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Employment impacts of industrial transformation in China: A case study of Yangtze River Delta

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The United Nations formally adopted 17 sustainable development goals (SDGs) at the summit in 2015. With the goal of SDGs, China has formulated the "3,060" dual carbon target, that is, to achieve a carbon peak before 2030 and carbon neutrality before 2060. Consequently, this goal will direct positive changes in industrial transformation, and employment quality will be impacted. In this article, 106 listed manufacturing enterprises in the Yangtze River Delta are selected to explore the impacts of industrial transformation and just transition on employment. The result shows that the industrial transformation has no significant promoting effect on employment quality in state-owned enterprises (SOEs), and just transition has no significant moderating effect. However, in private enterprises, industrial transformation has a significant negative impact on employment equality. Moreover, employee training can alleviate the negative impact of industrial transformation on employment quality. On the contrary, employee welfare will play a negative moderating role. The conclusions of this research can help enterprises make better strategies to guarantee the interests of employees and stimulate staff. In addition, the government should advise relevant enterprises to transform steadily.

KEYWORDS

industrial transformation, employment quality, just transition, Yangtze River Delta, moderating effect

Introduction

The United Nations (UN) Summit on Sustainable Development was held at the headquarters in New York in 2015. The 193 member countries of the United Nations formally adopted 17 sustainable development goals (SDGs) at the summit (United Nations, 2015). SDGs are to completely solve the development problems of social, economic, and environmental dimensions and turn to sustainable development (United Nations, 2015).

With the goal of SDGs, China formulated the "3060" dual carbon target, which is for carbon dioxide emissions to peak before 2030 and for China to become carbon neutral before 2060 (the 75th session of the United Nations General Assembly). However, the manufacturing industry in China is still in the transition period from low-quality extensive production to high-quality development. Thus, industrial transformation and low-carbon development driven by scientific and technological innovation are extremely urgent (Leeuwen and Mohnen, 2017).

In December 2021, the Chinese official document (the "14th Five-Year" Industrial Green Development Plan) was promulgated to emphasize the importance of a green and low-carbon transformation. The development mode should be transformed into sustainable mode as the core of the document. With the proposal of the dual carbon target, a lot of employment opportunities have been provided by manufacturing enterprises. In the process of industrial transformation, there is a large demand for employment in the job market.

Development concept (Busso et al., 2013), business mode (Haftor and Costa, 2022), production mode (Fare et al., 2007), and technological innovation (Wurlod and Noailly, 2018) are all changing accompanied by industrial transformation. According to China's official data (National Bureau of Statistics of China) disclosure, 54.2% of the 100 new jobs generated in 2021 are related to manufacturing. However, the supply–demand of jobs is unbalanced, given the huge difference in the number of highly skilled employees and ordinary ones.

Just transition aims to ensure that the benefits of the low-carbon transition are widely shared (Affolderbach and de Chardon, 2021). Meanwhile, it also supports countries, regions, industries, communities, and workers and consumers who suffer from economic, environmental, and social losses (Luke, 2022). Located downstream of the Yangtze River in China, the Yangtze River Delta is China's most advanced economic center and an important advanced manufacturing base. The manufacturing industry generates a large number of factories, workers, and capital, which is an absolute leader in China. Therefore, it is necessary to deeply explore the relevance between industrial transformation and the just transition of enterprises.

This article sorts out the theoretical research basis of industrial transformation, employment quality, and just transition, and then proposes the research hypothesis. In this research, 106 listed manufacturing enterprises in the Yangtze River Delta (location, see Figure 1) are selected to verify the impact of industrial transformation on employment quality and the moderating effect of just transition. The empirical analysis is based on the models mentioned earlier after the exclusion of the multicollinearity. Further research distinguishes the differences between state-owned enterprises and private ones.

Literature review

Industrial transformation inhibits employment, and environmental regulation will have a negative impact on industries with high energy consumption and high pollution (Ederington, 2009). This phenomenon causes so-called "brown unemployment" in these industries (Yu and Sun, 2017). More precisely, industries including steel, chemical, and heavy metal, and other industries

