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Can Environmental Regulation Improve Labor Allocation Efficiency? Evidence from China's New Environmental Protection Law

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Abstract: The environmental regulatory stringency and labor reallocation are two defining features in developing countries. This study empirically estimates the impact of environmental regulation on labor allocation efficiency. We adopt the implementation of New Environmental Protection Law (NEPL) as an exogenous shock on environmental regulation to carry out a quasi-natural experiment. We find that the increase in environmental regulatory stringency has a significant and positive impact on labor allocation efficiency. The impact is mainly driven by job transition from heavy polluting industries to non-heavy polluting industries. The heterogeneity analysis results show that NEPL promotes the allocation efficiency of economically developed cities, men, union members, and low- and middle-educated laborers. Our study provides empirical evidence for regionally differentiated environmental regulation policies.

Keywords: environmental regulation; labor allocation efficiency; China's New Environmental Protection Law (NEPL); job transition; regulatory cost

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1. Introduction

Over the past 40 years of reform and opening up, China's economy has maintained rapid growth, and its contribution to the world economy has increased. However, the economic development model long implemented by China has caused it to pay a high environmental price due to high energy consumption and high pollution. In 2019, of China's 337 prefecture-level and larger cities, 180 exceeded the upper limit of ambient air quality standards. The proportion was as high as 53.4%. These 337 cities reported a total of 452 days of heavy pollution and 1666 days of severe pollution.

Poor environmental quality can easily induce diseases of the respiratory system, digestive system, and cardiovascular system [1,2]. It can even lead to shortened life expectancies and increased mortality rates. The collective heating policy north of the Huai River in China has led to concentrations of TSP (total suspended particles with a particle size of less than 100 μm) as high as 184 $\mu g/m^3$, resulting in a reduction in life expectancy of nearly 5.5 years [3]. Kampa and Castanas [4] believe that environmental pollution is directly related to oxidative stress in the brain, which can reduce the sensitivity and reactivity of the sensory system and lead to distracted attention. Zivin and Neidell [5] test the impact of air pollution on the productivity of outdoor workers by using agricultural worker data from the United States. Their findings show that a 10 ppb increase in ozone concentration caused a 5.5% decrease in the productivity of agricultural workers. He et al. [6] conduct a study based on the daily productivity data of workers in textile factories in Jiangsu and Henan, China. They find that if the PM2.5 concentration on the day of production and the previous 25 days is greater than 10 $\mu g/m^3$, then the average daily labor productivity drops by 0.5–3%.

The issue of environmental pollution control has become increasingly important and urgent as China's economy shifts to a high-quality development stage. Environmental regulation policy has become the primary choice of tool to control environmental pollution [7]. In particular, the New Environmental Protection Law (NEPL), the strictest in history, came into force on 1 January 2015. The NEPL has further increased the environmental governance responsibilities of enterprises and the government, and the punishment of environmental violations has been made more severe. The implementation of the NEPL has led to much stronger environmental law enforcement, with considerable increases in the number of violations investigated and the amount of fines.

Enterprise entry and exit and the growth or decline of incumbents are all affected by environmental regulation policies [8]. Such policies may cause the movement of labor between regions, industries, and enterprises [9,10]. Naturally, the worker relocation caused by environmental regulation also affects the resource allocation efficiency in the labor market. If the labor force follows the market signals of employment opportunities and relative income and moves freely from low-productivity sectors to high-productivity sectors, then labor allocation efficiency can be improved. In recent years, China's increased environmental regulation policies and worker migration have a defining close relationship [11]. On the one hand, the pollution control costs of departments with extensive development of resources and environment will increase, and clean departments will gain the comparative advantage of green development. Employment transfer between sectors with different levels of pollution intensity will help improve labor allocation efficiency [12]. On the other hand, enterprises may obtain profits by lowering wages or increasing relatively low-cost labor input and transfer the costs of environmental regulation to labor. This effect would exacerbate the distortion of labor allocation. Under the interaction and game of these two effects (i.e., job transition and regulatory cost), what impact do environmental regulation policies have on labor allocation efficiency?

To answer the above question scientifically, this paper quantitatively measures the labor allocation efficiency from the perspective of individual labor. It empirically examines the impact of regional environmental regulation on labor allocation efficiency. The intensity of regional environmental regulation is not completely random, and regions with relatively lower labor allocation efficiency may have higher tolerance for environmental pollution. Based on the quasi-natural experiment of the implementation of the NEPL in 2015, this paper constructs a difference-in-differences (DID) method to test the causal relationship between environmental regulation and labor allocation efficiency. To exclude the influence of unobserved regional factors, we design more stringent placebo tests. The results show that environmental regulation improves labor allocation efficiency significantly and steadily. We also show a significant positive effect of the implementation of the NEPL on labor allocation efficiency in developed cities and both state-owned and non-state-owned enterprises. From the perspective of individual characteristics, the NEPL mainly has promoted the allocation efficiency of men, union members, and laborers with low and medium education levels.

