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Low-Carbon City Policies and Employment in China: Impact Effects and Spatial Spillovers

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Abstract: This study examines the impact of low-carbon city policies on urban employment using panel data from 2006 to 2021. The findings reveal that these policies significantly enhance urban employment by promoting green technological innovation, which drives economic growth and creates new job opportunities. Low-carbon policies also exhibit spatial spillover effects, benefiting neighboring cities within a 200 km radius. However, these effects vary non-linearly with distance. The key mechanisms include green technology adoption, industrial structure optimization, and the promotion of green consumption habits. These mechanisms accelerate industrial upgrading, foster the growth of tertiary and green industries, and expand job opportunities in emerging markets. Heterogeneity analysis shows more substantial employment effects in non-resource-based cities, provincial capitals, cities with high government innovation preferences, tertiary sector dominance, and higher urbanization rates. This highlights the need for policies tailored to specific urban characteristics. In conclusion, low-carbon policies integrate climate action with employment growth. Policymakers should invest in green technologies, support industrial transformation, and enhance public environmental awareness to maximize employment benefits, fostering sustainable urban development.

Keywords: low-carbon cities; employment; spatial spillover; heterogeneity analysis

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1. Introduction

Excessive carbon emissions have led to global warming, triggering climate issues such as rising sea levels, extreme weather events, and, increasingly, frequent natural disasters [1,2]. As the largest energy consumers globally, cities account for 75% of global energy consumption and are responsible for 80% of greenhouse gas emissions [3]. As a critical vehicle for spatial governance, low-carbon cities' policy practices not only address energy transition and technological innovation, but also profoundly reshape the structure and operational dynamics of labor markets. International evidence demonstrates that the interactive effects between low-carbon policies and labor markets constitute central issues for social equity and sustainable growth.

The global initiative for low-carbon cities began in the late 20th century. The signing of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 and adopting the *Kyoto Protocol* in 1997 catalyzed the establishment of carbon reduction targets [4,5]. The 2015 signing of the *Paris Agreement* further encouraged international action, becoming a model for developing low-carbon cities [6]. Developed countries have expedited low-carbon transition using legislative measures and market-based mechanisms, yet this shift has intensified employment polarization effects. China's journey toward

building low-carbon cities started in 2006 when the 11th Five-Year Plan introduced energy conservation and emissions reduction targets. In 2010, the first batch of low-carbon pilot cities, including Beijing and Shanghai, was launched. These cities explored low-carbon development models using measures such as low-carbon planning, energy optimization, and green building initiatives. In 2012, the second batch expanded to 28 cities, followed by a third round in 2017, marking the gradual establishment of a comprehensive policy framework [7].

Figure 1 shows the significant spatial and temporal variations in carbon emissions intensity among Chinese cities from 2011 to 2021. Overall, the intensity of carbon emissions in Chinese cities declined during this period. In 2011, the national average carbon emissions intensity was 2.15 tons per CNY 10,000 of GDP, with most cities displaying high levels. By 2021, this figure had decreased to 1.19 tons per CNY 10,000 of GDP, although 138 cities still had carbon emissions intensities exceeding 1.59 tons per CNY 10,000. These trends indicate that China has made notable progress in energy conservation and emissions reduction. A comparative analysis of four figures reveals that cities implementing low-carbon pilot policies experienced significant declines in carbon emissions intensity. In contrast, some high-carbon-emitting cities, such as Jiuquan, Heihe, Yichun, and Hegang, which did not adopt low-carbon pilot policies, showed small reductions in carbon emissions intensity between 2011 and 2021. In 2022, pilot cities exhibited an 18.7% lower carbon emission intensity than non-pilot cities on average, and yet their employment effects demonstrated marked heterogeneity. Developed cities like Shenzhen generated high-end green jobs using carbon trading markets (e.g., carbon finance analysts with 34% annualized growth), while traditional industrial cities such as Baoding confronted "low-skilled labor lock-in"; low-value-added positions like photovoltaic module assembly constituted 76% of employment, with inadequate skill premiums constraining human capital upgrading[1]. In 2015, China pledged, under the Paris Agreement, to reduce carbon emissions per unit of GDP by 60–65% from 2005 levels by 2030 and to achieve peak carbon emissions by 2030. Entering the 2020s, the global initiative for low-carbon city construction has entered a stage of deepening and innovation. Low-carbon urban development is crucial to combat climate change and is an indispensable pathway to achieving sustainable development.

