

Article

The Nonlinear Impact of Environmental Regulations on Urban Employment: Evidence from the Yangtze River Economic Belt of China

Wenyong Li ^{1,*} , Fei Wang ¹ and Caijing Zhao ²¹ School of Business, Henan Normal University, Xinxiang 453007, China; 2415183002@stu.htu.edu.cn² Institute of Information Sciences, Shanghai Academy of Social Sciences, Shanghai 200235, China

* Correspondence: wyl0605@163.com

Abstract

As an important policy tool for promoting green development, environmental regulation (ER) has exerted a profound impact on the employment sector. Using panel data from 106 prefecture-level and above cities in China's Yangtze River Economic Belt (YREB) from 2011 to 2022, we examine the impact and mechanisms of ER on employment scale and structure. Empirical results reveal that the strengthening of ER has a significant inhibitory effect on employment growth, but a positive impact on the optimization of the employment structure. As regulatory intensity increases, the suppressive effect on employment scale diminishes, while structural optimization strengthens. Moreover, the effects vary across regions. The scale-inhibiting effect is more pronounced in the Upper-Middle Yangtze regions, in areas with initially low regulation intensity, and in large cities. Structural optimization is most significant in the Lower Yangtze regions and in small/medium-sized cities. We also find that ER indirectly changes employment through three channels: industrial structure upgrading (ISU), green innovation (GV), and foreign direct investment (FDI). Our findings underscore the necessity of balancing environmental stringency with social sustainability, and the conclusions of our study are applicable to policymakers in China and other economies.

Keywords: environmental regulations; employment scale; employment structure; threshold effect; the Yangtze River Economic Belt

1. Introduction

In recent years, the frequent occurrence of extreme weather events globally has intensified concerns about climate change, environmental pollution, and resource depletion. These issues directly hinder the achievement of the United Nations Sustainable Development Goals (SDGs), particularly those related to Climate Action, Decent Work, and Economic Growth. As a result, governments globally have implemented increasingly stringent environmental regulations (ERs) to mitigate ecological degradation. While actively aligning with the international environmental governance agenda, the Chinese government has committed to peaking carbon emissions by 2030 and attaining carbon neutrality by 2060, and has also introduced various environmental protection policies, such as promoting a low-carbon economy and emission reduction [1]. However, the impact of these regulations on economic and social development, particularly on the labor market, is complex. Energy-intensive and highly polluting sectors, including manufacturing and heavy industries,



Academic Editor: Eric
Po-Keung Tsang

Received: 4 June 2026

Revised: 16 July 2026

Accepted: 20 July 2026

Published: 23 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

which are primarily subject to ER, play a crucial role in both regional and national economic development [2]. With increased regulatory oversight, the costs of pollution control and emissions reduction in these sectors have risen, forcing firms to reduce labor expenditures and resulting in employment declines [3]. Meanwhile, these regulations have spurred the development of eco-friendly technologies and clean manufacturing industries, creating new job opportunities. This structural transformation—characterized by simultaneous growth and decline—reflects a reallocation of labor market resources.

Notably, during the implementation of ER, different stakeholder groups often hold divergent positions. Wang et al. (2024) thought that business representatives generally express concerns that rising compliance costs squeeze profit margins, thereby compelling firms to reduce their workforce [4]; this anxiety is particularly acute in traditional high-polluting industries. Meanwhile, An (2026) pointed out that the interest divergence in the implementation of China's environmental policies is essentially a contradiction arising from the collision between bureaucratic governance and diversified interest demands [5]. Local government policymakers face dual pressures: they must meet emission reduction targets mandated by higher-level authorities while simultaneously safeguarding employment and social stability within their jurisdictions. This tension frequently leads to a recurrent trade-off between short-term aggressive emission reductions and the imperative of maintaining economic growth and employment stability when policies are put into practice. Therefore, the transition toward an environmental protection industry presents both opportunities and challenges for the labor market.

The Yangtze River Economic Belt (YREB), a pivotal strategic region for China's economy, bears the historic mission of "ecological priority and green development". In order to adhere to stricter ER, some firms have chosen to either exit the market or relocate their pollution-intensive operations from strictly regulated large cities to smaller cities with more lax regulations. This has triggered labor migration [6,7], potentially leading to regional imbalances in employment. Consequently, clarifying the relationship between ERs and employment—including their magnitude of influence and operational pathways—is essential for refining the theoretical framework of regional environment–employment coordination and for achieving the dual objectives of "lucid waters and lush mountains" and "employment-driven prosperity".

2. Literature Review

As environmental awareness intensifies, scholarly research on the impacts of ER continues to expand. However, measurement standards of ER remain inconsistent and fall primarily into two categories: comprehensive indicators and single-indicator metrics. The former integrates multiple proxies into a comprehensive indicator to measure the intensity of ERs [8]. The latter utilizes a single indicator [9]. These methodologies enable a multifaceted analysis of regulatory effects, which are predominantly explored through two lenses: employment quantity effects and employment structure effect.

Early studies largely focused on the net effect of ER on employment quantity, generating two competing theories. The theory of employment suppression primarily rests on the Cost Effect and the Pollution Haven Effect. The Cost Effect refers to the fact that environmental regulation increases firms' operating costs, shuts down highly polluting projects, and eliminates outdated equipment in the short term, thereby squeezing firms' profit margins, weakening their competitive advantages, and hindering their ability to absorb more labor [10,11]. For example, Lin et al. (2026) found that command-and-control ER, proxied by environmental penalties, significantly reduces the labor income share due to capital crowding out and financing constraints [12], reflecting enterprises' efforts to curb labor costs through income distribution adjustments. Wang et al. (2024) examined the "Air

Pollution Prevention and Control Action Plan” and observed divergent impacts: regulated firms initially reduced hiring, while non-regulated firms exhibited sustained employment growth [13]. Li et al. (2025) built a two-sector general equilibrium model incorporating abatement technologies and search-and-matching frictions in the labor market and revealed that ER leads to unemployment [14]. The Pollution Haven Effect, which involves the relocation of polluting firms to regions with laxer regulations when local stringency rises, causes local job losses [15]. Ma and Dai (2024) identified a dual pattern of labor market impact: regulations simultaneously suppress inflows (via job contraction) and increase outflows while also attracting workers to cities with improved environmental quality [16]. Chen et al. (2025) similarly demonstrated that stringent regulations are associated with local labor outflow into small cities with lower productivity and “dirtier” industrial structure, while the resulting improvements in environmental quality attract additional workers [17].

In contrast, the theory of employment promotion is primarily based on the Innovative Compensation Effect. The Innovative Compensation Effect, inspired by the Porter Hypothesis, wherein appropriate regulations stimulate technological innovation [18], offsets pollutant control costs through efficiency gains, fosters green transitions, creates eco-friendly jobs, optimizes labor allocation [19], and enhances overall employment. On this basis, previous studies have further confirmed the positive role of ER. For example, Li et al. (2025) found that formal, informal, and dual ERs all significantly facilitate corporate green transformation [20] and increase the number of eco-friendly workers. It is noteworthy that the low-carbon pilot policy also serves as one of the regulatory measures under environmental governance. Regarding this policy, Wang and Ge (2022) treated these pilot programs as quasi-natural experiments and found significantly higher employment growth in pilot cities versus non-pilot areas [21]. Similarly, Wang et al. (2023) demonstrated that low-carbon policies exogenously boost corporate labor demand [22].

Beyond aggregate employment quantity, a growing body of research examines employment structure, with particular emphasis on the differential impact observed among workers with varying skill levels. Javed (2025) noted that these regulations increase the demand for high-skilled labor while reducing the potential demand for low-skilled labor in traditional energy sectors [23]. Further observing the dynamic changes in labor, Zhong et al. (2021) found that the high-skilled worker demand increases with the strengthening of ER, while low-skilled worker demand first declines and then rises, exhibiting a U-shaped curve [3]. Tang et al. (2024) further found that the lower the degree of ER implementation, the greater its destructive effect, and that the impact on labor with different skill levels follows the pattern: low-skilled workers < high-skilled workers < medium-skilled workers [24]. These findings indicate that ERs induce skill upgrading, but the transitional costs are unevenly distributed.

The employment implications of ER, as a critical lever for sustainable development, have garnered significant attention; however, they remain under-explored. Although the relationship between ER and employment has been extensively examined in the existing literature, most studies focus solely on either “employment scale” or “employment structure” and often employ linear analytical frameworks. Furthermore, evidence supporting heterogeneous analyses of specific urban agglomerations (e.g., the YREB) remains limited. Therefore, compared with previous studies, the marginal contributions of this study are as follows: First, using a threshold effect methodology, we adopt a dual perspective that simultaneously considers employment scale and employment structure to quantitatively evaluate the nonlinear impacts. Unlike previous studies that typically assume a monotonic relationship, we identify a threshold pattern: the suppressive effect on employment scale diminishes marginally as regulatory stringency increases, whereas the optimizing effect on employment structure exhibits increasing marginal returns. This finding extends the

application of the Porter Hypothesis to the employment domain by introducing a non-linear perspective. Second, by systematically examining three underlying transmission pathways—industrial structure upgrading (ISU), green innovation (GV), and foreign direct investment (FDI)—we elaborately demonstrate how ERs both crowd out and create employment, thereby strengthening the intrinsic link between ER and sustainable development. Third, from the perspective of heterogeneity, we focus on different regions within the YREB, providing a theoretical basis for formulating differentiated regional policies that promote sustainable economic and social development.