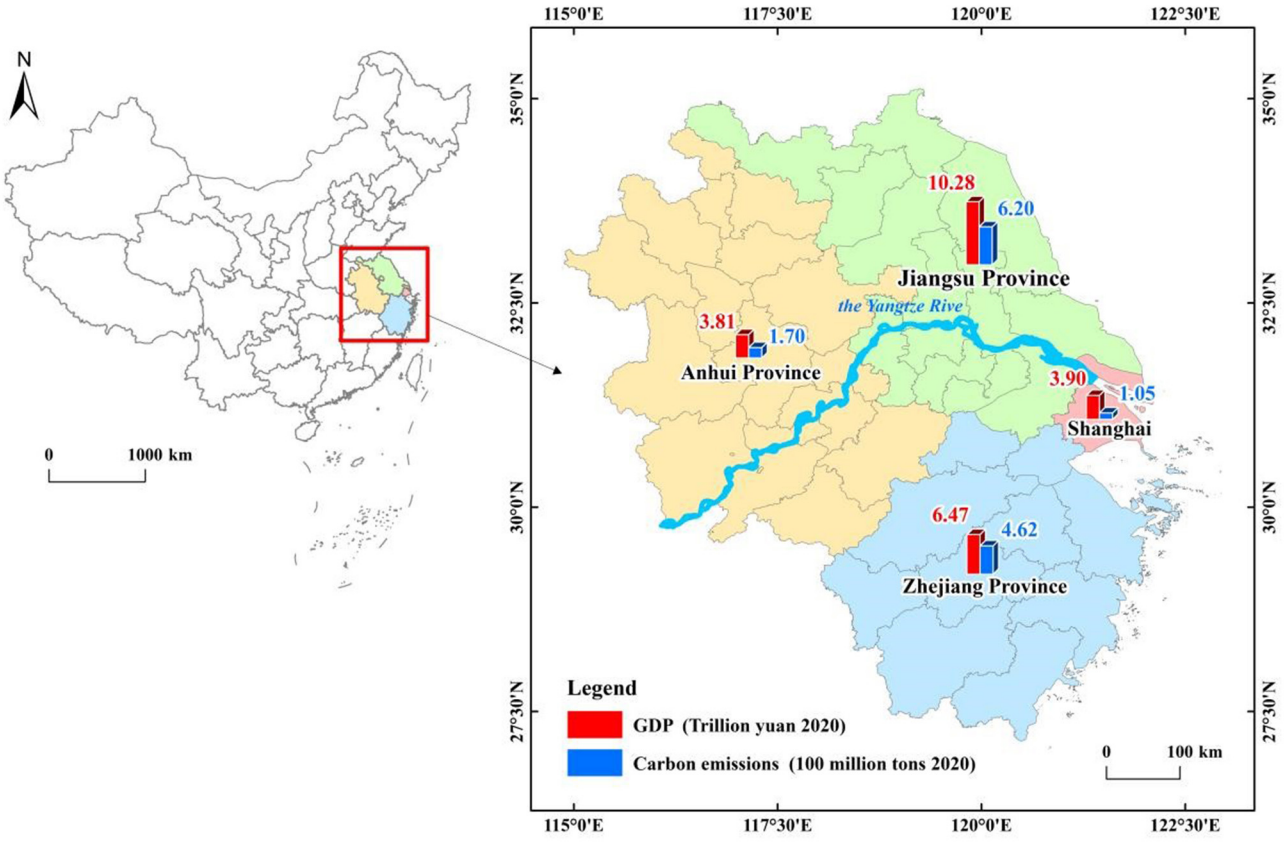

FIGURE 1
Geographical location map of the Yangtze River Delta.

with high pollution and high energy consumption will experience closure or reduced production of some enterprises. It results in a decline in job demand, increased unemployment in the process of integration, and the elimination of outdated production capacity (Wang and Ge, 2022). Industrial transformation can promote employment and will also empower the energy-saving and low-carbon industry (Fankhauser and Jotzo, 2018). It forces enterprises to produce cleaner products and increases employment to a certain extent. The growth of the clean energy industry has reduced unemployment and created jobs (George, 2012; Bulavskaya and Reynès, 2017; Cui and Jiang, 2019; Khobai et al., 2020).

In terms of employment scale, the development of clean energy has a positive effect on the employment level in China, especially the scale expansion of wind and solar industries (Mu et al., 2018). Other research found that it had a significant promoting effect on the development strategy of the Yangtze River Economic Delta based on the panel data of prefecture-level cities in China (Zhao et al., 2021). In terms of employment structure, one research shows that environmental regulation affects regional employment structure by affecting regional industrial transfer (Wagner and Timmins, 2010). Similarly, research shows that technological progress will increase the demand for highly skilled workers (Marouani and Nilsson, 2016). In terms of wage level, research finds that environmental regulations had the biggest impact on wages in industries such as oil, coal, chemicals, and paper (Kim et al., 2015). Moreover, the report shows that there is a *U*-shaped relationship between environmental regulation and skill premium, and China is at the left of the *U*-shaped inflection point at present (Tong, 2022).

The majority of the literature studies employment at the urban administrative level more from a macro perspective. They measure the quality of employment from one of the aspects of employment scale, employment structure, or salary level (Moser et al., 2010; Buera and Kaboski, 2012; Acemoglu and Restrepo, 2018). For influencing mechanisms, the current research focuses on technological progress, output effects, and cost effects, and the influence of element substitution effects, such as intermediary effects (Gray et al., 2014).

