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Does Low-Carbon Development Affect Employment in Manufacturing? Evidence from China's Low-Carbon City Pilots

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Abstract: To fulfill the "carbon peak and carbon neutrality" targets pledged in the 2016 Paris Agreement, China implemented the Low-Carbon City Pilot Policy (LCCP) in 2010, expanding its scope in 2012 and 2017. However, its effect on employment in manufacturing remains unexplored. This paper employs a difference-in-differences (DID) model and a micro-panel dataset of Chinese listed manufacturing firms from 2007 to 2021 to identify the casual effect of the LCCP on manufacturing employment. The findings reveal that (1) the LCCP leads to an average 3.9% increase in manufacturing employment; (2) this impact operates through output and factor substitution effects. These conclusions are validated through a series of endogeneity and robustness tests. The study provides new evidence supporting a win-win outcome between environmental protection and employment growth under low-carbon development initiatives.

Keywords: Low-carbon pilot, environmental regulation, employment in manufacturing industry.

1. Introduction

Global warming has led to a global consensus on the importance of ecological and environmental protection, prompting the introduction of numerous environmental policies.

In response to its commitments under the 2016 Paris Agreement, China launched the LCCP policy in 2010, with subsequent phases implemented in 2012 and 2017. The policy aims to encourage a low-carbon transition by transforming energy structures, adjusting industrial activities, and improving energy efficiency. Although prior research has addressed the environmental and economic impacts of LCCP, its impact on employment in the manufacturing sector has not been thoroughly explored. Given that LCCP may alter business operations, production processes, and technological upgrades, it is likely to influence labor demand in high-pollution, high-emission manufacturing sectors.

Understanding LCCP's effect on manufacturing employment is crucial, as environmental regulations often target high-energy and high-carbon sectors like manufacturing [1], which in China employs many low-skilled workers [2]. A significant impact on employment could have far-reaching social implications, as concerns over job losses are a key driver of resistance to green policies [3]. Therefore, exploring LCCP's impact on manufacturing employment is of great importance for environmental policy design and sustainable development strategies.

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This study treats LCCP as a "quasi-natural experiment" and employs a DID model to assess its impact on manufacturing employment and mechanisms. Findings indicate that LCCP significantly promotes employment in manufacturing firms through output and factor substitution effects.

The contributions of this paper are twofold: (1) it provides a micro-level analysis of LCCP's social effects on manufacturing employment; (2) it explores the mechanisms driving these effects.

2. Literature review

2.1. Environmental regulation and employment

A growing body of research has examined the economic and social impacts of environmental regulations, yet consensus on their effects on employment remains elusive.

Some empirical studies suggest that environmental regulation negatively affects employment. For example, research on the U.S. Clean Water Act shows adverse impacts on employment in chemical manufacturing [4] and on productivity and environmental jobs [5]. Similarly, studies have found that stringent environmental regulations in China significantly reduced labor demand and firm-level employment [6][7].

Conversely, other studies highlight a positive relationship with evidence that environmental regulations promoted long-term employment growth in China, especially in high-skilled positions [8]. The China's Carbon Emissions Trading Pilot (CET) policy has also been found to enhance employment in the pilot regions [2].

Theoretical work identifies three mechanisms by which environmental regulations affect employment: through increased costs [9][10], technological advancement [11][12], and a combination of cost and innovation effects [13][14].

2.2. Research on China's low-carbon city pilot

A substantial body of literature has assessed the effects of the LCCP from both environmental and economic perspectives. Environmentally, researchers have examined the LCCP's impact on various indicators, including carbon emissions [15], eco-efficiency [16], carbon emission efficiency [17], and carbon emission intensity [18].

Additionally, studies have analyzed the economic effects of the LCCP, focusing on factor productivity [19], economic growth [20], and technological innovation [21]. However, despite the extensive examination of its economic and environmental impacts, the LCCP's effect on manufacturing employment remains insufficiently explored. Since environmental regulation primarily targets sectors with high energy and carbon intensity, such as manufacturing [14], industry-wide analyses might obscure its specific effects on this sector.

To address this research gap, this paper uses DID and firm-level micro data from 2007 to 2021 to examine the LCCP's impact on employment in the manufacturing sector.