This study addresses these gaps by examining 106 cities in the YREB. We adopt a dual perspective that considers both employment scale and employment structure to quantitatively evaluate the nonlinear impacts and transmission mechanisms of ER, focusing on the mediating roles of ISU, GV, and FDI. Based on our findings, we propose targeted policies to achieve environment–employment synergies.

3. Theoretical Analysis and Research Hypotheses

3.1. Theoretical Analysis of Employment by ER

The employment impact of ER is primarily transmitted through the Cost Effect and the Pollution Haven Effect [25]. The Cost Effect indicates that pollution is often an inherent byproduct of production, and stringent ER imposes new cost burdens on polluting firms [26]. Compliance with elevated standards necessitates higher pollution discharge fees and higher operating expenditures, which constrains firms' expansion capacity and ultimately suppresses new job creation [16]. Conversely, the Pollution Haven Effect suggests that stringent regulations disproportionately increase production costs for pollution-intensive firms relative to competitors in less regulated regions. This erodes their price competitiveness, diminishes market share, and heightens the risk of bankruptcy. Consequently, such firms may relocate to jurisdictions with laxer environmental standards to reduce compliance costs [7], or exit the market entirely [6], resulting in a decline in local employment.

Concurrently, ERs catalyze employment restructuring through policy pressure. Firms may achieve a green transition via industrial upgrading or technological innovation [2], spurring demand for environmental R&D and services. Meanwhile, firms unable to absorb compliance costs face market exit, releasing labor toward emerging green sectors. This reallocation corrects resource misallocation in pollution-intensive industries and optimizes employment composition [17]. In summary, stricter ER will reduce overall employment scale through increased costs and industrial relocation while facilitating the reallocation of labor resources via green transformation, thereby increasing the share of emerging green industries in the workforce and optimizing the employment structure.

This yields Hypothesis H1:

H1. *Stringent ERs exert a constraining effect on employment scale expansion but positively moderate employment structure optimization.*

3.2. The Mechanism Analysis of Employment by ER

ER influences labor employment by catalyzing ISU. This effect manifests through three interconnected pathways: spatial reallocation, innovation upgrading, and industrial agglomeration. First, prior research confirms that regulatory heterogeneity drives spatial industrial restructuring [27]. Stringent regions increase compliance costs for polluters, incentivizing relocation to laxer jurisdictions [28,29], this spatial reallocation redistributes employment geographically: while regions losing polluting industries may experience short-term job losses, recipient regions gain employment in the transferred sectors, thereby

shifting labor from pollution-intensive sectors toward cleaner, more skill-intensive activities and optimizing the overall employment structure. Second, beyond spatial shifts, the Porter Hypothesis posits that ER stimulates innovation in pollution firms [30], reducing per-unit pollution control costs, improving productivity, and enabling a shift toward higher-value-added activities, optimizing structural optimization. This upgrading process generates new employment opportunities, as empirically confirmed by He et al. (2025) and He et al. (2023), who demonstrate at both national and regional levels that industrial upgrading and employment can achieve dynamic “win–win” outcomes [31,32]. Supporting this from a practical perspective, Malachi and Eslamipoor (2026) document that circular-economy interventions in West Africa not only reduced environmental stress but also created new income streams (e.g., compost sales, biogas energy), thereby generating local employment [33]. Third, strict regulations incentivize the clustering of related industries in specific regions (e.g., eco-industrial parks) to share environmental protection infrastructure, leveraging technology spillover effects [34,35]. Such agglomeration enhances productivity and employment density, reinforcing the positive employment effects of industrial upgrading. In sum, industrial upgrading serves as a crucial transmission channel through which ER affects both employment scale and structure. Through the spatial redistribution of polluting activities across regions, the innovation-driven elevation of industrial value chains, and the productivity gains from industrial agglomeration, ISU collectively reallocates labor from traditional, pollution-intensive sectors toward cleaner, more skill-intensive activities. This multifaceted process not only geographically reshapes the distribution of employment but also upgrades the skill and value content of existing jobs, thereby partially offsetting the short-term job losses induced by regulatory compliance, optimizing the employment structure, and ultimately contributing to a more optimized and sustainable employment landscape.

H2. *ER mediates employment scale and structure through industrial upgrading.*

ER further affects employment by facilitating GV. Under the Porter Hypothesis, regulatory stringency compels firms to reallocate resources toward R&D, thereby enhancing green innovation capabilities to maintain competitiveness [36]. Lu et al. (2025) argue that motivated by increasingly strengthened ER, enterprises intend to pursue both pollution reduction and competitive edge through developing green innovation [37]. Duan et al. (2026) corroborate this by using the data from China’s A-share listed companies as a quasi-experiment [38]. Collectively, these findings confirm that regulatory pressure serves as a crucial driver of corporate green innovation.

Importantly, GV has dual-scale employment effects. On the one hand, it drives the transition from traditional manufacturing to green innovation-oriented manufacturing through the adoption of intelligent environmental technologies, which in turn surges demand for green-technology talent (R&D specialists, sustainable engineers, etc.) [15]. This shift optimizes human capital deployment and improves skill matching. On the other hand, beyond firm-level R&D, ERs have also spurred innovations in green supply chain management. For instance, Eslamipoor (2025) investigated factories, warehouses, and retailers as a three-level supply chain network, employing a multi-objective goal programming approach to reduce the overall cost of the system and cut down on gas emissions [39]. This management-level green innovation, through systematic optimization of logistics, inventory, and production decisions, reshapes enterprises’ demand structure for skilled labor—creating emerging roles in green operations, data analytics, and low-carbon planning while driving traditional warehousing and transportation positions toward greater skill-intensivity. Therefore, the net employment effect of GV is not inherently positive but critically on two conditions. First, whether the newly created high-skilled green jobs can

adequately offset the displacement of medium- and low-skilled positions, which ultimately determines the overall impact on employment scale. Second, whether the efficiency gains from supply-chain innovations translate into tangible labor demand for high-skilled labor in the short term, which shapes the direction of employment structure optimization. When these conditions are not satisfied, GV can paradoxically accelerate job polarization—expanding both high-skilled and low-skilled service employment while simultaneously eroding routine-intensive manufacturing jobs. In sum, whether GV ultimately expands employment scale and optimizes employment structure hinges on the regional absorptive capacity of human capital and innovation systems.

H3. *ER mediates employment scale and structure through green technological innovation.*

ER influences labor employment by suppressing FDI. The theoretical analysis of the impact of ER on international competitiveness rests on the Pollution Paradise Hypothesis [40]. The hypothesis posits that stringent regulations increase firms' production costs, divert R&D investment funds, compress profit margins, and weaken the comparative advantages and relative competitiveness of local firms. Consequently, foreign investment is driven toward regions with lower regulatory intensity and stronger competitiveness, thereby reducing local FDI inflows and constraining the scale of investment [41].

However, FDI relates to global factor mobility and substantially contributes to employment development [42,43]. ER moderates this relationship through two mechanisms: First, stringent regulations raise operational costs across regions, creating entry barriers for pollution-intensive FDI projects [44]. High-potential yet pollution-intensive investments may fail to materialize due to diminished local competitive advantages, thereby directly reducing latent employment opportunities, and suppressing the expansion of local employment. Second, incoming FDI enables multinational corporations to leverage their technological capabilities and capital intensity, generating a crowding-out effect on domestic firms [45] and increasing job-market instability and unemployment risks. Yet the capital–skill complementarity hypothesis suggests that FDI inflows can upgrade industries and technologies in foreign-funded firms [46,47], increasing the demand for high-skilled labor, or reducing low-skilled workers. Consequently, ERs amplify contraction in overall employment via restricting FDI inflows and crowding out domestic firms, while promoting improvement in employment structure through skill-biased realignment.

H4. *ER mediates employment scale and structure through FDI inhibition.*

3.3. *The Nonlinear Impact of ER on Employment*

The existing literature tends to discuss the Cost Effect, Pollution Haven Effect, and Innovation Compensation Effect of ER in isolation, such fragmented approaches overlook the dynamic interplay among these forces. Therefore, we integrate them into a unified dynamic evolution framework to investigate the nonlinear impact of ER on employment, positing that the net effect of ER on employment depends on whether the Cost Effect or the Innovation Compensation Effect dominates, and the ultimate direction is determined by the relative strength of these two opposing forces in specific contexts [11]. Focusing on the YREB—a region characterized by a high concentration of polluting industries, numerous resource-based cities, intense intergovernmental performance competition, and significant inter-provincial labor mobility barriers—we observe that in the early stages of ER implementation, the Cost Effect rapidly takes precedence due to the high share of heavy and chemical industries, strong asset specificity, and substantial sunk costs of industrial transformation, which often force small firms, already burdened by high compliance costs, to curtail production and erode their market share [27]. This contractionary pressure is

further exacerbated by neighboring regions' race-to-the-bottom regulatory practices aimed at attracting mobile capital. As empirically confirmed by Li et al. (2024), ER exerts a significant negative impact on local employment levels during this phase [48]. At this juncture, the Innovation Compensation Effect remains insufficient to offset the contraction, largely because technological absorption and capability building are subject to considerable time lags [49]; consequently, the suppressive effect dominates.