This paper makes three contributions to the field. First, we relax the assumption of labor homogeneity, in contrast to the existing literature that uses regional or industry level factor allocation efficiency. We construct labor allocation efficiency indicators from the individual level, which helps reduce total bias and fully considers the heterogeneity of labor. Second, this paper adds to the literature on the effects of environmental regulation policies. Existing studies pay attention to the effect of environmental regulation on the total amount of employment but consider it less from the perspective of labor resource allocation. Third, this paper uses the exogenous shock of the NEPL on regional environmental regulation to improve the effectiveness and reliability of the conclusions.

The rest of the paper is organized as follows. Section 2 presents a literature review and hypotheses. In Section 3, we introduce the data sources, research design, and summary statistics. Section 4 reports the empirical results regarding how environmental regulations affect labor allocation efficiency. Section 5 further discusses the mechanism, and Section 6 presents the research findings, suggestions, limitations, and future work.

2. Literature Review and Hypotheses

2.1. Research on Environmental Regulation

Environmental pollution and sustainable development have become an increasingly important issue [13,14]. The economic effects of environmental regulation are widely concerned and studied. Some literatures explore the impact of environmental regulation on corporate behavior. Liu [15] finds that the New Environment Protection Law can improve regional green technology innovation using panel data of China province-level regions, which supports Porte hypothesis. Zhang and Cheng [16] show that more stringent environmental regulation leads to more cash flows in heavy polluting enterprises to cope with the regulatory costs. Heavy polluting enterprises respond to the New Environment Protection Law by increasing capital factors input and hiring high-skilled labor, which increases the capital–labor ratio [17]. Other documents have studied the impact of environmental regulations on the labor market. Cui et al. [18] argue that the New Environmental Protection Law reduces the labor income share due to capital deepening. Li and Lin [19] show that environmental regulation measured by Clean Air Action lowers the labor demand significantly.

2.2. Research on Labor Allocation Efficiency

The measurement methods used to study labor allocation efficiency can be divided into three main categories, which correspond to three bodies of literature. The first body of literature holds that in a perfect competitive market, the labor allocation among regions, industries, and enterprises achieves the convergence of marginal product and the convergence of wage levels. Therefore, the dispersion degree of the marginal product and the dispersion degree of wage levels can be used to measure labor allocation efficiency. Hsieh and Moretti [20] introduce labor force characteristics. They use the dispersion degree of surplus wages to represent labor allocation efficiency. In the second body of literature, Aoki [21] assumes that the distortion of production factor allocation exists in the form of ad valorem taxes and uses the "ad valorem tax wedge" to measure the efficiency of labor allocation. The third body of literature uses the distance between wages and labor marginal product to measure labor allocation efficiency. Lang [22] proposes that human capital endowment, rather than actual wages, determines the income boundary of workers. The income boundary is the maximum income that workers may obtain under the given human capital input portfolio, which can be used as a proxy variable of labor marginal product.

2.3. The Impact of Environmental Regulation on Labor Allocation Efficiency

The literature extensively discusses the impact of environmental regulation on the scale of employment, but the direction of this impact is still uncertain. One view posits a "Job Loss Effect" [23,24]. Environmental regulation may lead to an increase in enterprises' pollution control costs, reduce enterprises' profit margins and production scale, and reduce labor demand. These effects would ultimately lead to a negative impact on employment [25,26]. Some researchers hold that many enterprises reduce pollutant emissions through process improvement technology, and that technological progress may cause labor substitution, which would impede employment to a certain extent. However, some studies argue instead for a "Job Creation Effect" [27–31]. On this account, environmental regulation increases the relative prices of resource production factors, which may lead enterprises to invest more in labor. Environmental regulations may also create some jobs, such as green and clean technology developers, producers, and environmental regulation law enforcement supervisors. The installation and operation of terminal pollution treatment technology has created some skilled labor jobs [32]. The overall impact of environmental regulation on employment depends on whether the effect of job loss or of job creation is stronger [33]. Some researchers believe that there is a threshold effect or U-shaped relationship between environmental regulation and employment [34].

Environmental regulation does not only affect total employment across the economy [9]; it also affects the allocation of employment among sectors. There are few studies on the relationship between environmental regulation and labor allocation efficiency. We discuss

two mechanisms for environmental regulations that affect labor allocation efficiency: job transition and the regulatory cost.

In terms of job transition mechanism, strict environmental regulation policies have caused heavy polluting industries to face higher environmental pressure and gradually downsize or close. In contrast, industries that are environmentally friendly gain a comparative advantage in green development. Then, job transition occurs between industries with different polluting intensity levels [12]. The labor force flows from resource-based and pollution-based industries to high-tech and high-value-added green industries. The traditional growth model that relied on cheap labor has changed. Labor allocation efficiency may therefore be improved. Porter hypothesizes that reasonable levels of environmental regulation encourage enterprises to increase technological investment, improve enterprise competitiveness, and optimize resource allocation efficiency [35,36].