3. Theoretical framework

This study builds on a partial static equilibrium model [22], integrating "quasi-fixed" factors affected by environmental regulations, following the framework established by earlier research [13]. Specifically, capital investment in abatement, labor, and environmental costs are treated as quasi-fixed, while raw materials and other capital inputs are variable factors. Let the input vector be $\boldsymbol{x} = (\boldsymbol{v}, \boldsymbol{q})$, where $\boldsymbol{v} = (v_1, v_2, \dots, v_m)'$ denotes the variable factors, and $\boldsymbol{q} = (q_1, q_2, \dots, q_n)'$ represents the n quasi-fixed factors. Their respective prices are given by $\boldsymbol{w} = (\boldsymbol{w}_v, \boldsymbol{w}_q)$.

Assuming profit maximization, the profit function is:

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$$\pi = Py - \boldsymbol{w}_v^{'}\boldsymbol{v} - \boldsymbol{w}_q^{'}\boldsymbol{q} \tag{1}$$

where y is output, P is the market price of products, and $= f(\boldsymbol{v}, \boldsymbol{q})$ the production function. The first-order condition is:

$$P\frac{\partial f(\boldsymbol{v}^*, \boldsymbol{q})}{\partial v_i} = w_{vi} \ , \ \ i = 1,2, \dots, m \tag{2}$$

Solving these conditions yields the demand equation for variable factors:

$$\boldsymbol{v} = \boldsymbol{v}(P, \boldsymbol{w_v}, \boldsymbol{q}) \tag{3}$$

Substituting this into equation (1), maximum profit is expressed as:

$$\pi = \pi\ (P, \boldsymbol{w}, \boldsymbol{q}) \tag{4}$$

Applying the Hotelling Lemma, the labor demand function becomes:

$$L = L(P, \boldsymbol{w}, \boldsymbol{q}) = -\frac{\partial \pi\ (P, \boldsymbol{w}, \boldsymbol{q})}{\partial w_L} \tag{5}$$

The labor demand function can be approximated linearly as:

$$L = L(P, \boldsymbol{w}, \boldsymbol{q}) = \alpha + \beta P + \boldsymbol{\gamma}'\boldsymbol{q} + \boldsymbol{\delta}'\boldsymbol{w}_v + \ \psi\,'\,\boldsymbol{w}_q \tag{6}$$

Let R denote the environmental costs arise from the LCCP. The impact of R on labor demand is represented by:

$$\frac{\mathrm{d}L}{\mathrm{d}R} = \beta\frac{\mathrm{d}P}{\mathrm{d}R} + \boldsymbol{\gamma}'\frac{\mathrm{d}\boldsymbol{q}}{\mathrm{d}R} + \boldsymbol{\delta}'\frac{\mathrm{d}\boldsymbol{w}_v}{\mathrm{d}R} + \boldsymbol{\psi}'\frac{\mathrm{d}\boldsymbol{w}_q}{\mathrm{d}R} \tag{7}$$

Assuming a monopolistically competitive output market, the demand curve is downward sloping, with a linear form where $\mathrm{d}P/\mathrm{d}y = -k < 0$. Thus, equation (7) simplifies to:

$$\frac{\mathrm{d}L}{\mathrm{d}R} = \alpha\frac{\mathrm{d}y}{\mathrm{d}R} + \boldsymbol{\gamma}'\frac{\mathrm{d}\boldsymbol{q}}{\mathrm{d}R} + \boldsymbol{\delta}'\frac{\mathrm{d}\boldsymbol{w}_v}{\mathrm{d}R} + \boldsymbol{\psi}'\frac{\mathrm{d}\boldsymbol{w}_q}{\mathrm{d}R} \tag{8}$$

where, $\alpha = -k\beta$. The last two terms in equation (8) explain how environmental costs affect labor demand through factor price changes. Under a perfectly competitive input market, factor prices remain unchanged, reducing equation (8) to:

$$\frac{\mathrm{d}L}{\mathrm{d}R} = \alpha\frac{\mathrm{d}y}{\mathrm{d}R} + \boldsymbol{\gamma}'\frac{\mathrm{d}\boldsymbol{q}}{\mathrm{d}R} \tag{9}$$

where, $\alpha\frac{\mathrm{d}y}{\mathrm{d}R}$ is the output effect, and $\boldsymbol{\gamma}'\frac{\mathrm{d}\boldsymbol{q}}{\mathrm{d}R}$ is the factor substitution effect. The output effect describes how LCCP alters total firm output, thereby impacting labor demand, while the factor substitution effect describes how the LCCP influences employment by affecting capital investments in production processes and end-of-production. Figure 1 illustrates the detailed mechanisms of these two effects.