The rapid advancement of digital technologies has injected new momentum into the potential for ER to promote employment. A systematic review by Eslamipour (2026) indicates that artificial intelligence (AI), the Internet of Things (IoT), blockchain, big data, and machine learning are fundamentally reshaping resource management and governance efficiency, significantly enhancing environmental benefits while simultaneously generating employment opportunities at the societal level [50]. In the process of implementing ER at YREB, local governments can leverage digital platforms to publicly disclose firm-level emission data, compliance costs, and the progress of green technology adoption, thereby improving policy transparency and predictability. These measures will enable enterprises to gradually overcome regulatory barriers, cross a critical threshold, reduce excessive reactions to regulatory uncertainty, and mitigate undue employment contraction, specifically by diminishing the inhibitory effect of ER on the expansion of employment scale. Complementing this, Jing et al. (2023) empirically demonstrated a complex U-shaped relationship between ER and employment, with effects varying significantly along the curve's trajectory [51]. Meanwhile, as regulatory stringency accumulates and eventually crosses a critical threshold, sustained technological investment and policy pressure enable polluting-intensive firms to break through technological barriers. Green product innovation and process improvements begin to yield competitive market advantages, while vertical industrial chain specialization (e.g., upstream–midstream–downstream coordination) and cross-city knowledge spillovers gradually materialize. These dynamics collectively facilitate the reallocation of labor from traditional sectors to emerging green industries [52], and this structural optimization exhibits increasing marginal effects.

H5. *The impact of ER exhibits threshold-based nonlinear characteristics. Specifically, the suppressive effect on employment scale demonstrates diminishing marginal effects, while the optimizing effect on employment structure shows increasing marginal effects.*

As shown in Figure 1, this figure illustrates the theoretical framework of our study. ER influences employment through three mediating channels: ISU, GV, and FDI. These mechanisms jointly shape two employment outcomes: employment scale and employment structure. Furthermore, the effects of ER on employment exhibit threshold-based nonlinear characteristics: the suppressive effect on employment scale demonstrates diminishing marginal effects, while the optimizing effect on employment structure shows increasing marginal effects as regulatory intensity increases.

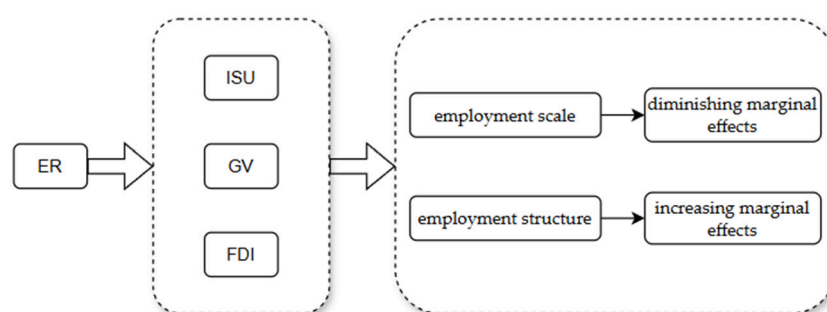


Figure 1. The theoretical framework of ER on employment.

4. Model Construction and Variable Definition

4.1. Modeling

4.1.1. Benchmark Regression Model

To examine the impact of ER on employment, the benchmark regression model can be formulated as follows:

$$\text{labor}_{it} = \alpha_0 + \alpha_1 \text{ER}_{it} + \alpha_2 \text{control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where

- α_0 is the constant term;
- ER_{it} represents core explanatory variable;
- labor_{it} is the dependent variable, including employment scale (labor_zl) and employment structure (labor_jg);
- control_{it} are a series of control variables, including financial development, government expenditure, urbanization level, etc.;
- μ_i and λ_t are city fixed effects and year fixed effects, respectively;
- ε_{it} is the random error term.

4.1.2. Mediating Effect Model

In line with the recommendations of Jiang (2022) regarding mediating effect analysis [53], and given that a substantial body of literature has empirically established the effects of ISU, GV, and FDI on employment [22,29,32,54], we focus primarily on examining the impact of ER on these three channels. This allows us to explore the transmission pathways through which ERs influence employment. Accordingly, building on Model (1), we specify Model (2) to conduct the mediating effect test.

$$\text{emp}_{it} = \beta_0 + \beta_1 \text{ER}_{it} + \beta_2 \text{control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where

- β_0, γ_0 are constant terms;
- emp_{it} is the mediating variable, including ISU, GV, and FDI;
- The remaining variables are consistent with Model (1).

4.1.3. Threshold Regression

To examine the nonlinear relationship between ER and employment, this paper employs a panel threshold regression model, which allows the effect to vary across different regimes based on a threshold variable:

$$\text{labor}_{it} = \theta_0 + \theta_1 \text{ER}_{it} \times I(\text{Mid} \leq \tau) + \theta_2 \text{ER}_{it} \times I(\text{Mid} > \tau) + \theta_3 \text{control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where

- θ_0 is the constant term;
- $I(*)$ represents the indicator function, which assumes a value of 1 when the expression within parentheses is true and 0 otherwise;
- Mid represents a threshold variable, including ER;
- The remaining variables are consistent with Model (1).

4.2. Variable Definitions

4.2.1. Predicted Variables

Employment Scale (labor_zl). Measured by the number of employed persons in an urban area. This indicator comprehensively covers the employment situations of various industries and forms of ownership, enabling direct and comprehensive comparison and assessment of basic employment conditions. Therefore, this paper adopts the number of employed persons in prefecture-level cities from 2011 to 2022 as the measurement of employment scale [55].

Employment Structure (labor_jg). Measured by the ratio of employed persons in the tertiary industry to those in the secondary industry. The concept of employment structure is highly comprehensive and can be categorized from various perspectives, roughly including the urban–rural structure of employment, the industrial structure of employment, and the technological structure of employment. Drawing on the research by Xiao et al. (2022), this paper measures the employment structure from an industrial perspective [56], using the ratio of employees in the tertiary sector to those in the secondary sector as a measurement indicator, it reflects the transformation of the manufacturing industry from “production-oriented manufacturing” to “service-oriented manufacturing”, which can effectively reflect the degree of urban employment structure transformation.

4.2.2. Explanatory Variable

ER is the core explanatory variable. This paper adopts the entropy method for measurement. Drawing on the construction of comprehensive environmental regulatory indicators from previous studies and considering the availability of data on prefecture-level cities in the YREB, we adopt the measurement method proposed by Xiao et al. (2024) on the measurement of ER [8]. Firstly, the four individual indicators of industrial sulfur dioxide emissions, industrial soot (dust) emissions, centralized treatment rate of sewage treatment plants (%), and harmless treatment rate of domestic garbage (%) are standardized. Secondly, the weight coefficients of each individual indicator are calculated. Finally, the ER intensity is obtained by weighted summation. A higher value of this indicator indicates stricter local ER. The specific calculation method is as follows:

Step 1, the data standardization process is as follows:

For positive indicators:

$$X_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (4)$$

For negative indicators:

$$X_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (5)$$

where

- x_{ij} is the value of the j – th indicator in region I ;
- X_{ij} is the standardized value.

To eliminate the influence of zero values, add a minimum unit value $\beta = 0.0001$ to the standardized data to obtain X' .

Step 2, normalization processing:

$$P_{ij} = \frac{X'_{ij}}{\sum_{i=1}^n X'_{ij}} \quad (6)$$

Step 3, calculate entropy value:

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n P_{ij} \times \ln P_{ij} \quad (7)$$

Step 4, calculate redundancy of entropy value:

$$D_j = 1 - E_j \quad (8)$$

Step 5, calculate weight:

$$W_j = \frac{D_j}{\sum_{j=1}^m D_j} \quad (9)$$

Step 6, calculate the environmental regulation index of the YREB:

$$G_j = \sum_j^m W_j \times X_{ij} \quad (10)$$

4.2.3. Mediation Variables

Industrial Structure Upgrading (ISU). In the development of various cities, as the industrial structure shifts from a basic form to a more advanced one, it plays a huge role in advancing employment levels in cities. Therefore, this paper adopts the ratio of the added value of the tertiary industry to that of the secondary industry as the measurement metric [29,45].

Green Innovation (GV). Green technology adoption exhibits dual effects on employment: substitution effects (eliminating high-pollution jobs) and compensation effects (creating new jobs). It serves to elucidate the divergent employment trajectories observed across various industrial sectors while providing critical evidence for the assessment of “environment–employment win–win” policies. In comparison to the number of green patent authorizations in each urban area, the number of green patent applications can better reflect an urban area’s level of green technological innovation. Consequently, the number of green patent applications is adopted as the measure [57].

Foreign Direct Investment (FDI). Opening up to the outside world is conducive to technological exchanges between China’s various regions and different countries, thereby advancing high-quality economic development. However, it may also lead to the relocation of some high-carbon emission industries, potentially affecting labor employment in China. Therefore, the amount of FDI in the YREB is transformed into RMB using the annual average exchange rate, and the level of FDI is measured by its ratio to the regional GDP [1,44].

