can readily acquire additional energy use licenses due to their market dominance, minimally affecting their production processes. Moreover, these firms typically boast advanced technology (Aghion et al., 2005), resulting in diminished benefits from technological progress in energy utilization. As a result, these firms may have less incentive to undertake additional technological upgrades to reduce energy consumption.

Both the production scale effect and technology upgrading effect suggest that enterprises with high market power are unlikely to react to energy pressure by reducing production or upgrading technology, thus exerting minimal impact on labor demand. Conversely, low-market-power firms that encounter insufficient energy quotas and delayed license procurement must curtail energy consumption through production reduction or technology enhancement, resulting in a greater impact on labor demand. Hence, we anticipate a more pronounced impact of the ECRTS on labor demand for low-market-power firms. To verify these hypotheses, we examined the heterogeneity among firms with varying market power. Following prior research (Datta et al., 2013; Gonçalves et al., 2018), we adopt the Lerner Index (price–cost margin) to gauge market power, categorizing firms above the median value as having high market power and the rest as having low market power. The results of the estimation depicted in Fig. 4(d) corroborate our expectations, demonstrating a more substantial impact of the ECRTS on the labor demand of low-market-power firms.

## 7. Welfare effects of the ECRTS

In our preceding analysis, we delved into the effects and mechanisms of the ECRTS on firm labor demand. However, two significant and intriguing issues remained unaddressed. First, as an environmental policy focusing on source control, does the ECRTS enhance the environmental performance of enterprises by curbing energy usage? Second, to comply with the policy, firms are compelled to curtail energy consumption through production downsizing and technology upgrades. Are the associated compliance costs of such regulations transferred to workers? In this section, we address these inquiries.

### *7.1. Has environmental quality been improved?*

In the realm of environmental governance, the Chinese government has implemented numerous policies aimed at curbing pollution emissions, which can be categorized into two main types: command-and-control and market-incentive policies. Command-and-control policies involve government enforcement of emission standards for enterprises through legal and administrative measures, while market-incentive policies leverage economic mechanisms to regulate emission behavior. Both types of policies tend to focus on end-of-pipe treatment, aiming to mitigate pollution at the discharge point, such as by promoting the installation of pollution control equipment. In contrast, the ECRTS diverges from typical market-based environmental policies by emphasizing source control, seeking to reduce emissions by curtailing energy consumption. While prior literature has extensively explored the effectiveness of end-of-pipe approaches in reducing pollution emissions (Haites, 2018; Hu et al., 2020; Zhang et al., 2020), the efficacy of source control strategies remains unclear. This study therefore assesses the impact of the ECRTS on corporate pollutant emissions in an attempt to close this gap in the literature.

Fig. 5 presents the regression results. Fig. 5(a) assesses the impact of ECRTS on total and per capita investment in environmental protection (*EPI* and *Per_EPI*). The results show that the policy variables have a nonsignificant positive impact on the environmental protection investment of enterprises, suggesting that the ECRTS does not incentivize firms to invest in environmental protection. Fig. 5(b) examines the program's effect on emissions of various pollutants, including nitrogen oxides (*NOx*), sulfur dioxide (*SO2*), carbon dioxide ($CO_2$), and smoke dust (*Smoke*), revealing no statistical significance for the estimated coefficients. This implies that the ECRTS has not significantly enhanced the environmental performance of firms. This could be attributed to the ECRTS primarily targeting energy consumption control and efficiency improvement, with environmental performance being a secondary outcome. Moreover, environmental governance at the enterprise level might not be its primary objective. Businesses might fulfill their energy requirements by purchasing energy use licenses on the market, instead of achieving substantial environmental improvements through technological improvements and reduced energy use.

### *7.2. Do workers bear the cost of the regulations?*

As previously discussed, to comply with energy regulations firms must reduce their total energy consumption either by decreasing production or upgrading technology, thereby increasing environmental governance costs. In the previous analysis, we confirmed that the ECRTS diminishes firms' labor demand through the production scale effect and the technology upgrading effect, meaning that firms have indeed taken measures to downsize their workforce in response to the ECRTS. From a labor standpoint, unemployment can be seen as the toll of policies on workers. However, beyond exacerbating unemployment, we have not yet explored whether the ECRTS also adversely affects the well-being of incumbent employees.

To investigate whether firms transfer regulatory compliance costs to their employees, we analyzed the effect of the ECRTS on employee salaries. Specifically, we examined the average salary for management (*Manager_Salary*), ordinary workers (*Worker_Salary*), and for all employees (*Salary*) utilizing logarithms for these variables. As seen in Fig. 6, the coefficients of policy variables are near 0 and lack statistical significance. This suggests that while the ECRTS decreases firms' labor demand, it does not affect the wages of incumbent employees.