In terms of regulatory cost mechanism, environmental regulation leads to an increase in enterprises' pollution control costs. This gradually strengthens the incentive for enterprises to pass on environmental regulatory cost through lower wages [37,38]. Mishra and Smyth [39] use employer–employee matching data from Minhang District, Shanghai, in the year 2007 to carefully examine the extent to which companies pass on environmental regulation costs to workers by reducing employee wages. They find that when other conditions remained unchanged, increased environmental regulation led to a decrease of 13.8–18.8% in average wages. This provides the most direct empirical evidence for the cost-passing effect. According to Hollenbeck [40], the 1970 American Clean Air Act amendment had a negative impact on income. Chai et al. [41] find that environmental regulation significantly reduces employee compensation, based on Chinese enterprise data from 2012 to 2017.

According to the above analysis, we propose the research hypotheses as follows:

H1a: *Environmental regulation has a positive impact on labor allocation efficiency when the job transition mechanism is stronger than the regulatory cost mechanism.*

H1b: *Environmental regulation has a negative impact on labor allocation efficiency when the regulatory cost mechanism is stronger than the job transition mechanism.*

3. Study Design

3.1. The Quasi-Natural Experiment Model

The implementation of environmental regulation policies is related to local economic characteristics. The regions with low labor allocation efficiency may have higher tolerance to environmental pollution. To solve the endogenous problem in the identification of causality, this paper constructs a DID model as Formula (1) based on the quasi-natural experiment implemented by the NEPL [15,42,43].

$$LAE_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 Post_{it} + \gamma Treat_{it} \times Post_{it} + \beta X_{it} + \varepsilon_{it} \quad (1)$$

The subscript i represents the individual worker. The subscript t presents the year. LAE_i is the labor allocation efficiency of individual i. $Post_{it} = \{0, 1\}$ is the period dummy; the value is 0 before the implementation of the NEPL (2014) and 1 after the implementation (2016). $Treat_{it} = 1$ reflects the treatment group, representing the provinces with strengthened environmental regulation after the implementation of the NEPL. $Treat_{it} = 0$ reflects the control group. The estimated coefficient of interaction term $Treat_{it} \times Post_{it}$ shows the impact of stricter environmental regulation after the implementation of the NEPL on labor allocation efficiency in the region. Reasonable control of irrelevant factors X_{it} can help reduce regression errors so that the difference in labor allocation efficiency can be explained more by experimental shocks. X_{it} reflects a set of individual-level and city-level characteristics.

3.2. Data and Variables Measurement

3.2.1. Environmental Regulation

This study employs the implementation of the New Environmental Protection Law (NEPL) to carry out a quasi-natural experiment [15,43]. The New Environmental Protection Law implemented from 1 January 2015 is called "the strictest environmental protection law in history". The revised environmental protection law focuses on strengthening legal responsibilities and increasing penalties, creating an exogenous shock on the country's environmental governance. The China NEPL provides a quasi-natural experimental setting for inspection of environmental policy effects. First, the extensive development model of excessive pursuing GDP growth rate for a long time has caused serious pollution problems and is not conducive to sustainable economic development. The NEPL has determined a series of relevant systems and is committed to reversing the trend of ecological environment deterioration. Second, there are differences in the understanding of economic development and environmental protection relationships and different degrees of public participation, which leads to a large gap in the implementation of the NEPL in different provinces. Thus, the provinces with a high degree of implementation of the NEPL are selected as a treatment group, and the provinces with weak implementation of the NEPL are used as a control group. Third, the NEPL is formulated at the national level to enhance the operability of environmental protection laws and systems. Local labor allocation efficiency has little impact on the national level legislation. The implementation of the NEPL is an exogenous event for labor allocation efficiency.

3.2.2. Labor Allocation Efficiency Measurement

This paper uses the distance between actual wages and labor marginal product to measure labor allocation efficiency. Assuming that y_i represents the actual wage of individual i, $f(X_i, \theta)$ is the highest wage rate that can be achieved with different human capital inputs in a perfectly competitive labor market; it represents the marginal product of individual i. ρ_i is the degree to which actual wages achieve marginal product and reflects the distance between them. Then y_i, $f(X_i, \theta)$, and ρ_i satisfy the following relations:

$$y_i = f(X_i, \theta)\rho_i \tag{2}$$

θ is the parameter to be estimated. X_i is the variable matrix that theoretically affects the labor marginal product. Existing studies show that in China's labor market, workers' actual wages are commonly lower than marginal product. It can therefore be assumed that $0 < \rho_i \leq 1$. When actual wages are equal to marginal product, $\rho_i = 1$. Suppose that m factors affect the marginal product, which may also be subject to random shocks e^{ν_i}. Take the natural logarithm on both sides to obtain:

$$Lny_i = \theta_0 + \theta_1 Lnx_{1i} + \theta_2 Lnx_{2i} + \cdots + \theta_m Lnx_{mi} + \nu_i + Ln\rho_i \tag{3}$$