4.2.4. Control Variables

In accordance with the selection of control variables in existing studies, the following control variables have been selected.

1. Government expenditure (Gover), measured by the ratio of general budgetary expenditure of local governments to regional GDP.
2. Urbanization level (Urban), measured by the urbanization rate.
3. Economic development (gdp), measured by per capita regional GDP.
4. Medical development (Doctor), measured by the ratio of doctors to the total permanent resident population.
5. Industrial intelligence (AI), measured by robot installation density.

4.3. Data Source

Our initial sample consists of 106 prefecture-level cities in the YREB from 2011 to 2022. The data are sourced from China City Statistical Yearbook, local prefecture-level city statistical yearbooks, and local statistics bureaus. To ensure data completeness, we excluded seven cities (Chaohu, Pu'er, Simao, Bijie, Jingsha, Tongren and Xiangyang) due to a high proportion of missing data for key variables (exceeding 5% of the sample period for key variables). For other cities, individual missing data were filled using the linear interpolation method. Specifically, the proportion of individual missing data does not exceed 5%, and there are no consecutive missing sequences lasting more than three years. Although linear interpolation may slightly reduce data variance, considering the proportion and distribution of missing values, this method does not substantially affect the primary empirical results. Table 1 presents the results of the descriptive statistical analysis.

Table 1. Descriptive statistics.

Variables	N	Mean	S.D.	Min	Max
labor_zl	1272	66.975	99.204	7.796	986.870
labor_jg	1272	1.376	0.940	0.199	8.293
ER	1272	0.957	0.060	0.609	0.9998
Gover	1272	0.193	0.079	0.076	0.675
Urban	1272	0.558	0.130	0.182	0.896
Doctor	1272	23.248	10.178	5.963	70.024
Al	1272	5.474	4.087	0.187	25.346
gdp	1272	5.890	3.547	0.888	19.902

5. Analysis of Empirical Results

5.1. Benchmark Regression Results

Table 2 presents the results of the benchmark regression. All explanatory and control variables were analyzed using the variance inflation factor (VIF), and all VIF values were below 10, with a mean of 2.880, indicating that there were no multicollinearity issues. The Hausmann test results show that a bidirectional fixed-effect model should be adopted.

The impact of ER on employment scale. Columns (1) and (2) report the impact of ER on employment scale. Column (1) presents results without controlling for any variables. The coefficient on ER is negative and statistically significant at the 5% level, equal to -137.560 . A one-unit increase in ER reduces employment by 137.560 workers, indicating that stringent ER suppresses employment growth. In Column (2) we add additional control variables. The coefficient on ER remains significant, which demonstrates that the inhibitory effect of ER on the expansion of employment scale persists even after controlling for other potential factors. The results suggest that, within the YREB, stricter ER imposes additional costs related to pollutant emissions and compliance. To reduce costs, firms either reduce their market share or relocate to regions with laxer regulations, leading to a reduction in local employment scale. These results thus empirically support Hypothesis H1.

The impact of ER on employment structure. Columns (3) and (4) report the impact of ER on employment structure. Column (3) presents results without controlling for any variables. As shown, the coefficient on ER is positive and statistically significant at the 10% level ($\alpha = 0.784$). For every unit increase in ER, the employment structure improves by 0.784%, implying that stringent ER positively affects the optimization of the employment structure. The coefficient on ER remains significant after including all control variables, as shown in Column (4), which demonstrates that the positive effect persists after controlling for other potential factors. Specifically, stringent ER reduce employment in high-pollution or high-energy-consuming industries, while driving a shift in the employment structure

from the secondary industry to the tertiary industry. These results reflect a reallocation of labor resources and an improvement in the employment structure. Therefore, stricter ER have a positive effect on optimizing the employment structure. These results thus support Hypothesis H1.

Table 2. Benchmark regression results of ER on employment.

Variables	Employment Scale		Employment Structure	
	(1) labor_zl	(2) labor_zl	(3) labor_jg	(4) labor_jg
ER	−137.560 ** (−2.33)	−132.701 ** (−2.19)	0.784 * (1.92)	0.800 ** (2.00)
Gover		18.026 (0.61)		−2.210 ** (−2.39)
Urban		2.962 (0.12)		−1.420 *** (−2.99)
Doctor		0.055 (0.26)		0.014 *** (3.21)
AI		0.813 (1.41)		−0.002 (−0.20)
gdp		1.372 (1.02)		−0.047 ** (−2.45)
_cons	198.629 *** (3.49)	175.045 *** (3.05)	0.626 (1.61)	1.791 *** (3.64)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1272	1272	1272	1272
R ²	0.894	0.894	0.790	0.797

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Regarding the estimated results for the control variables, the coefficients for economic development on the expansion of employment scale are positive, while their coefficients on the optimization of employment structure are negative. This indicates that improvements in economic development lead to employment expansion but may worsen the employment structure. The coefficients for government expenditure level and urbanization level on employment structure are negative, indicating that government expenditure is overly concentrated on heavy industry firms. Moreover, the urbanization process leads to an imbalanced distribution of resources, inhibits the development of industries with a high degree of marketization, and results in employment rigidity. The coefficient for the medical development on employment is positive, indicating that the pulling effect of medical development level on employment scale is limited. Nevertheless, the high-quality jobs created by the medical industry itself are technology-intensive and will, to some extent, optimize the employment structure. The coefficient for industrial intelligence on the expansion of employment scale is positive, while its coefficient on the optimization of employment structure is negative, though not statistically significant, which indicates that the level of industrial intelligence exerts a modest positive effect on employment scale and a potential inhibitory effect on the optimization of employment structure.

5.2. Robustness Testing

Winsorization. Referring to the research by Lu et al. (2025), to reduce the influence of extreme values on the research results, all observations were winsorized at the 1% and 99% levels [37]. Columns (1) to (4) of Table 3 report the fixed-effects results after the data were winsorized. Consistent with the main results, the coefficient of ER on employment scale remains significantly negative, regardless of the inclusion of control variables, whereas

the coefficient on employment structure remains significantly positive. This pattern shows that ER inhibits the expansion of employment scale and optimizes employment structure, thereby confirming the robustness of the benchmark regression results.

Table 3. Robustness tests results.

Variables	Winsorization				Core Explanatory Variables Lag One Period			
	(1) labor_zl	(2) labor_zl	(3) labor_jg	(4) labor_jg	(5) labor_zl	(6) labor_zl	(7) labor_jg	(8) labor_jg
ER	−56.239 ** (−2.14)	−49.712 * (−1.82)	0.462 * (1.71)	0.529 * (1.74)				
ER(−1)					−145.208 ** (−2.56)	−144.189 ** (−2.53)	1.164 *** (2.96)	1.165 *** (2.93)
_cons	119.544 *** (4.72)	94.285 *** (3.43)	0.914 *** (3.52)	1.862 *** (4.47)	206.888 *** (3.81)	198.126 *** (3.38)	0.275 (0.74)	1.452 *** (2.81)
Control	No	Yes	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1272	1272	1272	1272	1166	1166	1166	1166
R ²	0.935	0.936	0.831	0.836	0.902	0.903	0.815	0.824

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Lagged Explanatory Variable. Referring to the research by Wang et al. (2025), lagged variables can effectively alleviate concerns about reverse causality [58], confirming the reliability of our core conclusion. Therefore, Columns (5) to (8) of Table 3 report the results with the core explanatory variables lagged by one period. Columns (5) and (6) show the regression results for employment scale, and the coefficients on the lagged ER remain significantly negative, indicating that ERs still have an inhibitory impact on the expansion of employment scale. As presented in Columns (7) and (8), the coefficients on ER(−1) are both significantly positive, indicating that the lagged ER has a positive effect on the optimization of employment structure, thereby confirming the robustness of the benchmark results.

Excluding provincial capitals. Provincial capitals receive greater policy resource allocation, which significantly influences regression outcomes. Therefore, we exclude provincial capitals within the YREB. The results are presented in Columns (1) and (2) of Table 4. Compared to the baseline regression, ER continues to exert a robust impact on employment scale and structure even after excluding these cities.

Table 4. Other robustness tests results.

Variables	Excluding Provincial Capitals		Eliminate Policy Interference	
	(1) labor_zl	(2) labor_jg	(3) labor_zl	(4) labor_jg
ER	−135.069 ** (−2.15)	0.838 ** (2.03)	−44.754 *** (−2.79)	0.730 * (1.95)
_cons	167.249 *** (2.82)	1.895 *** (3.75)	88.789 *** (4.11)	1.855 *** (3.68)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1164	1164	977	977
R ²	0.889	0.806	0.886	0.787

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Eliminate policy interference. Referring to the research by Wang et al. (2025), since the estimates may be biased due to interference from other policies during the sample period [59], we reviewed the “Announcement on Implementing Special Emission Limits for Air Pollutants” issued by the Ministry of Ecology and Environment of the People’s Republic of China in 2013, along with the “Three-Year Action Plan for Winning the Blue Sky Defense Campaign” released in 2018. Both of these documents explicitly designated cities subject to special emission limits as key control areas. To eliminate potential interference from these key cities on the results, we excluded relevant cities within the key control areas. The results are presented in Columns (1) and (2) of Table 4. Compared with the baseline regression results, the conclusions remain robust.