Additionally, we investigated whether the ECRTS widens the wage gap between managers and ordinary workers by assessing its impact on wage inequality within firms (*Inequality*). We measure wage inequality using the ratio of *Manager_Salary* to *Worker_Salary*, applying logarithms to this variable as well. The results indicate that the coefficient of *ECRT*×*Post* is negative and statistically insignificant, suggesting that the program has no notable effect on income distribution within the enterprise. Overall, the ECRTS has no discernible impact on worker welfare, and firms do not pass on the compliance costs to incumbent employees, which is a novel and important finding.

## 8. Conclusions and implications

### *8.1. Conclusions*

Although there is continuous academic discourse surrounding the influence of environmental governance on employment, it has not yielded a universally accepted consensus. A review of existing literature revealed a predominant focus on the relationship between environmental governance and employment in developed economies such as the United States and Europe, with scant attention paid to developing

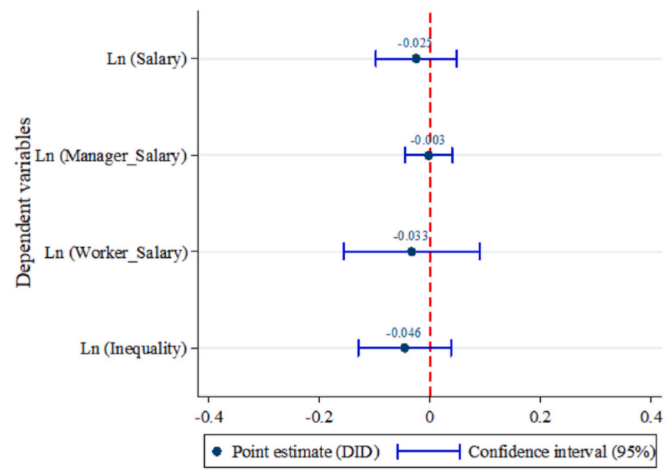


**Fig. 6.** Impact of ECRTS on employee wages. Notes: In Fig. 6, we use Model (1) to estimate the effects of ECRTS on various dependent variables, including *Ln* (*Salary*), *Ln* (*Manager_Salary*), *Ln* (*Worker_Salary*), and *Ln* (*Inequality*). Each of the four regression equations shown in Fig. 6 includes all of the control variables and fixed effects from Model (1). For ease of understanding, we do not report estimates for any control variables, as we are most interested in the coefficients of the interaction term (*ECRT*×*Post*) and their significance levels.

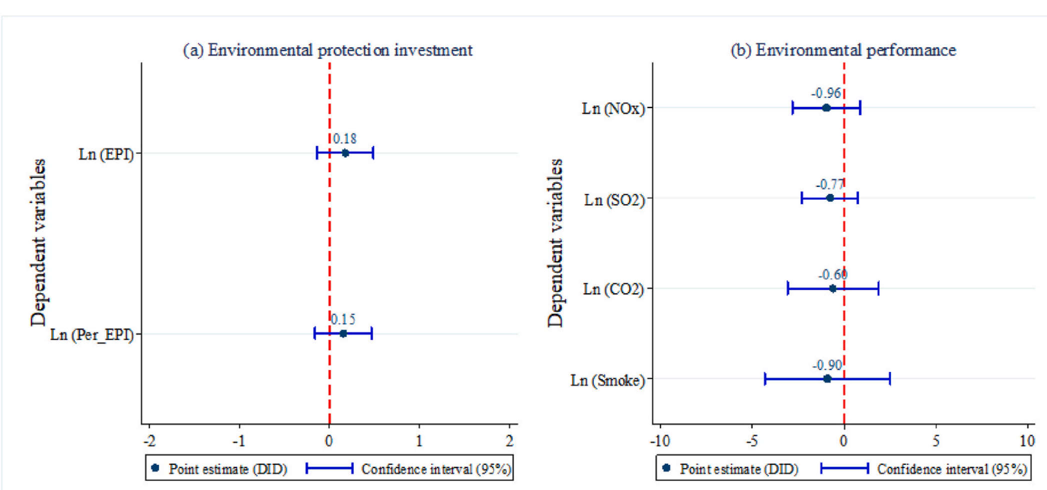


**Fig. 5.** Environmental governance effects of ECRTS. Notes: In Fig. 5, we use Model (1) to estimate the effects of ECRTS on various dependent variables, including *Ln* (*EPI*), *Ln* (*Per_EPI*), *Ln* (*NOx*), *Ln* (*SO2*), *Ln* (*CO2*), and *Ln* (*Smoke*). Each of the six regression equations shown in Fig. 5 includes all of the control variables and fixed effects from Model (1). For ease of understanding, we do not report estimates for any control variables, as we are most interested in the coefficients of the interaction term (*ECRT*×*Post*) and their significance levels.

nations. Existing studies have predominantly examined the employment implications of environmental policies that emphasize end-of-pipe treatments, overlooking the economic ramifications of policies that emphasize source control. This paper addresses this gap by utilizing a recent energy regulation policy in China (i.e., the ECRTS) as a quasi-natural experiment to investigate the impact of source-oriented environmental regulation on enterprise labor demand, thereby contributing to the literature on the employment effects of environmental governance in developing countries.