Because of $0 < \rho_i \leq 1$, $Ln\rho_i \leq 0$. Let $\mu_i = -Ln\rho_i$, $\mu_i \geq 0$. Then,

$$Lny_i = \theta_0 + \theta_1 Lnx_{1i} + \theta_2 Lnx_{2i} + \cdots + \theta_m Lnx_{mi} + \nu_i - \mu_i \tag{4}$$

Labor allocation efficiency LAE_i at the micro-individual level is

$$LAE_i = \rho_i = y_i / f(x_i, \theta) = e^{-\mu_i} = E\left(e^{-\mu_i} \middle| \varepsilon_i\right) \tag{5}$$

The larger the value of LAE_i is, the closer the distance between wages and marginal product and the higher the labor allocation efficiency are.

Based on the Mincer wage determination equation, this paper constructs an econometric model to measure the labor allocation efficiency as follows:

$$\begin{aligned} Lny_i = \quad & \theta_0 + \theta_1 Lnedu_i + \theta_2 Lnexp_i + \theta_3 Lnexp2_i + \theta_4 Gender_i + \theta_5 Health_i + Province_i \\ & + Industry_i + Owner_i + \nu_i - \mu_i \end{aligned} \tag{6}$$

Lny_i represents the logarithm of an individual's hourly wage. $Lnedu_i$ is the logarithm of years of education. The first term $Lnexp_i$ and the second term $Lnexp2_i$ reflect the worker's experience. $Gender_i$ is a gender dummy variable, with a value of 1 for male and 0 for female. $Health_i$ represents the health status: the higher the value, the better the health status. As China's labor market has serious regional, industry, and ownership divisions, it is necessary to increase the control of regions, industries, and the nature of ownership.

We use CFPS2014 and CFPS2016 to measure labor allocation efficiency. Table 1 reports the results. The average efficiency of labor allocation in 2014 and 2016 was 59.4% and 68.6%, respectively. Compared with 2014, the wage level of China's labor market in 2016 is closer to the "market price." Overall, the sample labor wage achieves 62.6% of the marginal product. Without increasing human capital investment, eliminating the distortion of labor market allocation can increase actual wages by 45.82%. The sample's average hourly wage is 14.25 yuan/hour, which can be increased to 22.76 yuan/hour by improving labor allocation efficiency.

Table 1. Labor Allocation Efficiency Measurement Results.

Year	Variable	Obs	Mean	Std.Dev	Min	Max
2014	Hourly wage/Yuan	8887	13.065	12.809	0.720	64.000
	Labor allocation efficiency	8557	0.594	0.106	0.296	0.842
2016	Hourly wage/Yuan	4497	16.581	22.359	0.446	156.250
	Labor allocation efficiency	4497	0.686	0.077	0.396	0.857
Full	Hourly wage/Yuan	13,384	14.246	16.723	0.446	156.250
	Labor allocation efficiency	13,054	0.626	0.107	0.296	0.857

Lang [22] finds that the wage level of the German labor market could reach 84% of the marginal output in 2000. Adamchik and King [44] use Polish full-time worker employment data from 2001. Their results show that the gap between the average wage and marginal output in the sample was approximately 14%. In a study of China's labor market, Pang et al. [45] find that the wage level of China's urban labor force has reached approximately 60% of marginal output, using data from the Chinese Household Income Project (CHIP 2007). These studies confirm the reliability of our labor allocation efficiency measurement results.

3.2.3. Individual-Level and City-Level Characteristics

We collect individual-level characteristics, including the worker's gender, marital status, labor union membership, and the logarithm of the family's annual per capita expenditure. Additionally, city-level characteristics conclude the per capita GDP, industrial structure, average salary, nature of enterprise ownership, industry, and province. Furthermore, we employ these variables as controls. Variable definition is shown in Table 2.

Table 2. The Variable Definition.

Variable Name	Variable Definition
LAE	Ratio of actual wage to marginal product
Treat	treatment group: the provinces with strengthened environmental regulation after the implementation of the NEPL
Post	period dummy(after the implementation of the NEPL = 1)
Gender	Gender (Male = 1)
Married	Marital status (married = 1)
Union	Whether is a labor union membership (Labor union membership = 1)
Expenditure	Logarithm of the annual per capita expenditure of the family
perGDP	Logarithm of per capita GDP
Structure	Secondary industry weight
Averagesalary	Logarithm of average salary
Gov	Nature of enterprise ownership (State-owned = 1)
Industry	Industry code
Province	Province code

3.2.4. Data and Sample

We employ the China Family Panel Studies (CFPS) data to calculate labor allocation efficiency at individual level. The individual-level controls are also from CFPS. CFPS covers 162 districts and counties in 25 provinces, representing 95% of China's population. It is a national and comprehensive social follow-up survey project, including social, economic, educational, demographic, and health data. Based on the economic meaning of the main variables, we delete some invalid and missing samples. We also perform a 2.5% bilateral tailing treatment on the original salary to avoid estimation errors caused by outliers. The hourly wage is the actual level after deflation, using the consumer price index. This paper selects two 2014 and 2016 issues of follow-up data to obtain information on labor work, income, family, and community. Finally, a total of 13,426 effective individual labor samples are retained from 2014 and 2016. The city-level controls come from China City Statistical Yearbook.