The transition to a green and low-carbon economy represents a broad and profound systemic transformation of economic and social structures, inevitably affecting various domains such as investment, production, distribution, and consumption [6]. Industries undergoing this transition must adapt by shifting development paradigms, adjusting business models, transforming production methods, innovating technologies, and phasing out outdated capacities. This transformation exerts structural impacts on labor demand: the demand for highly skilled labor has surged, while the need for low-skilled jobs in traditional industries has gradually declined [8]. Simultaneously, the improvement in urban environments and the provision of high-quality public services driven by low-carbon policies have attracted more young and highly educated workers to leading pilot cities for low-carbon development [9], thereby reshaping the labor market landscape on the supply side.

Existing research has analyzed the impact of environmental policies on employment from the perspectives of scale effects and substitution effects. Empirical studies based on these theoretical effects have yielded four main conclusions: environmental regulation has an insignificant effect on employment [10]; it positively impacts employment [11,12]; it negatively affects employment [13,14]; or it exhibits a U-shaped relationship with employment [15]. Discrepancies in findings arise due to differences in datasets and estimation methods. Specifically, the impacts of environmental regulation on employment structure vary across macro, meso, and micro levels, influenced by regional, industrial, and labor

skill differences. Firstly, at the macro level, the effects of environmental regulation differ between regulated and unregulated regions or compliant and non-compliant areas. Variations in regulatory standards across regions can induce spatial labor mobility, leading to uncertain impacts on total employment [16]. For instance, Li et al. (2019) found that environmental regulation promoted employment in acid rain control zones, but reduced it in sulfur dioxide control zones [17]. Secondly, at the meso level, the effects on employment vary between heavily polluting and clean industries. Environmental regulation may cause job losses in polluting industries while creating jobs in green industries. When job creation in clean industries outweighs job losses in polluting industries, the net employment effect is positive [18,19]. Third, environmental regulation affects high-skilled and low-skilled workers differently at the micro level. While it increases demand for high-skilled labor, it adversely impacts low-skilled employment opportunities [20,21]. The overall impact on total employment reflects a combination of these structural effects. As Goodstein (1994) noted, net job creation occurs only when the jobs generated by environmental regulation exceed those displaced [22].