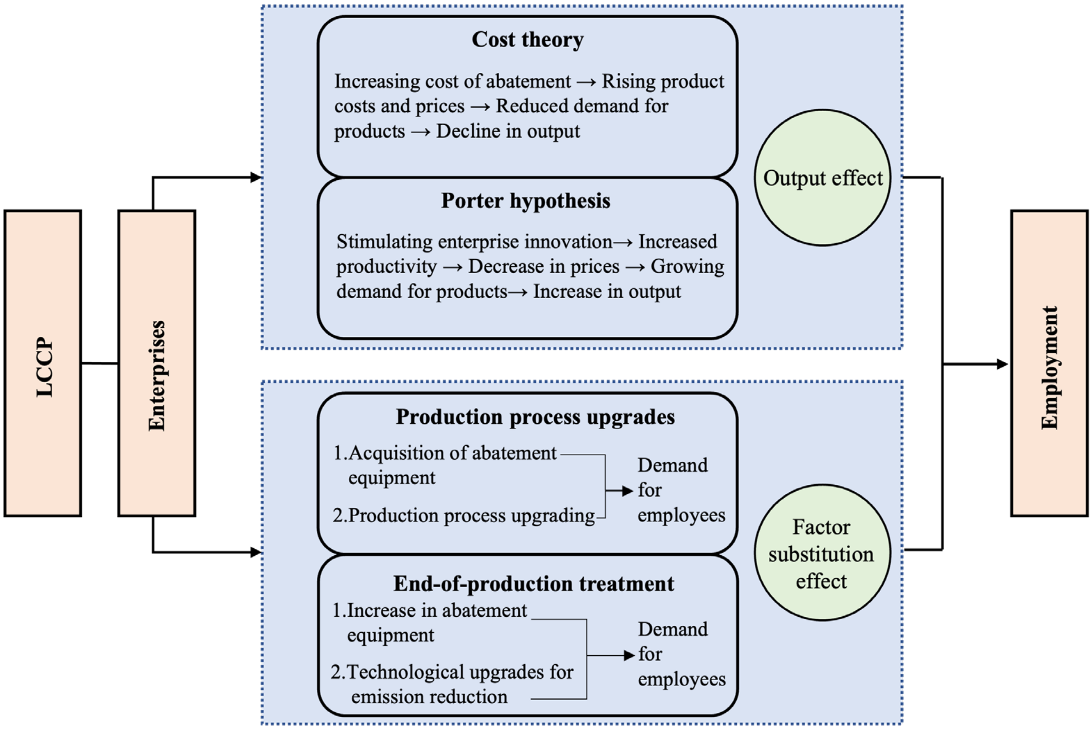

Figure 1: Mechanism of LCCP affecting employment in manufacturing firms.

The output effect may have both positive and negative employment implications. According to the Cost Theory of Neoclassical Economics, environmental regulations may raise production costs, leading to reduced output and employment [23]. Conversely, the Porter Hypothesis argues that regulation can drive innovation, potentially offsetting environmental costs and increasing both output and employment [11]. Empirical evidence supports that such regulation-induced innovation can lead to job creation [2][24].

The factor substitution effect arises when firms adjust quasi-fixed inputs, such as pollution control investments, in response to regulations. First, this paper assumes $\mathrm{d}\boldsymbol{q}/\mathrm{d}R > \boldsymbol{0}$,as environmental regulations generally increase firms' environmental investments to comply. Thus,the effect on employment depends on $\boldsymbol{\gamma'}$, which consists of a series of γ_i. If the quasi-fixed input q_i substitute labor, $\gamma_i < 0$, reducing employment; if it complements labor, $\gamma_i > 0$, potentially increasing jobs. For instance, acquiring equipment for emission control may require additional employees for operation and maintenance, while technological innovations and upgrades may reduce labor demand by enhancing efficiency [2]. Thus, the factor substitution effect encompasses both labor replacement and job creation.

4. Model and data

4.1. Model

This study utilizes DID to evaluate the impact of LCCP on employment in manufacturing firms, leveraging its "quasi-natural experiment" setup. Listed manufacturing firms in pilot cities are categorized as the treatment group, while firms in non-pilot cities serve as the control group. The model is specified as:

$$ln\ emp_{it} = \beta_0 + \beta_1 lccp_{it} + \sum_i \theta_i \cdot control_{it} + \lambda_i + v_t + \varepsilon_{it} \tag{10}$$

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where, the $\ln emp_{it}$ is the logarithm of total employees of firm i in year t. $lccp_{it}$ is the core explanatory variable, taking a value of 1 if firm i operates in a pilot city in year t, and 0 otherwise. $Control_{it}$ includes firm-specific control variables, while λ_i and v_t capture firm and year fixed effects.