Endogeneity Issues. Table 5 presents the results of the endogeneity analysis. To address potential endogeneity issues, we adopt an instrumental variable (IV) approach following Shi et al. (2024) [15]. The air circulation coefficient serves as our instrument for ER. This time-invariant variable is interacted with regulatory measures in the model specification. The selection rationale satisfies key conditions. First, a higher air circulation coefficient, indicating greater atmospheric dispersion capacity, is correlated with stricter environmental enforcement, establishing relevance for an instrumental variable. Second, from an exogenous perspective, as discussed by Ma et al. (2024) [16], the air circulation coefficient is determined by both average wind speed and atmospheric boundary layer height. Both of these factors are governed by natural conditions and do not directly affect labor productivity.

Table 5. Results of endogeneity analysis.

Variables	First Stage	Second Stage	
	Environmental Regulations	Employment Scale	Employment Structure
ER		−112.836 ** (−2.58)	2.044 ** (2.54)
IV	0.0001 *** (10.19)		
Control		Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1272	1272	1272
Kleibergen–Paap rk LM test		72.537 ***	
Cragg–Donald Wald F test		301.277 [16.38]	

** $p < 0.05$, *** $p < 0.01$.

As shown in Table 5, the K-P LM test yields a p -value below 0.01, indicating that there is no issue of under identification of the IV. The CDW F statistic surpasses the critical value at the 10% level, indicating that there is no issue of weak instrument problem and that the instrument is strongly correlated with ER. In the first stage, the IV (air circulation coefficient) is significantly and positively correlated with ER. The second-stage results show that the coefficient on ER is significantly negative, while the coefficient on employment structure is significantly positive, consistent with the benchmark regression.

5.3. Heterogeneous Analysis

Regional Heterogeneity. Table 6 presents the results after accounting for regional heterogeneity. The YREB spans the eastern, central, and western regions of China, we divide it into two subsamples: the upper–middle reaches and the lower reaches. The

upper–middle reaches include Chongqing, Sichuan, Guizhou, Yunnan (upper reaches), as well as Jiangxi, Hubei, and Hunan (middle reaches). The lower reaches comprise Shanghai, Jiangsu, Zhejiang, and Anhui. This paper conducts a heterogeneity analysis across the two segments of the YREB. Columns (1) and (2) show that in the upper–middle reaches, the coefficient of ER on employment scale (*labor_zl*) is -185.649 , significant at the 1% level, while its coefficient on employment structure (*labor_jg*) is 0.674 , significant at the 10% level. This indicates that in the upper–middle reaches, stricter ER significantly reduces the employment scale but simultaneously exerts a positive effect on optimizing the employment structure. Columns (3) and (4) show that in the lower reaches, the coefficient of ER on employment scale is 59.232 , but it is not statistically significant; however, the coefficient on employment structure is 1.298 , which is positive and significant at the 1% level. This suggests that in the lower reaches, stringent ER does not reduce total employment, but rather significantly promotes the optimization of the employment structure. The reason lies in the fact that the lower reaches are dominated by finance, technology, high-end manufacturing, and modern service industries, and their industrial structure possesses a strong capacity for innovation absorption. As a result, the “Innovation Compensation Effect” of ER can be fully realized, thereby expanding employment scale while optimizing employment structure. Zhou (2020) pointed out that when the industrial structure has been optimized to a certain degree, the effect of ER on employment shifts from suppression to promotion [60], a view consistent with our findings for the lower reaches. In summary, the impact of ER on employment exhibits significant regional heterogeneity.

Table 6. Regression results of regional heterogeneity.

Variables	Upper–Middle Reaches		Lower Reaches	
	(1) <i>labor_zl</i>	(2) <i>labor_jg</i>	(3) <i>labor_zl</i>	(4) <i>labor_jg</i>
ER	-185.649^{***} (-5.76)	0.674^* (1.70)	59.232 (1.64)	1.298^{***} (2.62)
_cons	246.675^{***} (5.20)	2.745^{***} (4.69)	6.610 (0.15)	1.061^* (1.77)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	780	780	492	492
R ²	0.820	0.787	0.970	0.896

* $p < 0.1$, *** $p < 0.01$.

Heterogeneity in ER Intensity. Table 7 reports results that account for heterogeneity in ER intensity. To examine the effect of ER intensity on employment, regions are categorized into two groups: those with intensity below the median are defined as low-intensity ER regions, and those with intensity above the median are defined as high-intensity ER regions. Columns (1) and (2) demonstrate that ER is significant at the 5% level for employment scale and at the 1% level for employment structure. Compared with the full sample, regions with low-intensity ER exhibit an inhibitory effect of increasing regulatory intensity on employment expansion and a positive effect on optimizing the employment structure, with both effects being significant. Moreover, the inhibitory effect on employment expansion is significantly stronger in low-intensity regions than in high-intensity regions. Columns (3) and (4) show results for high-level-intensity regulation regions: increases in ER intensity have a positive impact on both employment expansion and employment structure optimization, but these effects are not statistically significant.

Table 7. Regression results of heterogeneity in ER intensity.

Variables	Regions with Low-Level of ER		Regions with High-Level of ER	
	(1) labor_zl	(2) labor_jg	(3) labor_zl	(4) labor_jg
ER	−296.933 ** (−2.42)	1.268 *** (2.69)	4.003 (0.03)	3.280 (0.65)
_cons	316.086 *** (2.78)	0.288 (0.72)	43.045 (0.34)	−0.877 (−0.18)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes
N	636	636	636	636
R ²	0.902	0.752	0.888	0.843

** $p < 0.05$, *** $p < 0.01$.

Heterogeneity of Urban Size. Table 8 reports results that account for heterogeneity in urban size. According to China’s population-size classifications, medium-sized cities and small cities are merged into “small and medium-sized cities,” with the remaining cities classified as large cities. Columns (1) to (4) demonstrate that ER exerts an impact on both employment scale and employment structure, regardless of whether the cities are large or medium-sized. In comparison to small and medium-sized cities, stringent ERs in large cities have a stronger inhibitory effect on employment scale and a weaker positive effect on employment structure. The reason is that resource allocation in large cities is relatively more complete; once ER policy changes, it readily disrupts the existing balance, which places greater pressure on optimizing the employment structure while simultaneously exacerbating the inhibitory effect on employment scale.

Table 8. Regression results of urban size heterogeneity.

Variables	Small and Medium-Sized Cities		Large Cities	
	(1) labor_zl	(2) labor_jg	(3) labor_zl	(4) labor_jg
ER	−14.537 (−1.57)	0.910 * (1.92)	−240.845 ** (−2.50)	0.894 * (1.66)
_cons	45.258 *** (4.49)	1.643 *** (2.94)	308.058 *** (2.91)	1.507 (1.63)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	678	678	594	594
R ²	0.857	0.811	0.888	0.783

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4. Mechanistic Analysis

Table 9 examines the effect of the mechanistic analysis. As shown in Column (1), the coefficient of ER on ISU is 0.404 and statistically significant at the 5% level, indicating that stringent ER have a positive impact on ISU and promote the evolution of regional industrial structure towards a more advanced direction. Previous studies generally hold that when ER reduces employment in polluting industries, structural adjustment increases the demand for high-skilled labor through productivity gains [61]. This process partially offsets the negative impact on overall employment while reducing reliance on simple manual labor, thereby optimizing the employment structure, this finding is consistent with He et al. (2025) [32]. Thus, Hypothesis H2 is verified.

Table 9. Regression results of mechanism.

Variables	(1) ISU	(2) GV	(3) FDI
ER	0.404 ** (2.20)	0.667 ** (2.44)	−0.012 *** (−2.87)
_cons	1.084 *** (5.25)	4.495 *** (13.69)	0.028 *** (4.42)
Control	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1272	1272	1272
R ²	0.886	0.970	0.817

** $p < 0.05$, *** $p < 0.01$.

As shown in Column (2), the coefficient of ER on GV is 0.667 and statistically significant at the 5% level, indicating that stringent ER compels firms to pursue eco-innovation and effectively stimulates their green technological innovation activities. As a key form of technological progress, GV can mitigate the effects of increased regulatory pressure on pollution abatement only when it is fully integrated into the entire production process [54]. This process generates new, green-oriented jobs that require specialized skills [22], which in turn improves the employment structure and alleviates the negative employment scale impact of regulations. Consequently, Hypothesis H3 is verified.

As shown in Column (3), the coefficient of ER on FDI is −0.012 and statistically significant at the 1% level, indicating that heightened compliance costs deter pollution-intensive foreign projects, thereby suppressing FDI inflows. Liao et al. (2021) point out that FDI inflows not only directly create job opportunities but also affect the quantity and quality of employment through technology spillovers and industrial linkages [42]. Our results suggest that ER, by reducing FDI inflows, weakens the employment-creation effect of foreign capital, thereby exerting an indirect negative influence on employment scale. On the other hand, the reduction in FDI may force domestic firms to strengthen independent innovation and industrial upgrading, thus indirectly optimizing the employment structure. Therefore, Hypothesis H4 is supported.