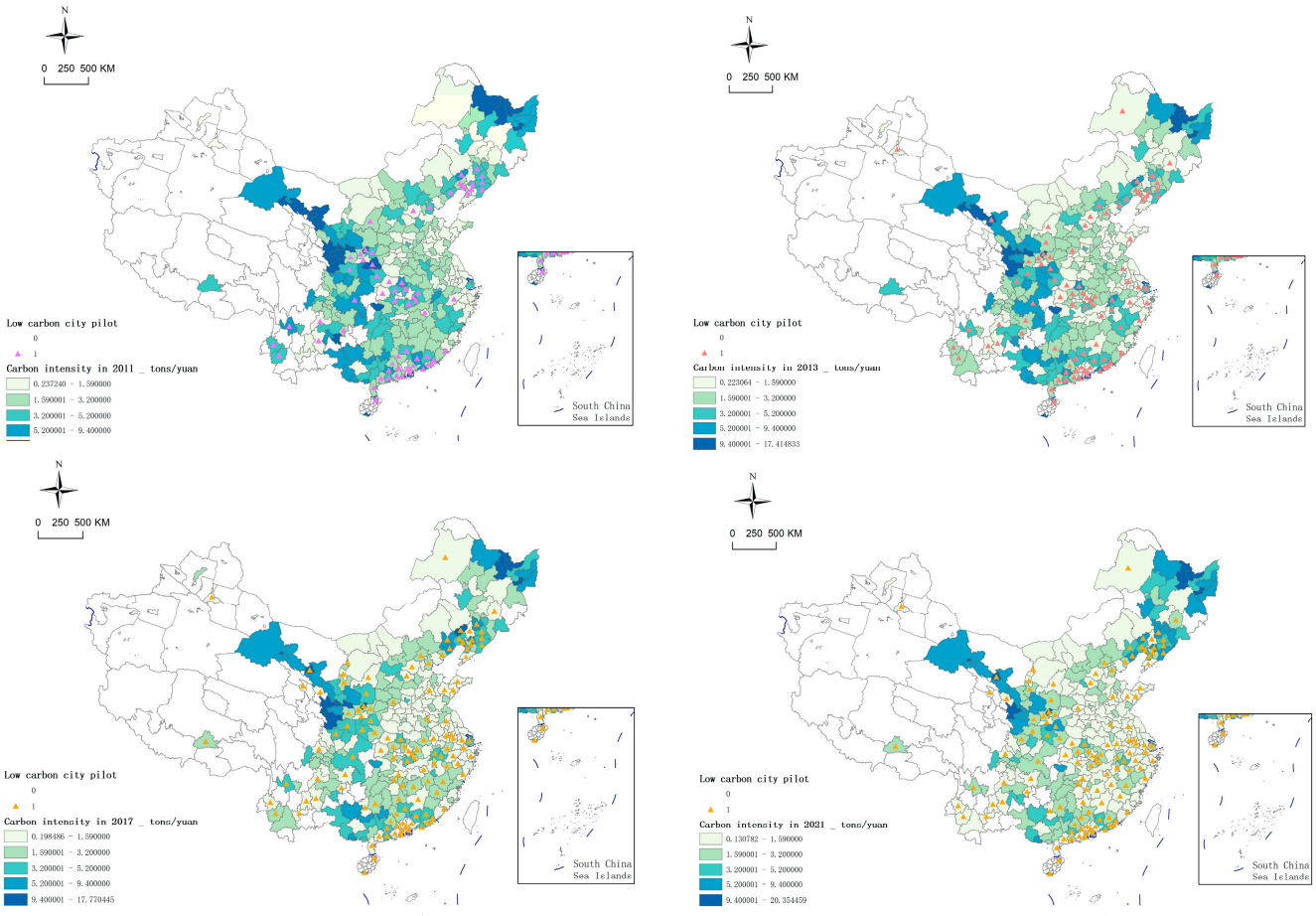


Figure 1. Distribution of three batches of low-carbon pilot cities and carbon emission intensity of Chinese cities. Note: This map is produced based on the standard map with approval number GS (2024) 0650, and the base map has not been modified.

In China, implementing the first batch of low-carbon pilot cities in 2010 has spurred extensive research on the impacts of such policies. However, most studies have focused on evaluating these policies' environmental and economic effects. Regarding ecological effects, some studies have analyzed the policies' contributions to pollution reduction. For example, Song et al. (2019) found that the policies reduced urban pollution through two main pathways: reduced corporate emissions and industrial upgrading [23]. Zhang (2020)

showed that the policies generally reduced carbon emissions, although their effects varied across cities and periods, primarily by reducing electricity consumption and enhancing technological innovation [24]. Other studies have investigated the impact of low-carbon policies on ecological efficiency [25], carbon efficiency [26,27], and energy efficiency [28]. On economic effects, scholars have examined the influence of these policies on total factor productivity at the urban and firm levels [29–32]. Research has also explored the policies' impact on technological innovation. Xu and Cui (2020) found that the policies promoted corporate green technological innovation using firm-level data [33]. Huang et al. (2021) confirmed that the policies stimulated R&D investment [34]. In addition, some studies have analyzed the effects of these policies on industrial upgrading. Zheng et al. (2021) used data from 285 Chinese cities between 2006 and 2015 to examine the impacts and mechanisms of low-carbon policies on industrial upgrading, showing that they promoted upgrading through technological innovation and reductions in the share of high-carbon industries [35]. There are also studies examining the effects of low-carbon pilot policies on corporate labor demand [8], while a few studies have assessed the policies from the perspective of individual labor choices [9]. However, existing research has primarily focused on the impact of urban low-carbon policies on corporate employment demand, with relatively limited attention being paid to their effects on total urban employment, especially the spatial spillover effects of such policies. Against this background, and considering the varying levels of urban economic and social development, this paper comprehensively analyzes the effects and mechanisms of low-carbon city policies on employment. By deconstructing China's pilot experiences, this study offers a novel paradigm for global economies to resolve the "emission reduction–poverty alleviation" dilemma. It aims to elucidate the interplay between low-carbon policies and employment dynamics, providing critical theoretical underpinnings and policy benchmarks for advancing regionally coordinated development and high-quality economic transitions. These insights further establish an efficiency-equity balanced framework for policy design in global transitioning economies.

The remainder of the paper is structured as follows: Section 2 presents the theoretical analysis. Section 3 outlines the data and methods. Section 4 presents the results of the benchmark regressions and a series of robustness tests. Section 5 is the spatial spillover analysis. Section 6 reports the results of the heterogeneity analysis. Section 7 summarizes the conclusions and policy implications.