Based on these findings, this article tests the impact of an industrial transformation on the employment quality of manufacturing enterprises in the Yangtze River Delta. For further research, we analyze the moderating role of a just transition to provide a new perspective. The contributions are as follows:

First, this article focuses on manufacturing enterprises that are in urgent need of an industrial transformation. Therefore, it provides results that cannot be obtained based on macro data testing.

Second, this article enriches the dimensions of employment quality. In this article, we use the entropy method to consider all three aspects and obtain a relatively comprehensive score of employment quality.

Third, this article introduces the concept of a just transition as a factor. This article considers the importance of safeguarding workers' rights and interests, introduces transformational justice, and studies its effect on employment quality regulation to realize common prosperity. Therefore, it has important practical implications.

Conceptual framework and hypothesis

Industrial transformation and employment quality

The research on employment quality mainly focuses on its connotation and assessment system. In 2001, the European Commission put forward the concept of job quality. Since then, a large number of studies on employment quality have emerged, and the definition of employment quality has been constantly enriched and improved (Grossmann, 2002). The relevant literature can be divided into three research levels. First, we can define employment quality from a macro perspective. The definition at the macro level can fully describe the overall state of the labor market and can usually be applied to a country, region, or industry. Second, we can define employment quality from the perspective of micro individuals. We believe that salary is not the only standard to measure the quality of employment. For this reason, there are also articles from the macro view and micro view on the combination of different research perspectives (Bonnet et al., 2010). Generally, employment quality is a comprehensive concept, reflecting the whole process of employment of workers and the means of production. Research on the connotation of employment quality is limited to qualitative research, lacking quantitative analysis. Therefore, some scholars have carried out further quantitative research by establishing an employment quality assessment system.

Industrial transformation creates new job categories, promotes the growth of total employment, increases the demand for highly skilled labor, and brings diversified employment modes (ILO, 2021). At the same time, industrial transformation also has negative effects on different groups, industries, and regions. It may widen the income gap, reduce economic efficiency, and increase the imbalance of regional development (Schmid and Wagner, 2017). Given other scholars have not considered these three aspects at the same time, this article selects three aspects comprehensively: employment scale, employment structure, and salary level (Tian et al., 2021).

In the respect of employment scale, the manufacturing industry is an important pillar industry. In the process of integration and upgrading of high-carbon sectors, the elimination of outdated production capacity will lead to the closure or reduction of production. These will result in a lack of job demand and increased unemployment (Yip, 2018). On the other hand, the industrial transformation will empower energy-saving and low-carbon manufacturing industries and produce cleaner products, thereby increasing jobs to a certain extent (Acemoglu, 2002). In general, the negative effect of an industrial transformation on the scale of employment is greater than the positive effect (Liu et al., 2021).

From the perspective of the employment structure, with the increase in employment opportunities, green manufacturing will stimulate the demand for workers of all skill levels (Rogers and Pleasants, 2011). As industrial transformation improves the ability of staff to adapt to the enterprise transformation, the demands of both highly skilled staff and ordinary ones are being met. Optimizing the labor market structure will balance the gap between job demand and labor supply, in order to alleviate the risk of

structural unemployment (Muñoz, 2016). In terms of the salary level, the industrial transformation will lead enterprises to innovate technology and upgrade enterprise infrastructure. This process will cause an increase in the production cost and pollution control cost and weaken the salary level (Sheriff et al., 2019). At the same time, due to the increasing demand for high-skilled talent, the income gap between high-skilled staff and low-skilled ones will widen. In view of this, livelihood issues will be difficult to solve (Guo and Hu, 2020; Tong, 2022).

As discussed earlier, there are both positive and negative effects on the employment scale, employment structure, and salary level of industrial transformation enterprises. However, it is necessary to determine whether the overall impacts of the industrial transformation on employment quality are positive or negative, given that employment quality is composed of these three dimensions. Thus, this article proposes Hypotheses 1a and 1b.

H1a: Industrial transformation has a significant positive impact on employment quality.
H1b: Industrial transformation has a significant negative impact on employment quality.

Industrial transformation, just transition, and employment quality

With the deepening of industrial transformation, the skill structure of manufacturing workers is changing rapidly, and the structural employment contradiction is becoming increasingly prominent. Skill training is an important way of human capital investment after individuals enter the labor market. It helps to improve employees' vocational skills, production efficiency, and increase competitiveness. It is not only an important foundation for promoting industrial transformation and upgradation but also an important guarantee for achieving high quality and full employment. Therefore, it is necessary to carry out skill training correctly to effectively promote the construction of a skill talent system, expand employment capacity, and improve employment quality.

The effect of skill training on employment quality has always been one of the themes of labor economics. Research in China mainly focuses on the effect of participation in vocational skills training on employment quality. Most of the research support that participation in vocational skills training can effectively improve the quality of employment of workers, mainly in terms of higher job pay, shorter working hours, and more stable employment. Most of them focus on the wage effect of skill training. Studies have found that it cannot only effectively improve the market competitiveness of workers, and then promote a significant increase in the wage level of workers (Luchinskaya and Dickinson, 2019; Girsberger et al., 2022; Jiang and Gong, 2022) but also indirectly affect other dimensions such as working hours and job satisfaction by improving the level of the human capital of workers. Although skills training will improve employment quality to some extent, based on the uncertainty of the impact of industrial transformation on employment quality, the role of employee skills training in this process is also uncertain, so Hypotheses 2a and 2b are proposed in this article.