We match individual-level data with city-level data and delete some invalid and missing main variables. The descriptive statistical results for the main variables are shown in Table 3.

Table 3. The Descriptive Statistics for the Main Variables.

	Year = 2014			Year = 2016		
Variable	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
LAE	8557	0.594	0.106	4497	0.686	0.077
Gender	8895	0.616	0.486	4497	0.568	0.495
Married	8895	0.764	0.424	4498	0.723	0.448
Union	8895	0.021	0.144	4497	0.087	0.282
Expenditure	8847	8.404	1.125	4412	8.455	1.052
PerGDP	8856	10.448	0.829	4464	10.647	0.799
Structure	8895	0.388	0.203	4498	0.376	0.219
Average salary	8785	10.283	1.727	4339	10.518	1.539

4. Empirical Results

4.1. The Pre-Test Results of Group Randomization

The basic regression results face interference from endogenous problems. Is the positive impact of environmental regulation on labor allocation efficiency due to the role of environmental regulation, or is it because areas with higher allocation efficiency choose relatively stricter environmental regulation? This section is based on the quasi-natural experiment of the NEPL, using a DID model for testing.

The NEPL was officially implemented in China on 1 January 2015. However, the policy enforcement capabilities of local governments and the strategic game between the government and enterprises have led to relative differences in the enforcement of the new environmental law in different regions [46,47]. We construct a DID model of the differences in the implementation of the NEPL in various regions. First, we rank the five standardized sewage charges (SO_2, soot, NO_x, wastewater, and solid waste) in the sample provinces in descending order. The higher the standardized sewage fee, the higher the ranking and the stricter the environmental regulation. Second, if a province's ranking of five standardized sewage charges is advanced after the implementation of the NEPL, or if four rankings are advanced and one ranking fluctuates backward by no more than two, then it is put into the treatment group. The treatment group consists of provinces with strengthened environmental regulation after the implementation of the NEPL. All other provinces are put into the control group.

As a quasi-natural experiment, the use of the differences in changes in the environmental regulation from before and after the implementation of the NEPL must meet the exogenous assumptions of random time and random grouping. The NEPL's implementation time is given exogenously, but the actual implementation intensity of each province may not be completely random. It is therefore necessary to check whether the differences in environmental regulation in the provinces before and after the NEPL are approaching randomness. If the degree of implementation of the NEPL is systematically related to the explained variable of concern (labor allocation efficiency), then an effective treatment group and control group cannot be formed. This could be the case if, for example, the local government believes that higher labor allocation efficiency provides a basis for environmental governance or if there are unobserved factors related to labor allocation efficiency that also affect a region's behavioral choices after the NEPL. We therefore need to conduct pre-experimental testing to examine whether the labor allocation efficiency of the provinces that strengthened environmental regulation after the NEPL share certain characteristics, and whether labor allocation efficiency could

have affected the province's implementation of the NEPL. Table 4 reports the pre-test results of group randomization. There is no specific trend in the labor allocation efficiency of provinces that have strengthened environmental regulation. Labor allocation efficiency is not the reason why provinces have strengthened their environmental regulation. We believe that the division of the treatment group and the control group is approximately exogenous according to the difference in environmental regulation levels before and after the NEPL.

Table 4. The Pre-test Results of Group Randomization.

	(1) LAE	(2) LAE	(3) Treat	(4) Treat
Treat	0.001	−0.000		
	(0.003)	(0.003)		
LAE			0.009	−0.002
			(0.023)	(0.023)
Controls	No	Yes	No	Yes
R^2	−0.000	0.322	−0.000	0.158
F	0.165	491.74	0.165	97.784
N	13,054	12,687	13,054	12,687

Note: Standard errors in parentheses are calculated by clustering over regions. Controls include individual-level characteristics and city-level characteristics.

4.2. The Main Results

The choice of the control group greatly affects the accuracy of the DID estimation results. This accuracy depends on whether the control group provinces can objectively reflect changes in the treatment group's labor allocation efficiency under the counterfactual situation of not strengthening environmental regulation. To reduce the estimation error, two types of methods are used to select the control group. The level and trend of the treatment group's labor allocation efficiency should be close to that of the control group before strengthening environmental regulation. The first method is to select a control group whose average labor allocation efficiency and change rate are similar to those of the treatment group. Before the NEPL, the average labor allocation efficiency of the five treatment groups was in the range of [0.38, 0.4]. First, the provinces with labor allocation efficiency in this range are selected as the candidate control group from those that did not strengthen environmental regulation. Second, we calculate the change rate of the treatment group's labor allocation efficiency from 2010 to 2014. We select the provinces with a similar change rate to the treatment group as the control group from the candidate control group. In the second method, propensity score matching (PSM) is used to improve the degree of matching between the treatment group and the control group. A probit model is used to estimate the probability that environmental regulation will be strengthened in all samples after the NEPL. The control group is selected according to the propensity score to verify the robustness of the regression results.