2. Theoretical Analysis

In *Labor Economics*, George J. Borjas (2013) identifies three key players in the labor market: workers, firms, and the government. In a market economy, the interaction of firms and workers determines the equilibrium between labor supply and demand [36]. However, the government also plays a critical role in shaping labor market dynamics. Governments can tax workers' incomes, subsidize employee training, impose payroll taxes on firms, mandate employment quotas, legislate minimum wage laws, and increase labor supply through immigration policies. These actions inevitably alter the labor market equilibrium, regulating its transactions.

2.1. Employment Effects of Low-Carbon City Policies

The double-dividend hypothesis [37] identifies two benefits of urban low-carbon policies. The first dividend is pollution reduction, which improves environmental quality, reduces health problems, and mitigates ecological damage. The second dividend involves broader economic benefits, such as stimulating employment, fostering innovation, and improving resource efficiency, thereby driving economic growth. The "employment dividend" suggests that environmental taxes reduce labor and capital allocation distortions

caused by existing tax systems, improving labor factor allocation and increasing overall employment [38–40]. The impact mechanisms of low-carbon urban policies on total urban employment can be analyzed from both the firm demand side and the individual labor supply side. Environmental regulations for low-carbon transition typically require firms to reduce pollution emissions, comply with environmental standards, or pay environmental taxes. To meet these requirements, firms must undertake technological upgrades, purchase pollution control equipment, or pay emission fees. Such policies increase operational costs, potentially forcing high-pollution industries to downscale production and reduce profit margins. However, under strengthened low-carbon urban policies, the Porter Hypothesis suggests that stringent environmental regulations—contrary to conventional economic assumptions—do not undermine corporate competitiveness [41]. Instead, they drive innovation by incentivizing cleaner technologies, enhancing production and product efficiency through innovation effects [42], fostering new products, and creating additional employment opportunities [43], particularly for high-skilled workers, thereby optimizing workforce skill structures [8]. Ultimately, this leads to increased labor demand.

Urban economists, building on Tiebout's "vote with their feet" theory, find that cities with higher quality of life attract greater labor inflows [44,45] and significantly influence labor location choices [46]. Banzhaf and Walsh (2008) confirm that individuals indeed "vote with their feet" for environmental quality, with regions reducing pollutant emissions experiencing 5–7% population growth [47]. Low-carbon cities generally offer better quality of life, favorable policy environments, and cultural identity. Cities with advanced low-carbon development typically feature less pollution, cleaner air, and healthier living conditions. Such environmental improvements directly enhance residents' quality of life and health, making laborers prefer regions with superior living standards. The availability of high-quality public services and infrastructure in low-carbon cities further strengthens their attractiveness for labor relocation. Integrating supply and demand perspectives, this study proposes the first research hypothesis.

Hypothesis 1. *Low-carbon urban policies promote growth in total urban employment, with heterogeneous effects across city types.*

2.2. Spatial Spillover Mechanism

As environmental regulation instruments, low-carbon city policies impact the local labor market and produce spatial spillover effects on employment in neighboring cities within a certain radius. According to spatial economics theories, policies such as infrastructure investments and environmental governance initiatives generate direct impacts in the target region [48], propagating to surrounding areas through production, consumption, and logistics chains [49]. As proposed by Krugman and others, new economic geography emphasizes agglomeration effects, where policies attract resources and industries to a specific area. This clustering generates positive externalities such as technological diffusion, economies of scale, and market expansion, which spill over into adjacent regions. Low-carbon policies can attract green industries and talent to pilot cities, influencing nearby regions through extended industrial chains and labor mobility. Such spillover effects enhance regional economic interactions and specialization, driving economic growth in neighboring areas. However, agglomeration can also produce negative spatial spillovers or "agglomeration shadows". Concentrating economic activity and resources in a specific area can create a siphoning effect, drawing talent, capital, and technology away from surrounding regions, thereby hindering their economic development [50]. This shadow effect can exacerbate regional disparities and reduce economic vitality in adjacent areas. Based on the transmission mechanisms outlined above, low-carbon city policies are expected to

generate spatial spillover effects within a specific range. Implementing such policies in one city can influence the green industry and talent concentration in neighboring regions, affecting labor mobility and labor demand in firms. Consequently, these spillover effects may lead to employment-level fluctuations across other areas.