The control variables, inspired by previous studies [2][25][26], include: (1) Wage ($wage_{it}$), measured by average wage; (2) Firm size ($size_{it}$), measured by the logarithm of total assets; (3) Sales expense ratio ($sale_{it}$), calculated as total sales expense to total revenue ratio; (4) Debt-to-asset ratio (DTA_{it}), calculated as total liabilities over total assets; (5) Tobin's Q (q_{it}), defined as the ratio of market value to asset replacement cost; (6) Income tax (tax_{it}); (7) Return on assets (ROA_{it}), measured by the ratio of total profit to total assets.

4.2. Data

The baseline model employs panel data from listed manufacturing firms in the Shanghai and Shenzhen A-share markets (2007-2021), sourced from the China Stock Market & Accounting Research Database (CSMAR). This period provides sufficient pre-policy data for parallel trend testing. The dataset is "unbalanced" due to firm exits, mergers, or new listings, assumed to be exogenous to the LCCP.

The data cleaning involved: (1) Excluding companies labeled as "ST" or "*ST" (indicating financial and operational abnormalities); (2) Removing firms with significant missing data; (3) Filling gap with linear interpolation. The final sample consists of 3,077 firms, with 1276 in the treatment group and 1801 in the control group. The statistics for data set are shown in Table 1.

Table 1: Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
ln emp	17213	7.731	1.303	2.708	13.223
lccp	17213	0.552	0.497	0.000	1.000
wage	17213	12.581	24.876	0.513	2348.366
Size	17213	12.992	1.498	10.066	21.826
sale	17213	0.075	0.093	0.000	1.356
DTA	17213	0.404	0.207	0.008	1.352
Q	17213	1.943	1.245	0.699	31.400
Tax	17213	17.257	1.880	0.000	25.172
ROA	17213	0.049	0.058	-1.057	0.526

5. Empirical results

5.1. Baseline results

The LCCP program was launched in three phases: July 2010, November 2012, and January 2017, and these years are identified as the treatment times. The baseline results are shown in Table 2.

Three model specifications are presented: pooled OLS (column 1), fixed effects without controls (column 2), and fixed effects with controls (column 3). The LCCP coefficient's sign change between pooled and fixed effects models necessitates the use of fixed effects. The DID estimators in columns (2) and (3) are positive and significant at the 95% level. Including control variables slightly decreases

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the coefficient from 0.046 to 0.039, implying that the controls partially account for employment effects. Economically, the LCCP leads to an average 3.9% increase in employment in manufacturing firms, consistent with findings on CET's impact on employment [2][27].

Table 2: Baseline results.

Variables	*ln emp*	*ln emp*	*ln emp*
	(1)	(2)	(3)
lccp	-0.123^{***}	0.046^{***}	0.039^{***}
	(0.025)	(0.017)	(0.013)
Controls	Y	N	Y
Year FE	N	Y	Y
Firm FE	N	Y	Y
Obs	17213	16979	16979
Adj R-squared	0.596	0.894	0.935

Values in parentheses are cluster-robust standard errors clustered by firms. * p<0.1, ** p<0.05, *** p<0.01. The same applies hereafter.

5.2. Parallel trend test

To validate the parallel trend assumption, an event study [28] is conducted. Figure 2 illustrates the parallel trend test results, using the $t = -4$ as the baseline. The coefficients before the treatment are not significantly different from zero, confirming no pre-existing systematic distinction between the treatment and control groups. The baseline model thus satisfies the parallel trends assumption, confirming the robustness of the DID estimates.