Table 5 reports the DID estimation results. We take the provinces with strengthened environmental regulation after the NEPL as the treatment group. The method for selecting the control group differs from Columns (1) to (4). In Column (1) of Table 5, the provinces without strengthened environmental regulation after NEPL are taken as the control group. In Column (2), the provinces with similar average labor allocation efficiency to the treatment group are taken as the control group. In Column (3), the provinces with a similar rate of change of labor allocation efficiency are added on the basis of Column (2). In Column (4), the control group is selected through PSM. Table 5 shows that when other conditions remain unchanged, the labor allocation efficiency in provinces that strengthened environmental regulation after the NEPL has improved by an average increase of 1.3 percentage points. The strengthening of environmental regulation caused by exogenous shocks can improve labor allocation efficiency, which confirms the basic conclusion of this paper.

Table 5. The DID Estimation Results.

	(1) DID	(2) Control Time Trend	(3) Control Time Trend	(4) PSM-DID
Treat × Post	0.011 *	0.012 *	0.013 *	0.013 *
	(0.006)	(0.006)	(0.007)	(0.006)
Controls	Yes	Yes	Yes	Yes
R^2	0.32	0.29	0.31	0.15
N	12,687	8913	4014	9980

Note: * indicates significant level at 10%. Standard errors in parentheses are calculated by clustering over regions. Controls include individual-level characteristics and city-level characteristics.

4.3. Placebo Tests

We design two placebo test programs to verify that the change in labor allocation efficiency is due to the change in environmental regulation intensity rather than other unobservable factors.

4.3.1. Placebo Test of Replacement Samples

If the improved labor allocation efficiency in the treatment groups is caused by the change in environmental regulation intensity, then the implementation of the NEPL will not have an impact on labor allocation efficiency for provinces with relatively no change in environmental regulation intensity. Otherwise, the causal relationship between environmental regulation intensity and labor allocation efficiency may be caused by other unobserved factors. In this section, the provinces with basically no changes in standardized sewage charges before and after the NEPL are used as the placebo treatment group for a falsification test. After implementation of the NEPL, the rankings of standardized sewage charges in Beijing, Jiangsu, and Anhui in the full sample are essentially unchanged. In Columns (1) and (2) of Table 6, Beijing, Jiangsu, and Anhui are taken as the placebo treatment group. The estimated coefficient is not significant, showing that the empirical analysis in this paper is reliable.

Table 6. The Placebo Tests Results.

	(1) DID_Placebo	(2) PSM-DID_Placebo	(3) DID_Placebo (Random)
Treat × Post	0.005	0.004	0.003
	(0.006)	(0.005)	(0.006)
Controls	Yes	Yes	Yes
R^2	0.32	0.14	0.32
N	12,687	9863	12,687

Note: Standard errors in parentheses are calculated by clustering over regions. Controls include individual-level characteristics and city-level characteristics.

4.3.2. Placebo Test of a Randomly Generated Treatment Group

To examine whether the improvement effect of environmental regulation on labor allocation efficiency is caused by other random factors, another placebo test is conducted by randomly generating treatment groups. In theory, the randomly generated treatment group will not have a real impact on labor allocation efficiency. If the estimated coefficient tends toward 0 and is not significant, then it can be inferred that environmental regulation itself has a significant impact on labor allocation efficiency, which is not affected by other regional characteristics outside of the model setting. In this section, the treatment group is randomly selected from the full sample. Column (3) of Table 6 reports a regression result of the placebo test.

We simulate the random extraction process 10,000 times [48–50]. The estimated coefficients and *t* values are shown in Figures 1 and 2, respectively. The coefficients of the randomized treatment group are all concentrated around 0, and the absolute values of T are concentrated in the interval less than 2, thus eliminating interference from other random factors.

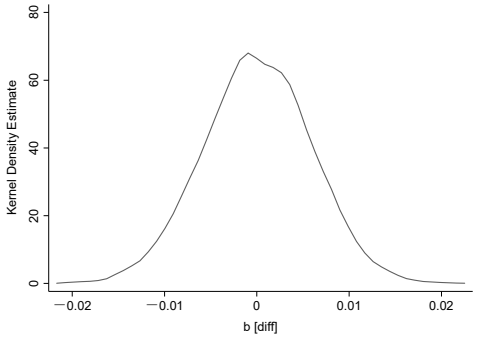

Figure 1. Coefficient of placebo test for 10,000 random shocks.