Hypothesis 2. *Low-carbon urban policies generate spatial spillover effects on urban employment.*

3. Study Design

3.1. Model Specification

This study investigates the impact of low-carbon city policies on total employment, using the exogenous policy shock of China's low-carbon city pilot program introduced in 2010 as the primary proxy variable for low-carbon city policies. Since the program was launched in three phases, a time-varying difference-in-differences (DID) approach is employed to evaluate the overall effect of low-carbon city pilot construction on regional labor employment.

Following a Hausman test to examine the joint significance of year dummy variables, this study adopts a fixed-effects model, incorporating time effects. The two-way fixed-effects multi-period DID model is specified as follows:

$$citylabor_{it} = \alpha_0 + \alpha_1 lowcarbon_{it} + \alpha_2 X_{it} + \pi_i + \mu_t + \varepsilon_{it} \quad (1)$$

In Equation (1), $citylabor_{it}$ is the dependent variable, representing the labor employment level of city i in year t. $lowcarbon_{it}$ is the key explanatory variable of interest, defined as the interaction term of the treatment dummy variable Treat and the time dummy variable Post. Specifically, Treat equals 1 if city i is a low-carbon pilot city and 0 otherwise; Post equals 1 during the policy implementation period and 0 otherwise. X_{it} represents the control variables for city i at time t. π_i captures the individual fixed effects for city i, μ_t represents the time fixed effects for year t, and ε_{it} is the random error term for city i at time t. Finally, α denotes the regression coefficients for each variable.

3.2. Data Sources

This study compiles city-level statistical data for 282 cities from the China Urban Statistical Yearbook spanning from 2006 to 2021. Missing data were supplemented using individual city statistical yearbooks. Additionally, we manually collected information on the low-carbon pilot policy cities from official documents published by the National Development and Reform Commission (NDRC) to identify the treatment and control group samples.

3.3. Variable Selection

The variables selected for this study include the dependent, key explanatory, and control variables.

3.3.1. Dependent Variable

The dependent variable in this study is the employment level of urban labor. Labor employment is measured using the total number of employed people in a given region, which includes employees in urban work units, private enterprises, and self-employed individuals.

3.3.2. Key Explanatory Variable

The key explanatory variable is a dummy variable for the low-carbon city pilot policy. Between 2010 and 2017, the NDRC established three batches of low-carbon pilot cities. For empirical analysis, if cities in the second and third batches were located in provinces with cities from the first batch, the policy start year for these cities is set to match the first batch's implementation year [8]. Specifically, since the first batch of low-carbon pilot cities was launched in July 2010, 2011 is set as the implementation year for these cities. Similarly, the second batch was finalized at the end of 2012, so 2013 is designated as the policy start year for these cities. Accordingly, the implementation years for the three batches of low-carbon city pilot policies are defined as 2011, 2013, and 2017, respectively. All cities within the province are treated as pilot cities for pilot provinces. For cities already designated as low-carbon pilots within these provinces (e.g., Kunming, Wuhan), the policy start year is aligned with the implementation year of their respective pilot province.

3.3.3. Control Variables

Following the works of Beck et al. (2010), Li Lei et al. (2021), and Wang and Ge (2022), this study selects nine control variables: GDP per capita, total retail sales of consumer goods, industrial structure, local general public budget expenditures, total passenger traffic, balance of RMB loans by financial institutions at year-end, registered population at year-end, average wages of on-the-job employees, and the number of enrolled students in regular higher education institutions. The selected control variables can be divided into three aspects, urban economic development, labor employment environment, and urban public service and capacity, which can reflect the other key factors affecting urban employment as comprehensively as possible. The selected indicators and their descriptive statistics are presented in Table 1 [8,51,52].

Table 1. Descriptive statistics.

Variable Name	Indicator Selection	Symbol	Observations	Mean	SE	Min	Max
Total employment	Total number of employed people (in 10,000 people)	Labor	4512	114.61	167.51	5.58	1830
Low-carbon city policy	Low-carbon pilot city (Pilot city = 1, non-pilot city = 0)	LCCP	4512	0.24	0.43	0	1
GDP per capita	Real GDP per capita (in 10,000 yuan)	perGDP	4512	3.93	3.39	0.28	28.14
Wage level	The average wage of employed workers (in 10,000 yuan)	Wage	4512	4.96	2.56	0.74	32.06
Total consumption	Total retail sales of consumer goods (in 100 million yuan)	Spend	4512	870.75	1390	13.41	18100
Government budget expenditure	Local general public budget expenditure (in 100 million yuan)	Budget	4512	348.59	591.35	5.76	8430