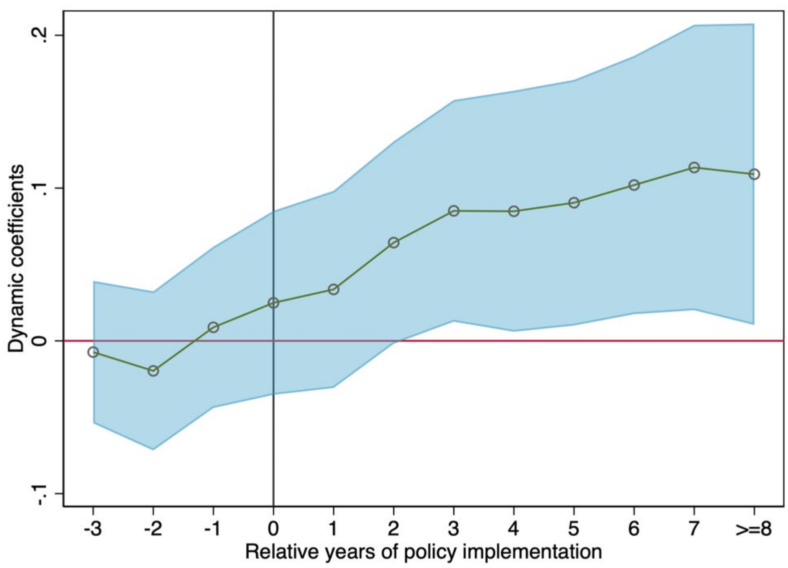

Figure 2: Parallel trend test.

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5.3. Robustness tests

5.3.1. Placebo test

To verify the baseline model's robustness, a placebo test was conducted by randomly assigning treatment groups and treatment times. Specifically, treatment units were randomly selected, in the same number as in the baseline sample, while a false treatment time was randomly drawn from the period $[2005, t-1]$, where t denotes the actual treatment time. A DID regression was then performed on the pseudo-sample to obtain a placebo estimator. Repeating this process 500 times yielded a coefficient distribution (shown in Figure 3), centered around zero, with the baseline coefficient at the distribution's tail. This suggests no significant bias from unobserved variables, affirming the model's robustness.

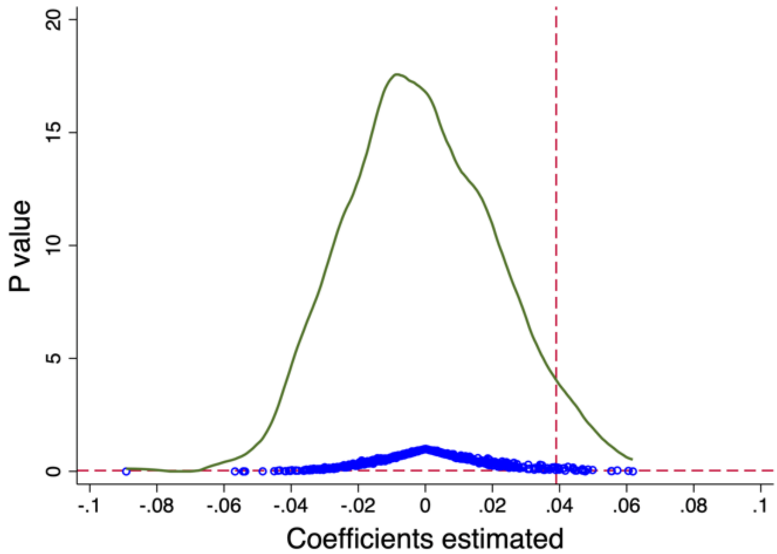

Figure 3: Placebo test.

5.3.2. Propensity score matching

To address potential sample selection bias, the study employs a propensity score matching (PSM) approach. Firms in treatment and control groups were matched based on control variables, using K-nearest neighbor, radius, and kernel matching techniques. Columns (1) – (3) of Table 3 report the results, demonstrating that the treatment effects significantly positive across all methods, indicating that potential sample selection bias does not significantly affect conclusions.

Table 3: Robustness tests by PSM and data winsorization.

Variables	*ln emp*	*ln emp*	*ln emp*	*ln emp*	*ln emp*
	PSM-DID			Censored data	
	K-nearest	Radius	Kernel	1%	5%
	(1)	(2)	(3)	(4)	(5)
lccp	0.056***	0.038**	0.060***	0.035**	0.036**
	(0.018)	(0.017)	(0.023)	(0.016)	(0.016)
Controls	Y	Y	Y	Y	Y

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Table 3: (continued).

Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Obs	12536	16972	8347	16634	15248
Adj R-squared	0.943	0.945	0.940	0.942	0.925

5.3.3. Data winsorization

To further test robustness, outliers were excluded by removing the top and bottom 1% and 5% of firms based on dependent variable. The results (Table 3, columns 4 and 5) show that the coefficient remains positive and significant, confirming that outliers do not bias the baseline results.