H2a: Employee training will strengthen the impact of industrial transformation on employment quality.
H2b: Employee training will alleviate the impact of industrial transformation on employment quality.

In response to the requirements of industrial transformation, global society is faced with the task of phasing out and transforming carbon-intensive industries. This will lead to a change in job types and a reduction in the number of jobs. Workers in high-carbon industries face the risk of relocation or unemployment, leading to the emergence of a "green unemployed community". It is undoubtedly a thorny problem in the process of industrial transformation in China to solve the placement, compensation, training, and other issues of these workers (Li et al., 2020). The fundamental purpose of a just transition is to guarantee a fair transition for all people. Industrial transformation should not only aim at a low-carbon society but also actively prevent and eliminate the negative impact of "decarbonization" on social justice.

Strengthening social security to guarantee employee welfare can enhance the sense of social justice for the unemployed during the green transition period. Here, employee welfare refers to five social insurances and one fund, including endowment insurance, medical insurance, unemployment insurance, work-related injury insurance, maternity insurance, and a housing provident fund. The unemployed can have more chances to find jobs that match their abilities, thus promoting employment reallocation. Although employee welfare will play a role in ensuring the bottom, it will also enhance the work inertia of the unemployed, reduce the enthusiasm for job searching, and thus reduce the quality of employment. Therefore, in order to explore the role of employee welfare in the uncertain impact of green transition on employment quality, Hypotheses 3a and 3b are proposed in this article.

H3a: Employee welfare will strengthen the impact of industrial transformation on employment quality.
H3b: Employee benefits will alleviate the impact of industrial transformation on employment quality.

Methodology

Sample selection and data sources

In this article, the research area is the Yangtze River Delta of China. The research objects are the manufacturing companies in China's A-share market. The research data are cross-section data in 2020. After removing enterprises with special treatment, delisting warnings, or lacking financial data, 106 samples are finally obtained. The explained variables are calculated by the entropy method. Core explanatory variables, intermediate variables, and some missing values are obtained manually from the annual report. Control variable data are obtained from the China Stock Market & Accounting Research (CSMAR) Database and the Wind Financial Terminal database, both of which are Chinese economic and financial databases. To avoid the influence of extreme outliers on the research results, the continuous variables with outliers and extreme values are winnowed by up and down 1%.

Variable definitions

Core explained variable: Employment quality

Employment quality is a variable used to measure the remuneration of workers through the input of production factors in the labor process. From the micro perspective, employment quality refers to the factors that affect the employment status of individual workers, such as income, working time, environment, and social security. Employment quality is measured from three dimensions of employment scale, employment structure, and salary level, comprehensively considering the research of other scholars (Rogers and Pleasants, 2011; Kim et al., 2015; Wang and Ge, 2022).

After standardizing the data, the entropy method (Appendix 1) is used to assign weight to the data. All three indicators are positive, and the specific weights are calculated (Table 1). Among them, employment structure has the largest weight, and the salary level has a smaller weight.

Explanatory variable: Industrial transformation

Based on the research results of scholars (Hafstead and Williams, 2018; Li et al., 2022), carbon productivity is used to represent the economic benefit produced by the unit carbon emissions of enterprises. It can better reflect the effect of the industrial transformation of enterprises.

Moderating variables: Employee training and employee welfare

Based on the research results of scholars (Hawley et al., 2012; Konings and Vanormelingen, 2015; Dezhao and Zhibin, 2020), employee training and employee welfare are selected as the proxy variables of just transition. Among them, Train (employee training) is represented by the enterprise's training expenditure for employees, and Welf (employee welfare) is measured by the coverage of five social insurance and housing funds.

Control variables: The enterprise scale, asset–liability ratio, return on assets, enterprise growth, and ownership concentration

Controlling financial indicators that may affect employment quality can better explain the relationship between principal variables. Based on previous studies (Buallay et al., 2021; Aiping et al., 2022), the following control variables are selected in this article. Size (the logarithm of the total enterprise assets) is used to control the impact of enterprise size. Lev, ROA, and growth rate of the main business are used to control the influence of debt-paying ability, profitability, and development ability. Topt (ownership concentration) is used to control the influence of corporate governance ability on employment quality.

Each variable is defined (Table 2).

TABLE 1 Employment quality evaluation results.