5.5. Threshold Effect Analysis

Table 10 reports the test results for the single and double thresholds. This paper employs the Bootstrap method with 500 repetitions to derive LM statistics, F-value and p -value for threshold testing. The results indicate that when ER stringency serves as the threshold variable, both the single and double thresholds are statistically significant for employment scale (labor_zl), while for employment structure (labor_jg) only the single threshold is significant. Table 11 presents the threshold estimates along with their 95% confidence intervals. As shown in Table 11, for employment scale, the two thresholds are 0.8994 (with a 95% confidence interval of [0.8837, 0.9052]) and 0.9116 (with a 95% confidence interval of [0.8975, 0.9164]). For employment structure, the single threshold is 0.9915 (with a 95% confidence interval of [0.9909, 0.9917]). Figures 2 and 3 present likelihood ratio statistics for both relationships. As shown in the figures, there are clear threshold effects in the model.

Table 10. Significance test of the threshold effect.

Threshold Variable	Predicted Variables	Number of Thresholds	F	<i>p</i>	BS	Critical Values		
						10%	5%	1%
ER	labor_zl	Single	30.54	0.016	500	19.1310	21.9633	35.3936
		Double	30.76	0.054	500	22.8524	32.2273	44.2515
		Triple	10.36	0.708	500	39.7237	47.9499	64.9606
	labor_jg	Single	64.60	0.028	500	50.6294	58.5364	74.8066
		Double	15.79	0.188	500	19.5382	23.9785	34.2133

Table 11. Threshold estimation and confidence intervals.

Threshold Variable	Predicted Variables	Threshold	Value	Confidence Intervals of 95%
ER	labor_zl	Single	0.8994	[0.8837, 0.9052]
		Double	0.9116	[0.8975, 0.9164]
	labor_jg	Single	0.9915	[0.9909, 0.9917]

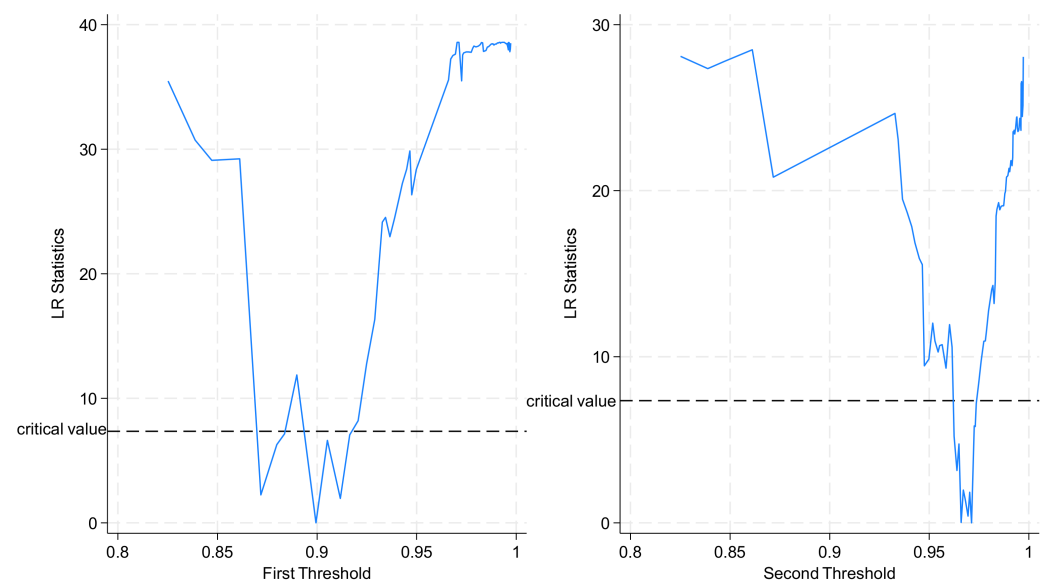
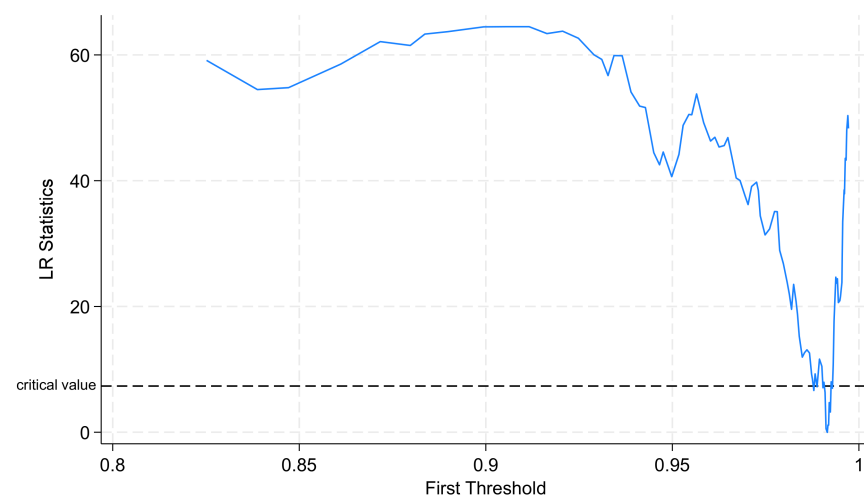
**Figure 2.** Likelihood comparison chart of employment scale.**Figure 3.** Likelihood comparison chart of employment structure.

Table 12 shows the regression results of the threshold effect. For employment scale, two thresholds divide ER into three regimes. When the regulatory stringency is low ($ER \leq 0.8994$), the coefficient is -315.188 ; when it is moderate ($0.8994 < ER \leq 0.9116$), the coefficient is -275.069 ; when it is high ($ER > 0.9116$), the coefficient is -258.724 . The absolute values of the coefficients gradually decrease as the intensity of ER increases, and all three coefficients are statistically significant. These findings indicate that as ER stringency intensifies, polluting firms progressively adapt to compliance pressures. Consequently, the suppressive effect on employment expansion diminishes marginally, revealing a concave relationship characterized by progressively smaller employment reductions per unit increase in regulatory intensity. For employment structure, a single threshold splits ER into two intervals. When regulations are lenient ($ER \leq 0.9915$), the coefficient is 1.433 ; when regulations become stricter ($ER > 0.9915$), the coefficient rises to 1.698 , with both coefficients being statistically significant. The absolute value of the coefficient gradually increases as the intensity of ER rises. This indicates that once the intensity of ER exceeds the first threshold value, the industrial structure of firms can be effectively adjusted, and the positive effect on optimizing the employment structure is further strengthened, showing a nonlinear impact with increasing marginal effects. Hypothesis H5 is verified.

Table 12. Threshold regression results.

Variable	Employment Scale	Employment Structure
	(1) labor_zl	(2) labor_jg
ER (Mid ≤ 0.8994)	-315.188^{***} (-7.84)	
ER ($0.8994 < \text{Mid} \leq 0.9116$)	-275.069^{***} (-7.85)	
ER (Mid > 0.9116)	-258.724^{***} (-7.73)	
ER (Mid ≤ 0.9915)		1.433^{***} (5.15)
ER (Mid > 0.9915)		1.698^{***} (6.39)
_cons	324.542^{***} (9.81)	-0.079 (-0.30)
N	1272	1272
R ²	0.053	0.110

*** $p < 0.01$.

6. Conclusions and Implications

6.1. Research Conclusions

ER, as a critical policy instrument for advancing green development, has a profound impact on employment while fostering high-quality development. Based on theoretical analysis, this paper analyzes the effects and mechanisms of ER on employment scale and structure. We find that strengthening ER significantly suppresses employment expansion while simultaneously optimizing employment structure. The result that ER reduces employment is consistent with the study by Raff et al. (2019) [62] and is further corroborated by Amjadi et al.'s (2025) research, which demonstrates a significant negative impact of ER on employment levels in the paper and pulp industries [10]. Unlike a single negative effect, Piekkola et al.'s (2025) research results support Porter's hypothesis [30]. The shift from secondary to tertiary employment induced by ER resembles a form of job polarization,

where routine-intensive manufacturing jobs decline while service-oriented and knowledge-intensive jobs expand. In comparison, our threshold-effect analysis reveals that ER has nonlinear effects with diminishing marginal effects on employment scale, while it exhibits nonlinear effects with increasing marginal effects on employment structure. Heterogeneity analysis demonstrates stronger scale-suppression effects in the Upper–Middle Yangtze zones, in regions with low regulatory stringency, and in large cities. Conversely, structural optimization dominates in the Lower Yangtze zones and in small and medium-sized cities. The uneven employment effects across regions highlight a potential equity concern: cities already facing economic disadvantages may bear a disproportionate employment burden from ER. This finding underscores the need for place-based policies that compensate losing regions, a key theme in sustainable urban transitions literature. Mechanistic analysis reveals three transmission channels: advancement of ISU, acceleration of GV, and attraction of FDI. In sum, these findings suggest that ER does not pose a static trade-off between ecological protection and urban employment. Instead, it triggers a dynamic transformation process: when regulatory rigor exceeds a certain threshold, short-term job losses can be offset by long-term structural benefits, thereby steering the urban labor market toward greater sustainability.

Furthermore, our results also carry important implications for China's export policy and its international positioning. As ER raises production costs in polluting sectors, export-oriented firms may face a short-term competitiveness loss, potentially reducing their market share in price-sensitive foreign markets. However, the concurrent stimulus to GV and ISU can enhance the long-term quality of China's exports, enabling domestic firms to comply with the increasingly stringent environmental standards imposed by developed economies. This alignment with global green trade norms could improve China's reputation as a responsible trading partner and facilitate its participation in international climate negotiations.