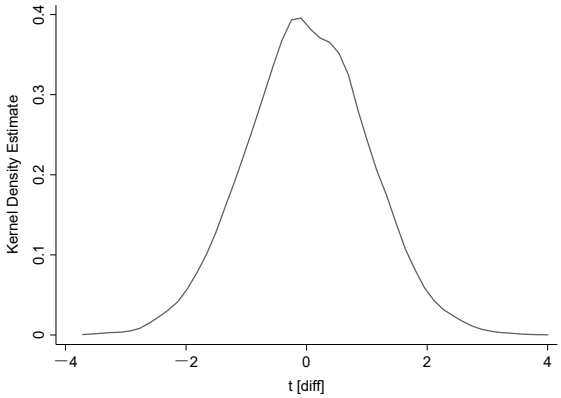

Figure 2. T value of placebo test for 10,000 random shocks.

4.4. Heterogeneity Analysis

4.4.1. City Heterogeneity Analysis

The above sections show that environmental regulation can help improve labor allocation efficiency. Does this impact vary among cities? This section divides the sample into economically developed cities and economically underdeveloped cities according to the per-capita GDP. Columns (1) and (2) of Table 7 report the impact of environmental regulation on labor allocation efficiency in both types of cities. The implementation of the NEPL has a significant positive effect on labor allocation efficiency in developed cities but not in underdeveloped cities. On one hand, economically developed cities have a higher degree of factor marketization. Accordingly, they can quickly adjust the allocation of labor resources to adapt to the changes brought about by environmental policies. On the other hand, the labor rights protection system in developed cities is more mature than that in less developed cities. This can restrict the transfer of enterprises' environmental governance costs to workers.

Table 7. The Results of City Heterogeneity Analysis.

	(1) **Underdeveloped Cities**	**(2)** **Developed Cities**	**(3)** **SOEs**	**(4)** **Non SOEs**
Treat × Post	0.007	0.019 *	0.021 *	0.016 *
	(0.011)	(0.008)	(0.009)	(0.008)
Controls	Yes	Yes	Yes	Yes
R^2	0.31	0.32	0.08	0.30
N	6409	6278	2739	9948

Note: * indicates significant level at 10%. Standard errors in parentheses are calculated by clustering over regions. Controls include individual-level characteristics and city-level characteristics.

Columns (3) and (4) of Table 7 report the impact of environmental regulation on state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), respectively. The estimated coefficient of labor allocation efficiency of the NEPL is significantly positive in both SOEs and non-SOEs. The

policy effect of the NEPL therefore shows no obvious difference between enterprises with different types of ownership.

4.4.2. Individual Heterogeneity Analysis

This section divides the labor groups along the three dimensions of gender, labor union membership, and education level. Table 8 reports the differences in the policy effects of the NEPL between different labor groups. After the implementation of the NEPL, the increase in environmental regulation intensity significantly promotes the allocation efficiency of the male labor force but has no significant impact on the female labor force. To some extent, this reflects the male gender premium in China's labor market. Environmental regulation policies have a positive effect on the allocation efficiency of union members compared to non-union members, which shows that unions play a practical role in protecting the rights and interests of workers. In terms of education level, the implementation of the NEPL significantly improves the allocation efficiency of the labor force with low- and middle-level education (less than junior college). The reason for this phenomenon relates to the labor demand structure of regulated enterprises. Laborers with low and medium education levels constitute the main employment groups in polluting industries and polluting enterprises. However, we cannot further discuss the problem of low- and middle-educated labor unemployment caused by environmental regulation.

Table 8. The Results of Individual Heterogeneity Analysis.

	(1) Male	(2) Female	(3) Union Members	(4) Non-Union Members	(5) High Edu	(6) Medium and Low Edu
Treat × Post	0.018 **	0.002	0.045 **	0.010	−0.006	0.015 **
	(0.008)	(0.010)	(0.020)	(0.007)	(0.014)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.31	0.35	0.25	0.31	0.29	0.31
N	7585	5102	550	12,137	1565	11,122

Note: ** indicates significant level at 5%. Standard errors in parentheses are calculated by clustering over regions. Controls include individual-level characteristics and city-level characteristics.

5. Further Discussion

Previous analysis has revealed that the NEPL positively affects labor allocation efficiency. This part further empirically tests the internal mechanism of the relationship between the environmental regulation and labor allocation efficiency. The research hypotheses in the literature review provides two potential channels. On the one hand, the NEPL added severe punishment to pollution emissions, placing the heavy polluting industries at a competitive disadvantage. Many heavy polluting enterprises have to downsize or close. Thus, environmental regulation typically has an impact on the distribution of jobs among industries in accordance with industry pollution density [9]. Table 9 reports the results of mechanism analysis. Columns (1) and (2), respectively, show the impact of the NEPL on employment in the heavy polluting industry and the non-heavy polluting industry. The coefficient for *Teat* × *Post* is significantly positive for non-heavy polluting industries, while it is significantly negative for heavy polluting industries. The results show that the implementation of the NEPL may lead to the employment from the heavy polluting industry and enterprises to the non-heavy polluting industry and enterprises, which is conducive to improving labor allocation efficiency.