The target layer	Level indicators	Type	Weight coefficient
Employment quality	Employment scale	Positive	33.99%
	Employment structure	Positive	57.35%
	Salary level	Positive	8.66%

Model building

To verify the impact of an industrial transformation on employment quality, Model 1 is constructed in this article as follows:

$$Emp = \beta_0 + \beta_1 CO_2 + \sum Control + \varepsilon_1 \quad (1)$$

To verify the moderating effect of a just transition, this article centralizes core explanatory variables and core explained variables on the basis of Model 1 and introduces the cross-multiplication term, and then constructs Models 2 and 3 as follows:

$$Emp = \beta_0 + \beta_1 CO_2 + \beta_2 Train + \beta_3 CO_2 * Train + \sum Control + \varepsilon_2 \quad (2)$$

$$Emp = \beta_0 + \beta_1 CO_2 + \beta_2 Welf + \beta_3 CO_2 * Welf + \sum Control + \varepsilon_3 \quad (3)$$

Results

Descriptive statistics

All the data were analyzed by using SPSS version 15. The mean and standard deviation (SD) were calculated by the group (Table 3). In the study sample, *Emp* has a mean of 6,788.99 and a standard deviation of 5,138.84. It shows that the employment quality of the sample enterprises is generally high, but there is a large gap and the distribution is unbalanced. Co_2 of the mean (M = 0.000067) and standard deviation (SD = 0.00027) is small. It shows that Chinese manufacturing enterprises generally have a large amount of greenhouse gas emissions in the production process, and it is urgent to promote industrial transformation. Among the moderating variables, *Train* (M = 1,689.44, SD = 2,981.75) and *Welf* (M = 655.52, SD = 1,447.76) indicate that there are great differences in the just transition measures adopted by different companies. The standard deviation of each control variable is small. It shows that the distribution of enterprises in scale is relatively balanced, and most of the enterprises are in good operating conditions, with strong growth and a high concentration of ownership.

Sequence correlation test

The DW test is a method of autocorrelation test, which can judge whether there is a correlation between the expected values of random error terms. The closer the DW value is to 2, the better the test result is. Generally, the test can be passed between 1 and 3.

TABLE 2 Variable definitions.

Variable types	The variable name	Variable symbol	Variable declaration
Core explained variable	Employment quality	Emp	The entropy method was used to calculate the score
Core explanatory variable	Industrial transformation	Co_2	Carbon productivity = output value/carbon emissions
Moderating variables	Employee training	Train	Enterprise's training expenditure for employees
	Employee welfare	Welf	The coverage of five social insurance and housing fund
Control variables	The enterprise scale	Size	The logarithm of total enterprise assets
	Asset-liability ratio	Lev	Total liabilities/equity
	Return on assets	ROA	Net profit/total profit
	Enterprise growth	Growth	Main business growth rate
	Ownership concentration	Topt	The top ten shareholders' shareholding ratio

TABLE 3 Descriptive statistics.

Variable types	Variable	Obs	Mean	Std. Dev	Min	Max
Explained variable	Emp	106	6,788.99	5,138.84	1,475.51	36,209.35
Core explanatory variable	Co_2	106	0.000067	0.00027	1.38e-09	0.0028
Moderating variables	Train	106	1,689.44	2,981.75	0	15,619.46
	Welf	106	655.52	1,447.76	−1.63	10,731.77
Control variables	Size	106	22.39	1.06	19.20	26.59
	Lev	106	2.29	10.03	0.08	95.53
	ROA	106	0.84	0.51	7.29	10.49
	Growth	106	0.52	1.78	−12.59	8.73
	Topt	106	52.89	13.31	16.97	88.81

TABLE 4 Sequence correlation test.

Model	*R*	*R2*	The adjusted *R2*	Error in standard estimation	DW
1	0.698	0.487	0.456	0.317	1.547

A value of <1 indicates that the residuals have autocorrelation and that the test cannot be passed.

The DW test is conducted on the relevant data. The DW value is 2, which is between 1 and 3, through the DW test (Table 4). It indicates that there is no autocorrelation between the random error terms.

Test of correlation

If there is multicollinearity between variables, the regression results will be inaccurate. Therefore, the Pearson correlation test is conducted in this article (Table 5).

The correlation coefficient between *Emp* and *Size* is 0.65, which is relatively high. In addition, the correlation coefficients between other variables are between −0.5 and 0.5. Therefore, it is considered that there is no serious multicollinearity among the variables selected in this article, and the conclusion is reliable.

Multicollinearity test

To improve the scientific rigor of the study, the size of the variance inflation factor (VIF) is used to determine whether there is collinearity.

A default inflation factor of <10 is the tolerable range. If the VIF is <10, it is considered that the model does not have multicollinearity. If the VIF is >10, it is reasonable to assume that the model has multicollinearity. All the VIF values are <10, which means that the model does not have multicollinearity (Table 6).

Heteroscedasticity test

To ensure the accuracy of the regression data, this article conducts a heteroscedasticity test and adopts the White test.