6.2. Policy Implications

First, local governments should adopt a phased and adaptive implementation approach rather than one-size-fits-all stringency. Specifically, in regions with high dependence on polluting industries, particularly resource-based cities and areas with initially low regulatory intensity, where the scale-suppressing effect is most pronounced, policymakers should devise gradual phase-in schedules. These timelines would allow firms sufficient time to adjust their production processes and labor arrangements. Concurrently, these transition periods should be accompanied by targeted retraining programs for displaced workers, with a focus on skills required in emerging green sectors. Such measures would mitigate short-term job losses while facilitating long-term structural adjustment.

Second, governments should offer direct financial support for industrial upgrading and green innovation, including low-interest loans or subsidies to small and medium-sized enterprises (SMEs) adopting certified green technologies, and accelerated depreciation for firms that reduce emission intensity. At the same time, targeted policies should be adopted to attract environmentally friendly foreign investment and guide foreign capital toward low-carbon, high-skill sectors. These measures would jointly mitigate financial constraints and preserve employment opportunities.

Third, governments should build cross-regional cooperation platforms with clear operational protocols. Specifically, we recommend launching pilot inter-provincial environmental supervision platforms in each city of the YERB, with quarterly data sharing on ER implementation and employment outcomes. These platforms should include a joint enforcement task force and standardized reporting templates. This reduces redundant policy efforts and accelerates effective employment-friendly ER practices across regions.

Fourth, policies should be regionally differentiated based on explicit local conditions. Central authorities should require each prefecture-level city to publish a biennial “Key Development Catalog” aligned with local resource endowments, labor skills, and industrial clusters. Simultaneously, by promoting vertical specialization and cross-regional industrial chain collaboration, the YERB can achieve regional complementarity, ecological protection, and high-quality full employment simultaneously. Our findings can help policymakers have a more comprehensive understanding of the causes of employment adjustment and further evaluate the Chinese economic growth model.

Author Contributions: Conceptualization, W.L. and F.W.; methodology, W.L.; validation, W.L., F.W. and C.Z.; formal analysis, W.L.; investigation, F.W.; resources, F.W.; data curation, F.W.; writing—original draft preparation, F.W.; writing—review and editing, W.L.; visualization, F.W.; supervision, W.L.; project administration, W.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Fund for Young Scholars of China (Project 24CSH050) and the Henan Philosophy and Social Sciences Planning Youth Project (Project 2023CJJ167).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ER	Environmental Regulations
YREB	Yangtze River Economic Belt
ISU	industrial structure upgrading
GV	green innovation
FDI	foreign direct investment

References

1. Kong, X.; Li, Z.; Lei, X.; Jiang, X.; Bao, X. Environmental Regulation, Outward Foreign Direct Investment, and China’s Green Total Factor Productivity. *Environ. Dev. Sustain.* **2024**, *27*, 27761–27780. [CrossRef]
2. Carlé, R.; Hautamäki, P. Industrial Sales Responding to Environmental Sustainability Regulations: A Role Theory Perspective. *Ind. Mark. Manag.* **2026**, *135*, 72–90. [CrossRef]
3. Zhong, S.; Xiong, Y.; Xiang, G. Environmental Regulation Benefits for Whom? Heterogeneous Effects of the Intensity of the Environmental Regulation on Employment in China. *J. Environ. Manage.* **2021**, *281*, 111877. [CrossRef]
4. Wang, H.; Chen, H.; Zhu, L.; Yin, J. “Hidden price”: Energy conservation and emission reduction targets and employment growth. *Energy Policy* **2024**, *189*, 114135. [CrossRef]
5. An, S. How Environmental Public Policies are Effective: An Analysis of the Mechanism of Consultative Democracy to Bridge the Interest Gap. *Philosophy and Social Sciences Preprint Platform*. Available online: <https://zsyb.cn/abs/202601.02943> (accessed on 29 June 2026).
6. Luo, S.; Cai, X.; Qian, Q.; Xia, H. How Can Market-Based Environmental Regulation Drive Industrial Transformation Upgrading? Evidence from China’s Carbon Emissions Trading Pilot Policies. *Int. Rev. Econ. Financ.* **2025**, *102*, 104300. [CrossRef]
7. Sun, W.; Yang, Q.; Ni, Q.; Kim, Y. The Impact of Environmental Regulation on Employment: An Empirical Study of China’s Two Control Zone Policy. *Environ. Sci. Pollut. Res. Int.* **2019**, *26*, 26472–26487. [CrossRef] [PubMed]
8. Xiao, Y.; Zhang, B.; Liao, S. Research on the Impact of Environmental Regulation on Green Technology Innovation: An Analysis of the Moderating Effect of Phased Digital Transformation. *Sci. Res. Manag.* **2024**, *45*, 99–108. [CrossRef]

9. Guo, L.; Du, C.; Tan, W. Research on the Impact of Environmental Regulation on Green Technology Innovation from the Perspective of Innovation Investment. *SAGE Open* **2025**, *15*, 21582440251337327. [\[CrossRef\]](#)
10. Amjadi, G.; Bostian, M.; Lindström, H.; Lundgren, T.; Vesterberg, M. The Effect of Environmental Protection Expenditures on Industrial Employment in Sweden. *Environ. Resour. Econ.* **2025**, *88*, 1071–1110. [\[CrossRef\]](#)
11. Xu, H.; Liu, X. Urban Environmental Regulation, Firms' Emission Reduction Strategies and Labor Demand: Evidence from China. *Econ. Anal. Policy.* **2024**, *84*, 589–609. [\[CrossRef\]](#)
12. Lin, X.; Liu, H.; Luo, Y.; Sun, L.; Long, H. Does Command-Based Environmental Regulation Affect Corporate Labor Income Share? Micro Evidence from China. *Financ. Res. Lett.* **2026**, *89*, 109332. [\[CrossRef\]](#)
13. Wang, Q.; Li, Z.; Cao, Y. Will Environmental Regulations Change the Labor Demand Structure? Theoretical Analysis and Empirical Testing Based on the "Atmosphere Ten Articles". *J. Quant. Technol. Econ.* **2024**, *41*, 191–212.
14. Li, Z.; Lyu, P.; Sun, J. Environmental Regulation and Equilibrium Unemployment in China: Evidence from a Multiple-Sector Search and Matching Model. *China Econ. Rev.* **2025**, *89*, 102336. [\[CrossRef\]](#)
15. Shi, D.; Luo, C.; Zhang, K.; Bu, C. Does Stringent Environmental Regulation Improve Labor Force Employment? Evidence from China. *Environ. Dev. Sustain.* **2024**, *27*, 17187–17213. [\[CrossRef\]](#)
16. Ma, K.; Dai, S. How Environmental Regulations Affect Labor Mobility: An Analysis Based on the Dual Perspectives of Population Inflow and Outflow across Cities. *J. Quant. Technol. Econ.* **2024**, *41*, 156–175.
17. Chen, S.; Liang, E.; Liu, C. "Size-Dependent" Environmental Regulations and Spatial Labor Allocation. *J. Environ. Econ. Manag.* **2025**, *132*, 103158. [\[CrossRef\]](#)
18. Zhang, A. Innovating for Sustainability: Employment Impacts of Diverse Environmental Regulations and Incentives. *J. Knowl. Econ.* **2024**, *16*, 11599–11616. [\[CrossRef\]](#)
19. Huang, J.; Xu, X.; Zhao, T. The Moderating Effect of Clean Technology Innovation in the Process of Environmental Regulation Affecting Employment: Panel Data Analysis Based on 22 Industrial Sectors in China. *J. Clean. Prod.* **2023**, *414*, 137672. [\[CrossRef\]](#)
20. Li, Q.; Cai, Y.; Qiao, Y.; Tan, H. Dual Environmental Regulation and Corporate Green Transformation: How Does Digital Leadership Affect Transformation Effectiveness? *Financ. Res. Lett.* **2025**, *86*, 108690. [\[CrossRef\]](#)
21. Wang, F.; Ge, X. Can Low-Carbon Transition Impact Employment—Empirical Evidence from Low-Carbon City Pilot Policy. *China Ind. Econ.* **2022**, 81–99. [\[CrossRef\]](#)
22. Wang, C.; Liu, X.; Li, H.; Yang, C. Analyzing the Impact of Low-Carbon City Pilot Policy on Enterprises' Labor Demand: Evidence from China. *Energy Econ.* **2023**, *124*, 106676. [\[CrossRef\]](#)
23. Javed, A.; Usman, N. Skill-Biased Labour Market Effects of Environmental Policy and Green Energy Transition in Italy. *Energy Policy* **2025**, *207*, 114833. [\[CrossRef\]](#)
24. Tang, L.; Liu, C.; Ding, C.; Mohamed, O. Environmental Regulation on Employment: Creation or Destruction?—Measurement and Calculation Based on Two-Tier Stochastic Frontier Model. *SAGE Open* **2024**, *14*, 21582440241281225. [\[CrossRef\]](#)
25. Ma, S.; Xue, Y.; Huang, Z. Impact of Environmental Regulation on Employment Scale in the Beijing-Tianjin-Hebei Urban Agglomeration. *China Soft Sci.* **2023**, *9*, 171–181. [\[CrossRef\]](#)
26. Curtis, E.M. Who Loses under Cap-and-Trade Programs? The Labor Market Effects of the Nox Budget Trading Program. *Rev. Econ. Stat.* **2018**, *100*, 151–166. [\[CrossRef\]](#)
27. Liu, W.; Luan, J.; Xie, Q. Environmental Regulation, Abatement Strategies, and Industrial Concentration: Theory and Evidence from China. *Energy Econ.* **2026**, *158*, 109319. [\[CrossRef\]](#)
28. Fan, R.; Su, S. Comparison of Industrial Structure Optimization Paths under Environmental Regulation: Efficiency Improvement or Structure Improvement? *Int. Rev. Econ. Financ.* **2025**, *102*, 104297. [\[CrossRef\]](#)
29. Bu, C.; Shi, D.; Zhang, K. Labor Market Impact of China's Cross-Regional Environmental Regulation on Pollution-Intensive Firms. *J. Environ. Plan. Manag.* **2024**, *67*, 3026–3050.
30. Piekkola, H.; Rahko, J. The Effects of Environmental Innovations on Labor Productivity: How Does It Pay to Be Green. *Econ. Innov. New Technol.* **2025**, *34*, 1122–1143.
31. He, Z.; Chen, Z.; Feng, X. The Role of Green Technology Innovation on Employment: Does Industrial Structure Optimization and Air Quality Matter? *Environ. Sci. Eur.* **2023**, *35*, 59. [\[CrossRef\]](#)
32. He, Y.; Pan, Y.; Yuan, X. Whether Financial Inclusion Improves Employment Structure and Labor Allocation: Evidence from China's Industrial Restructuring. *SAGE Open* **2025**, *15*, 21582440251340215. [\[CrossRef\]](#)
33. Malachi, G.I.; Eslamipoor, R. Circular economy as peacebuilding: Enhancing socio-ecological resilience for agro-pastoral frontiers in West Africa. *J. Sustain. Bus.* **2026**, *11*, 11. [\[CrossRef\]](#)
34. Becker, R.; Henderson, V. Effects of Air Quality Regulations on Polluting Industries. *J. Polit. Econ.* **2000**, *108*, 379–421. [\[CrossRef\]](#)
35. Xu, Y.; Liang, J.; Dong, Z.; Shi, M. Can Environmental Regulation Promote Green Innovation and Productivity? The Moderating Role of Government Interventions in Urban China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 13974. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Li, G.; Gao, D.; Li, Y. Impacts of Market-Based Environmental Regulation on Green Total Factor Energy Efficiency in China, China. *World. Econ.* **2023**, *31*, 92–114. [\[CrossRef\]](#)