Table 9. The Results of Mechanism Analysis.

	(1) Employment_Heavy Pollution	(2) Employment_Non Heavy Pollution	(3) Sales_Heavy Pollution	(4) Sales_Non Heavy Pollution
Treat × Post	−0.116 ***	0.361 ***	−0.119 ***	0.165
	(0.031)	(0.117)	(0.041)	(0.107)
Controls	Yes	Yes	Yes	Yes
R^2	0.69	0.35	0.67	0.32
N	8920	3966	8920	3966

Note: *** indicates significant level at 1%. Standard errors in parentheses are calculated by clustering over regions. Controls include individual-level characteristics and city-level characteristics.

On the other hand, the NEPL adopts new and more stringent pollution standards. The heavy polluting enterprises have to put more resources into controlling pollution due to the environmental regulatory stringency changes. Enterprises may reduce labor wages in response to increased environmental regulatory costs. In this sense, regulatory costs may lower labor allocation efficiency. Columns (3) and (4) in Table 9, respectively, report the coefficient of the NEPL on sales in the heavy polluting industry and the non-heavy polluting industry. The results show that the NEPL significantly reduces the sales of heavy polluting industries. As far as the sample is concerned, environmental regulations have no significant impact on sales of the non-heavy polluting industries. Empirical results indicate that regulatory cost effect does exist, but its role is lower than the job transition effect. That is why the NEPL significantly promotes labor allocation efficiency.

The results of mechanism analysis support the research hypotheses H1a. The increase in environmental regulatory stringency has a significant and positive impact on labor allocation efficiency. Heavy polluting enterprises tend to reduce labor wage facing stronger environmental regulation, while more jobs have also transferred to non-heavy polluting enterprises. The latter's role is higher than the former, and the ultimate environmental regulation promotes labor allocation efficiency.

To be honest, this paper discusses the job transition effect and regulatory cost effect, but there may still be other unrecognized conduction mechanisms which need to be studied in the future.

6. Conclusions

6.1. Research Findings

China's economy is in a key period of transforming its mode of development. Environmental pollution and labor reallocation are intertwined, which restricts the sustainable development of economy and society. This study measures the labor allocation efficiency at the individual level using China Family Panel Studies (CFPS) data and empirically tests the causal relationship between environmental regulation and labor allocation efficiency adopting the matched data from CFPS and China City Statistical Yearbook. This study shows that environmental regulation is one of the important factors promoting labor allocation efficiency. We also provide new evidence based on micro-data to understand the social effects of China's environmental regulation policies during the transition period. The research findings are as follows:

(1) The average labor allocation efficiency of the sample is 62.56%. On average, the wage is 37.44% lower than the marginal product of labor. The deviation of wages and marginal output in China's labor market is very common.

(2) Environmental regulation has a significant positive impact on labor allocation efficiency. We construct a DID model based on the quasi-natural experiment of the NEPL. The DID results and a series of robustness tests all prove that environmental regulation significantly improves labor allocation efficiency. We also use two placebo tests, replacing samples and randomly generating treatment groups to exclude the interference of other random factors on the results.

(3) The heterogeneity analysis results show that the NEPL mainly promotes the allocation efficiency of economically developed cities, men, union members, and low- and middle-educated laborers.

6.2. Implications

The empirical results suggest the positive relationship between environmental regulation and labor allocation efficiency. The further discussion reveals job transition and regulatory costs when environmental regulations are strengthened. The above findings have important implications for the enterprises, labor union organization, and government departments.

(1) Enterprises within the scope of environmental regulation policies should strengthen green investment and promote green technology innovation to cope with the continuous environmental regulatory pressure. The green transformation of the heavy pollution industry helps create new competitive advantages, reduce uncertainty, and enhance enterprises competitiveness. (2) Labor union organization should pay attention to unemployment and income loss caused by environmental regulation policies. Efforts should be made to organize employment training and promote the reemployment of structurally unemployed groups. Establishing and improving the unemployment early warning mechanism has an important role in the orderly upgrade of the industrial structure. (3) The impact of environmental regulation policies varies in different regions and industries. There are certain transformation costs in job transition between industries and enterprises. The government should formulate differentiated environmental regulation policies and steadily promote the comprehensive implementation of environmental policies in various regions and industries.

6.3. Limitations and Future Work

This study has some limitations that should be addressed in future work. (1) The actual cost related to environmental regulation policies is still unclear. Future work could try to accurately estimate these costs, including not only explicit regulatory costs but also potential unemployment risks and income losses in the process of job transition and adjustment. This helps comprehensively understand the overall welfare impact of environmental regulation policies. (2) This study investigates the effect of environmental regulation on labor allocation efficiency in short run. Future work can focus on the impact of environmental regulatory shocks on the labor market and sustainable economic development in long run. (3) There are many other important research issues under this framework, such as the impact of environmental regulation policies on financial allocation efficiency. In the future, more research will be required to supplement and expand environmental policies and resource reallocation areas.

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