Our analysis revealed four key findings. First, the ECRTS notably diminishes firm labor demand, particularly affecting low-skilled workers. Specifically, the program led to an average decline in local enterprise employment of approximately 8%. High-skilled labor decreased by 4.6%, while low-skilled labor witnessed a sharper decline of 8.2%. Second, mechanism analysis highlighted that the ECRTS diminishes labor demand through both production scale effects and technological upgrading effects, albeit at the cost of displacing more low-skilled workers. Third, the impact of the ECRTS on labor demand displays significant variability across firms, exhibiting a greater impact on employment in low energy-intensity industries, domestic firms, those with weaker innovation capacities, and those with lower market power. Lastly, welfare analysis findings indicated that the ECRTS neither enhances environmental performance nor reduces employee wages. This suggests the program has a neutral impact on both the environment and employee welfare.

### 8.2. Policy implications

The findings of this study yield three primary policy implications. First, the interplay between environmental governance and employment in developing countries requires cautious handling in. Environmental policies emphasizing source control notably diminish the labor demand of Chinese enterprises, particularly impacting low-skilled labor. Regrettably, developing countries often have a higher proportion of low-skilled workers, and the widespread loss of jobs among this demographic carries substantial social costs and may even jeopardize government creditworthiness. Consequently, developing nations should implement complementary support policies to stabilize the labor market while advancing environmental governance efforts.

Second, policymakers should adopt tailored strategies to mitigate policy costs, recognizing the varied impacts of environmental policies across diverse industries and enterprises. Our research highlights substantial heterogeneity in the employment effects of energy regulation policies among firms with varying energy intensities, capital types, innovation capacities, and market power. Providing support to enterprises that face heavier environmental governance burdens is crucial for their sustainability amidst environmental protection initiatives. Governments could offer additional subsidies to such enterprises or enhance policy flexibility to minimize overall policy costs.

Third, it is crucial to remain vigilant, as enterprises might attempt to unfairly burden workers with the costs of environmental governance, leading to increased welfare losses. To adhere to environmental regulations, companies may alter production processes or implement end-of-pipe treatments, inevitably raising production costs. Without proper legal oversight, corporate executives may exploit their managerial authority and offload a greater share of compliance costs onto workers, exacerbating income inequality within the enterprise. Hence, regulatory authorities must comprehensively monitor and evaluate the environmental governance practices of enterprises to minimize the risk of further welfare losses.

### 8.3. Limitations

This study is not without limitations. First, it focused solely on Chinese publicly traded firms for analysis, potentially overlooking significant insights from numerous small and medium-sized enterprises. Although the Chinese Industrial Enterprises Database (CIED) offers a more comprehensive dataset, at the time of this study it only contained data through 2015, rendering it unsuitable for the research objectives of this study. Future access to a more diverse range of corporate data could yield more robust conclusions. Second, our analysis only examined the static impact of the ECRTS on enterprise labor demand, neglecting the dynamic process of labor reallocation across sectors or industries, which restricts the breadth of our findings. Future research by the authors or other scholars may explore this dynamic aspect further.

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## CRediT authorship contribution statement

**Hao Wang:** Conceptualization, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Chengkui Liu:** Conceptualization, Formal analysis. **Peihao Shi:** Conceptualization, Formal analysis, Methodology, Software. **Yuqin Wang:** Conceptualization, Formal analysis.

## Declaration of competing interest

I declare that I have no financial and personal relationships with other people or organizations that can inappropriately influence this work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

## Data availability

Data will be made available on request.

## Appendix

**Table A1**
Variable definitions

| Control variables | Definition |
|---|---|
| Firm-level | |
| *Capital* | Ratio of a firm's net assets to its total assets |
| *SER* | Ratio of a firm's selling expenses to its operating income |
| *Tax* | Logarithm of corporate income tax |
| *ROA* | Ratio of a firm's net profit to its total assets |

(*continued on next page*)

**Table A1** (*continued*)

| Control variables | Definition |
|---|---|
| *Growth* | Ratio of a firm's market value to its total assets (i.e., Tobin's Q) |
| *Size* | Logarithm of a firm's total assets at the end of the year |
| *Age* | Logarithm of the number of years since the company was established |
| *SOE* | An indicator variable taking a value of 1 for state-owned enterprises, otherwise 0 |
| City-level | |
| *GDP* | Logarithm of the city's per capita gross domestic product |
| *Wage* | Logarithm of the average wage of a city employee |

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