When the probability of Prob > chi2 is <0.05, heteroscedasticity exists. The probability of this article is 0.2746, which is >0.05 (Table 7). It means that there is no heteroscedasticity.

Regression results

The relationship between employment quality and industrial transformation is tested through Model 1 (Table 8).

TABLE 5 Test of correlation.

	Emp	Co_2	Size	Lev	ROA	Growth	Topt	Train	Welf
Emp	1								
Co_2	0.01	1							
Size	0.65	0.22	1						
Lev	−0.17	0.16	−0.00	1					
ROA	0.19	0.22	0.13	0.08	1				
Growth	−0.13	−0.03	0.03	−0.17	0.22	1			
Topt	0.29	0.14	0.25	0.06	0.08	−0.12	1		
Train	0.02	−0.11	0.02	0.13	−0.14	0.04	−0.16	1	
Welf	0.08	0.02	0.13	0.09	−0.17	−0.39	0.06	0.05	1

TABLE 6 VIF test of variance.

Variable	Tolerance	VIF
Co_2	0.925	1.082
Size	0.837	1.194
Lev	0.938	1.066
ROA	0.921	1.086
Growth	0.906	1.103
Train	0.978	1.022
Welf	0.919	1.088

TABLE 7 White's test.

White's test for H_0: Homoskedasticity
Against H_a: Unrestricted heteroskedasticity
chi2 (20) = 71.37
Prob > chi2 = 0.2746

TABLE 8 Regression results of industrial transformation and employment quality.

	Emp	Employment scale	Employment structure	Salary level
Co_2	−0.021*	−0.067**	0.004*	−0.015*
Size	5.959***	1.794***	0.821*	3.843***
Lev	−0.074***	−0.018	−0.124***	0.039*
ROA	0.262*	0.025	0.442**	0.006
Growth	−0.172*	−0.444**	−0.147*	0.731***
Topt	0.126*	0.286**	0.083*	−0.222*
R- squared	0.487	0.686	0.125	0.120

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

The coefficient of the industrial transformation is significantly negative, indicating that the industrial transformation will significantly inhibit the improvement of employment quality. It supports Hypothesis H1b. Specifically, industrial transformation has a significant negative impact on the employment scale and salary level. On the contrary, it has a significant positive effect on employment structure. Among them, the impact on employment scale is the largest and most significant, while the impact on employment structure is relatively small. Overall, the industrial transformation still presents a negative impact on employment quality.

At the same time, employment quality is significantly positively correlated with enterprise scale, return on assets, and ownership concentration. It shows that the higher the enterprise scale, the better the efficiency, and the more concentrated the equity, the better the employment quality will be. The coefficient of the enterprise scale is 5.959, which is the largest, indicating that the enterprise scale has the highest influence on employment quality. Employment quality has a significant negative correlation with asset–liability ratio and enterprise growth. It shows that the higher the degree of debt and the faster the growth scale of the enterprise, the quality of employment of employees will be reduced.

The moderating effect of just transition on the impact of green transition on employment quality is tested through Model 2 and Model 3 (Table 9).

After the addition of *Train* and Co_2^*Train, the regression coefficient of Co_2 is still significantly negative. The regression coefficients of *Train* are 0.012 and 0.030, which are both significantly positive at the level of 10%. The results show that the increase in employee training is conducive to the improvement of employment quality. Moreover, Co_2^*Train is significantly positive at the 10% level, which means that the negative impact of the industrial transformation on employment quality is reduced. Enterprises should strengthen skills training. It can not only improve the working ability of employees and their own value and competitiveness in job transition but also reduce the opportunity cost of reemployment and ensure just transition.

As shown in M3, after the addition of *Welf* and Co_2^* *Welf*, the regression coefficient of Co_2 is still significantly negative. The regression coefficient of *Welf* is −0.001, which is significantly negative at the level of 10%. It indicates that the increase in employee welfare is not conducive to the improvement in employment quality. In addition, Co_2^* *Welf* is significantly positive at the level of 10%, which also weakens the negative impact

of the industrial transformation on employment quality. Perfect employee security can guarantee the reemployment of structural unemployment, enhance the sense of social justice, and promote the just transition in the industrial transformation of enterprises.

Thus, Hypotheses H2b and H3b are verified.

Heterogeneity analysis

Based on the research of the above models, this article carries out the analysis of enterprise heterogeneity (Table 10). This is to study whether industrial transformation will have different effects on employment quality under different ownership types of enterprises and whether there are differences in the regulatory effects of just transformation.

The industrial transformation coefficient of state-owned enterprises is not significant, but it is significantly negative in private enterprises. This suggests that the industrial transformation of private enterprises will reduce the quality of employment of employees, and the negative impact of industrial transformation on employment quality is more obvious in private enterprises.

After adding adjustment variables and interaction terms, respectively, the coefficients of state-owned enterprises are still not significant. The interaction coefficients of private enterprises are positive. These indicate that the improvement of employee training and employee welfare in private enterprises can improve the impact of industrial transformation on employment quality. The just transition plays a moderating effect and alleviates the negative impact of green transition on employment quality.