5.3.4. Ruling out confounding effects from other policies

To isolate the LCCP's effect, potential confounding policies were controlled for, including the Innovative City Pilot policy, Air Pollutant Emission Limitation policy, and Industrial Incentive policy. Each was included as a dummy variable indicating its presence in city i at time t. The Innovative City Pilot Policy is an economic policy aimed at fostering entrepreneurship and promoting new industries, indirectly boosting employment. The Air Pollutant Emission Limitation Policy, aligned with LCCP's goal, focuses on reducing carbon emissions. The Industrial Incentive Policy supports the development of specific industries, potentially affecting corporate employment.

Table 4 presents these results, showing that after controlling for confounding effects from other policies, the treatment effect of LCCP remains significantly positive. However, controlling for the Air Pollutant Emission Limitation Policy reduces the coefficient, indicating some overlap in policy effects. Overall, results confirm the robustness of the baseline conclusion.

Table 4: Robustness test by controlling for other policies.

Variables	*ln emp*	*ln emp*	*ln emp*	*ln emp*
	Controlling for other policies			
	(1)	(2)	(3)	(4)
lccp	0.038**	0.032*	0.039**	0.031*
	(0.015)	(0.016)	(0.016)	(0.017)
Innovative City Pilot policy	Y	N	N	Y
Air pollutant emission restriction policy	N	Y	N	Y
Industrial Incentive policy	N	N	Y	Y
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Obs	16979	16979	16979	16979
Adj R-squared	0.935	0.935	0.935	0.935

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5.4. Mechanism analysis

5.4.1. Output effect

To verify the output effect, a mediation model is constructed. The mediator for the output effect is the firm's total revenue (*output*), and the regression results are shown in columns (1) and (2) of Table 5. Obviously, both the coefficient of *lccp* and *output* are significantly positive, indicating that the LCCP enhances employment in manufacturing sector through increased output.

Table 5: Mechanism analysis.

Variables	Output effect		Factor substitution effect	
	Output	*ln emp*	*Environmental investment*	*ln emp*
	(1)	(2)	(3)	(4)
lccp	0.068^{*}	0.056^{*}	0.002^{**}	0.002^{**}
	(0.363)	(0.308)	(0.001)	(0.000)
Output		0.040^{***}		
		(0.001)		
Environmental investment				0.221^{**}
				(0.091)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs	16979	16979	16972	16972
Adj R-squared	0.882	0.935	0.546	0.935

5.4.2. Factor substitution effect

The factor substitution effect is also examined with the same approach. This effect represents how changes in quasi-fixed inputs, such as equipment or innovations related to environmental protection, influence employment. Due to a lack of data on firm's environmental treatment investments, this study uses the ratio of spending on fixed assets, intangible assets, and other long-term assets to total assets as a proxy. Results in columns (3) and (4) of Table 5 reveal that both the coefficients of *lccp* and of environmental investment are significantly positive, suggesting that the LCCP promotes manufacturing employment through factor substitution.

6. Conclusions and implications

This paper evaluates LCCP's effect on manufacturing employment by using panel data from listed manufacturing firms in the Shanghai and Shenzhen A-share markets (2007–2021) based on a two-way fixed-effects DID model. Results reveal that (1) LCCP significantly increased employment in

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listed manufacturing firms by 3.9% on average. This finding supports the Porter Hypothesis, challenging the traditional view that overstates the negative impact of environmental regulation on employment; (2) The treatment effects of LCCP can be decomposed into output and factor substitution effects.

Based on the findings, the following policy implications are drawn: (1) Continue to extend the experience of LCCP to more cities. LCCP has proven effective in reducing emissions, boosting economic growth, and increasing employment. To achieve balanced environmental and economic development, the policy should be extended to more cities to encourage broader participation in emission reduction. (2) The government should enhance support for innovation and technological upgrades in the manufacturing sector, particularly targeting high-pollution, high-carbon industries, to facilitate a green transition. The LCCP increases employment by boosting firm output and optimizing "quasi-fixed" factor inputs, with innovation serving as the key driver for output growth and job creation. Therefore, the government should provide R&D subsidies, technological transformation incentives, and rewards for achieving emission reduction targets to encourage the adoption of clean production technologies and improve energy and resource efficiency. This approach not only aids in achieving emission reduction goals but also increases labor demand, promoting a win-win scenario for economic growth and environmental protection.

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