37. Lu, H.; Zhang, Y.; Jiang, J.; Cao, G. Do Market-Based Environmental Regulations Always Promote Enterprise Green Innovation Commercialization? *J. Environ. Manag.* **2025**, *375*, 124183. [\[CrossRef\]](#)
38. Duan, X.; Liu, X.; Ren, X.; Tao, M. Green Transformation or Greenwashing? Strategic Options for Competitiveness in Corporate Green Activities. *J. Environ. Manage.* **2026**, *398*, 128546. [\[CrossRef\]](#)
39. Eslamipoor, R. An integrated approach for three-layer location-allocation in a green supply chain. *Int. J. Logist. Syst. Manag.* **2025**, *52*, 308–322. [\[CrossRef\]](#)
40. Liu, J.; Wan, G. Does Environmental Regulation Restrain Fdi Inflow? *Res. Econ. Manag.* **2021**, *42*, 20–34.
41. Cai, X.; Lu, Y.; Wu, M.; Yu, L. Does Environmental Regulation Drive Away Inbound Foreign Direct Investment? Evidence from a Quasi-Natural Experiment in China. *J. Dev. Econ.* **2016**, *123*, 73–85. [\[CrossRef\]](#)
42. Liao, H.; Yang, L.; Dai, S.; Van, A.A. Outward Fdi, Industrial Structure Upgrading and Domestic Employment: Empirical Evidence from the Chinese Economy and the Belt and Road Initiative. *J. Asian Econ.* **2021**, *74*, 101303. [\[CrossRef\]](#)
43. Vu, D.H.; Jemberu, E.T.; Pavelková, D. The Impact of the Movement of Labor between Fdi and Domestic Firms on the Labor Productivity of Domestic Firms. *Struct. Change Econ. Dyn.* **2025**, *74*, 373–386. [\[CrossRef\]](#)
44. Qiu, S.; Wang, Z.; Geng, S. How Do Environmental Regulation and Foreign Investment Behavior Affect Green Productivity Growth in the Industrial Sector? An Empirical Test Based on Chinese Provincial Panel Data. *J. Environ. Manage.* **2021**, *287*, 112282. [\[CrossRef\]](#)
45. Zhao, Y.; Shen, C.; Han, C. The Impact of Environmental Regulations and Foreign Direct Investment on Industrial Structure Upgrading. *Financ. Res. Lett.* **2025**, *76*, 107004. [\[CrossRef\]](#)
46. Yu, J. Research on the Impact of Fdi and Environmental Regulation on the Industrial Structure Upgrading in the Yellow River Basin. *Front. Earth Sci.* **2024**, *12*, 1379870. [\[CrossRef\]](#)
47. Son, S.H.; Kim, Y.H. Productivity Spillover Effects of Participation in Global Value Chains and Fdi Inflows. *Econ. Model.* **2025**, *153*, 107341. [\[CrossRef\]](#)
48. Li, Z.; Li, Y. Environmental regulation and employment: Evidence from China's new Environmental Protection Law. *Econ. Anal. Policy.* **2024**, *82*, 400–416. [\[CrossRef\]](#)
49. Horbach, J.; Rennings, K. Environmental Innovation and Employment Dynamics in Different Technology Fields—An Analysis Based on the German Community Innovation Survey 2009. *J. Clean. Prod.* **2013**, *57*, 158–165. [\[CrossRef\]](#)
50. Eslamipoor, R. Digital Technology's Role in Circular Waste Management: A Systematic Review. *Bus. Strategy Environ.* **2026**, 1–40. [\[CrossRef\]](#)
51. Jing, Y.; Hu, M.; Zhao, L. The Effect of Heterogeneous Environmental Regulations on the Employment Skill Structure: The System-Gmm Approach and Mediation Model. *PLoS ONE* **2023**, *18*, e0290276. [\[CrossRef\]](#) [\[PubMed\]](#)
52. Zhu, X.; Chen, H.; Liao, Z.; He, R. Green Technology Transfer Driven by Environmental Policies: A Fuzzy-Set Qualitative Comparative Analysis Approach. *Clean Technol. Environ. Policy* **2025**, *27*, 7417–7438. [\[CrossRef\]](#)
53. Jiang, T. Mediating Effects and Moderating Effects in Causal Inference. *China Ind. Econ.* **2022**, *5*, 100–120.
54. Qin, B.; Yang, K.; Ge, L. Green for Labor: Environmental Regulation and Employment of Heavy Polluting Enterprises—Based on the Green Technology Innovation in the Whole Production Process. *China Environ. Sci.* **2023**, *43*, 1449–1459.
55. Li, Z.; Lin, B. Analyzing the Impact of Environmental Regulation on Labor Demand: A Quasi-Experiment from Clean Air Action in China. *Environ. Impact Assess. Rev.* **2022**, *93*, 106721. [\[CrossRef\]](#)
56. Xiao, W.; Wang, J.; Zhao, X. Industrial Structure, Employment Structure and Urban-Rural Income Disparity. *Macroecon. Res.* **2022**, *9*, 78–86+96.
57. Wang, W.; She, Y.; Peng, Y.; Liu, Y. Unleashing Green Technology Innovation in Agribusiness: Traditional Environmental Regulations, Carbon Trading, or Synergies? *Humanit. Soc. Sci. Commun.* **2025**, *12*, 116. [\[CrossRef\]](#)
58. Wang, Q.; Wang, Y. What Shapes Export Competitiveness of Home Country Firms? Host Country Environmental Regulations or Labor Standards. *Int. Rev. Financ. Anal.* **2025**, *103*, 104243. [\[CrossRef\]](#)
59. Wang, B.; Tian, H.; Hu, Y. Low-Carbon Pilot Policies, Enterprise Digital Empowerment and Employment Stabilization. *Collect. Essays Financ. Econ.* **2025**, 16–26. [\[CrossRef\]](#)
60. Zhou, W.; Tao, L. Regional Difference of the Impact of Environmental Regulation on the Employment of Chinese Labor Force: Empirical Test Based on the Threshold Effect of Industrial Structure. *West Forum* **2020**, *30*, 100–110.
61. Tang, H.; Hui, G. Research on the Employment Effect of Heterogeneous Environmental. *Front. Sci. Technol. Eng. Manag.* **2025**, 1–10. Available online: <https://link.cnki.net/urlid/34.1336.N.20251016.1800.008> (accessed on 2 July 2026).
62. Raff, Z.; Earnhart, D. The Effects of Clean Water Act Enforcement on Environmental Employment. *Resour. Energy Econ.* **2019**, *57*, 1–17. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.