TABLE 9 Regression analysis of industrial transformation, just transition, and employment quality.

Variable	M2		M3	
Co_2	−0.019**	−0.013**	−0.021**	−0.022**
Train	0.012*	0.030*		
Co_2^*train		0.003*		
Welf			−0.001*	−0.001*
Co_2^*welf				0.012*
Size	5.894***	5.956***	5.954***	6.013***
Lev	−0.027***	−0.078***	−0.074***	−0.075***
ROA	0.279*	0.276*	0.263*	0.271*
Growth	−0.181*	−0.176*	−0.170*	−0.156*
Topt	0.141**	0.136*	0.126*	0.105*
R- squared	0.490	0.491	0.487	0.489—

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

Robustness test

To look for similarities in the estimates of the key variable across all the models, *Emp* is estimated as the explained variable with the core explanatory variable Co_2, then with each of the control variables separately, and finally with all the control variables (Table 11).

It is found that each control variable is significant, and *Size* has the strongest significance. In addition, by comprehensively observing the coefficient of Co_2, the coefficient result in the last column is very close to the sum of the coefficient results, considering a single control variable. Co_2 has a negative impact on employment quality, approximately −0.021, which is significant at the 10% level.

To improve the reliability of the research results, the measurement method of the industrial transformation is changed in this article. The industrial transformation level of enterprises is measured by replacing carbon productivity with environmental protection investment. Then, the robustness test is conducted

TABLE 10 Heterogeneity analysis.

	M1		M2		M3	
	State-owned enterprises	Private enterprise	State-owned enterprises	Private enterprise	State-owned enterprises	Private enterprise
Co_2	0.007	−0.032**	−0.169	−0.027**	0.024	−0.033**
Train			−0.037	0.025*	−0.008	
Co_2^*train			0.316	0.074*		
Welf					−0.008	0.015*
Co_2^*welf					−0.014	0.027**
Size	6.197***	5.644***	6.212***	5.766***	6.011***	5.246***
Lev	−0.053	−0.072**	−0.078	−0.076***	−0.054	−0.084**
ROA	0.576***	0.125	0.595***	0.138	0.537**	0.150**
Growth	−0.748***	−0.039	−0.759**	−0.046	−0.793***	0.028
Topt	0.127	0.154	0.129	0.165	0.159	0.142
R-squared	0.745	0.334	0.755	0.337	0.748	0.346

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

TABLE 11 Robustness of the control variables.

	Emp	Emp	Emp	Emp	Emp	Emp	Emp
Co_2	0.016	−0.023**	0.006*	−0.007*	0.001*	−0.005*	−0.021*
Size		6.412***					5.959***
Lev			−0.073*				−0.074***
ROA				0.349**			0.262*
Growth					−0.027*		−0.172*
Topt						0.4567***	0.126*
R- squared	0.001	0.436	0.030	0.035	0.003	0.087	0.487

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

TABLE 12 Test for robustness.

	Emp	M2	M3
Green	−0.063*	−0.045**	−0.026**
Train		−0.057**	
Green*train		0.006*	
Welf			−0.003*
Green*welf			0.002*
Size	6.862**	5.642***	6.032***
Lev	−0.057***	−0.058***	−0.084**
ROA	0.352**	0.257**	0.194*
Growth	−0.172*	−0.097**	−0.098***
Topt	0.204*	0.189**	0.160*
R- squared	0.492	0.490	0.487

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

(Table 12). The final results and significance do not change significantly, which means that the results are robust.

Discussions and implications

Through the empirical test, the industrial transformation has a negative impact on the quality of employment, especially on the aspects of employment scale and salary level, while it has a positive impact on the employment structure. It is different from the previous literature. Mu et al. (2018) measured the employment level based on the employment scale and concluded that the development of clean energy has a positive effect on the employment level in China. Zhang and Du (2020) also chose the Yangtze River Delta as the research area and evaluated the net effect of the development strategy of the Yangtze River Economic Belt on employment based on the panel data. The finding shows that the development strategy of the Yangtze River had a positive effect on employment.

In terms of employment scale, Wagner and Timmins (2010) and Wang and Ge (2022) show that the elimination of outdated production capacity will lead to a reduction in production capacity and unemployment. However, they are more focused on industries with high pollution and energy consumption. In terms of employment structure, Marouani and Nilsson (2016) and Rogers and Pleasants (2011) show that the green transition will stimulate the diversity of workers' employment skills, thus enriching the employment structure. In terms of the salary level, Kim et al. (2015) hold the view that salary levels will decline under the industrial transformation. These authors come to the same conclusions, as we do in terms of one dimension of employment.

For the test of intermediary variables, both employee training and employee welfare significantly enhance the impact of the green transition on employment quality. Dongyang and Yuxiao (2019) shows the impact of skills training and social security is positive to transition too. Employee training promotes two-way communication between the company and its employees, as well as between management and employees. Communication enhances cohesiveness and creates an outstanding corporate culture. Employee welfare guarantees the basic quality of life of employees and helps smooth the process of transformation.

Industrial transformation technology puts forward higher requirements for talent, and enterprises absorb more talent which not only optimizes the employment structure to some extent but also increases structural unemployment. Therefore, the positive impact is small. The findings still show a negative impact of the industrial transformation on employment quality. Private enterprises will respond quickly and take greater emission reduction measures when facing stricter environmental constraints. The change will have a greater impact on employment. All factors lead to the conclusion about the influence of state-owned enterprises and private enterprises mentioned earlier.

Low-carbon economy has been a hot spot in academic circles. At present, the transformation is in the preliminary stage. After the in-depth transformation of enterprises, it is necessary to further study the mechanism of industrial transformation and employment quality. Through this research, the article obtains the following suggestions:

Enterprises should provide detailed and comprehensive employment information to reduce information asymmetry and frictional unemployment. Enterprises could cooperate with the government to establish employment training centers through big data to provide cross-industry employment information sources.

Enterprises should make comprehensive use of welfare and incentive mechanisms. They should improve the salary and welfare level to promote capital structure and human capital, especially to balance the salary gap between high-skilled employees and ordinary ones. For example, they could encourage ordinary staff to

take the initiative to obtain the qualification certificate through an incentive mechanism. In addition, to ensure the material welfare of employees, enterprises should also provide staff and their families with humanistic care.

Local government should introduce a vocational training subsidy policy with discretion to improve subsidy efficiency. Due to the opportunity cost of vocational training, when the economy goes down, the unemployed have a lower opportunity cost to receive training and are more willing to receive training. At this time, more targeted training subsidy policies will be introduced in due time.

In terms of state-owned enterprises, the government should establish scientific and reasonable transformation goals. State-owned enterprises actively invest in R&D and innovation to drive the industrial transformation of private enterprises. In terms of private enterprises, the government should strengthen positive incentives for green behaviors, such as establishing incentive policies for benchmark enterprises. In the bidding activities, the low-carbon and environmental attributes of private enterprises are included in the reference factors. Private enterprises themselves should improve the selection and appointment mechanism and provide good treatment and stable career development paths for employees.

Conclusion

This research objects are manufacturing enterprises in the Yangtze River Delta, which are in China's A-share market. We empirically tested the relationship between industrial transformation and employment quality. We brought in staff training and welfare to measure just transition as moderating variables to research the impact of just transition on industrial transformation. We also explored whether the above conclusions had differences between state-owned enterprises and private ones. The conclusions are as follows:

Industrial transformation has significantly negative effects on employment scale and salary levels while having positive effects on employment structure. As a whole, industrial transformation eventually has a negative effect on employment quality.

Despite that employee training can alleviate the negative impact of industrial transformation on employment quality. On the contrary, employee welfare will play a negative moderating role. The reason may be that welfare will lead to employee inertia and reduce employment enthusiasm.

In state-owned enterprises, industrial transformation has no significant positive effect on employment quality, and just transition has no significant moderating effect. The reason why state-owned enterprises can promote employment may be that they have the advantage of obtaining resources and absorbing the additional cost of environmental policies.

In private enterprises, industrial transformation has a significantly negative impact on employment quality, while just transition can alleviate the negative impact of industrial transformation on employment quality. The reason may be that private enterprises do not have these advantages. Therefore, when faced with stricter environmental constraints, they will respond quickly to take greater emission reduction measures and affect employment.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2023.1076971/full#supplementary-material

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Appendix 1

The steps of entropy weight method are as follows:

1. Data standardization:

$$x_{ij} = \frac{x_{ij} - min\left\{x_{ij}\right\}}{\max\left\{x_{ij}\right\} - min\left\{x_{ij}\right\}} \text{or } x_{ij} = \frac{\max\left\{x_{ij}\right\} - x_{ij}}{\max\left\{x_{ij}\right\} - min\left\{x_{ij}\right\}}$$

where x_{ij} is the data of the J-th index of the I-th company.

2. Calculate the proportion of the value of the I-th company in the J-th index as follows:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}$$

3. Calculate the information entropy of the J-th index as follows:

$$e_j = -\frac{1}{lnn} \sum_{i=1}^{n} P_{ij} * ln(P_{ij})$$

4. Calculate the difference coefficient of the J-th index as follows:

$$d_j = 1 - e_j$$

5. Calculate the index weight, namely, to normalization processing difference coefficient as follows:

$$w_j = \frac{d_j}{\sum_{i=1}^{m} d_j}$$

6. Calculate the overall score of employment quality as follows:

$$Digtal_i = \sum_{i=1}^{m} w_j * x_{ij}$$