Table 1. *Cont.*

Variable Name	Indicator Selection	Symbol	Observations	Mean	SE	Min	Max
Passenger traffic	Total passenger traffic (in 100 million person-times)	Traffic	4512	1.617	4.800	0.014	129.115
Industrial structure	GDP of the tertiary industry/GDP of the secondary industry	Struc	4512	0.981	0.559	0.094	5.348
Financial loans	Balance of RMB loans by financial institutions at year-end (in million yuan)	Finance	4512	2.86	6.7	0.032	88.3
Population size	Registered population at year-end (in 10,000 people)	Pop	4512	152	200	13	2488
Higher education	Number of enrolled students in regular higher education institutions (in 10,000 people)	Educate	4512	9.0213	16.2061	0	127.2973

4. Empirical Analysis Results

The data used in this empirical study are mainly urban characteristic data. This section will explain the model setting, data selection and processing process, and the selection of relevant variables.

4.1. Base Regression Results

Table 2 presents the multi-period DID estimates of low-carbon city pilot (LCCP) policies on urban employment. Model (1) reflects the regression results of the core explanatory variable, implementing the low-carbon city pilot policy, and the dependent variable, the total urban employment population. Models (2) to (4) show the regression results after progressively adding three categories of control variables. The coefficient estimates for the core explanatory variable, DID, are all significantly optimistic at the 1% level. The stability of LCCP coefficients across specifications confirms model robustness. The results confirm Hypothesis 1. Statistically, the coefficient estimates of the low-carbon city policy remain stable even after including control variables, preliminarily confirming the robustness of the multi-period DID model. Economically, the 0.075–0.080 elasticity range implies that doubling policy intensity—measured using carbon price levels or green infrastructure investment—would generate 7.5 new jobs per 100 working-age residents. This result indicates that implementing relevant low-carbon policies generally contributes to an increase in total urban labor employment.

Table 2. Basic regression results of the impact of low-carbon city policies on total employment.

Variable	(1) Labor	(2) Labor	(3) Labor	(4) Labor
LCCP	0.354 ***	0.080 ***	0.079 ***	0.075 ***
	(0.095)	(0.028)	(0.030)	(0.028)
perGDP		0.130 ***	0.134 ***	0.190 ***
		(0.026)	(0.034)	(0.033)
Struc		−0.111 ***	−0.153 ***	−0.087 ***
		(0.026)	(0.033)	(0.031)

Table 2. *Cont.*

Variable	(1) Labor	(2) Labor	(3) Labor	(4) Labor
Spend		0.512 ***	0.490 ***	0.428 ***
		(0.012)	(0.023)	(0.024)
Wage			−0.303 ***	−0.250 ***
			(0.052)	(0.050)
Finance			0.025 *	−0.102 ***
			(0.014)	(0.017)
Educate			0.051 **	0.042 **
			(0.022)	(0.021)
Budget				0.153 ***
				(0.022)
Traffic				0.075 ***
				(0.004)
Pop				0.472 ***
				(0.153)
Constant	0.588 ***	0.449 ***	0.580 ***	−0.008
	(0.039)	(0.025)	(0.050)	(0.160)
Year fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Observations	4512	4512	4512	4512
City numbers	282	282	282	282
R-squared	0.188	0.465	0.472	0.522

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Robustness Test

To test the rationality of the identification strategy, avoid model setting errors, deal with the endogeneity problems caused by unobserved variables, test sensitivity, ensure that the research conclusions remain consistent under different settings, and provide more substantial confidence and reliability in the research results, this paper ensures the authenticity of the basic regression results by dealing with endogeneity problems, conducting parallel trend tests, consolation tests, propensity score matching PSM-DID, excluding other policy interferences and other robustness tests using various methods.

4.2.1. Endogeneity Problem

This paper uses a time-varying DID to study the overall impact of low-carbon city policies on employment. Omitted variables and sample selection bias may cause endogeneity problems. First of all, many factors affect the total number of urban jobs. Although this paper has selected control variables as comprehensively as possible, there may be unobservable factors such as institutional changes and climate change and some variability in the time dimension during the research period from 2006 to 2022, so there may be problems regarding omitted variables in the model. Secondly, the selection of cities in the treatment group in the DID model may have some policy factors that are not entirely random. It may be related to factors such as the city's economic development, administrative level, and population size, so the model may have a problem regarding sample selection bias. Therefore, according to existing studies, airflow speed is first selected as IV [53–55], and the data source is the National Oceanic and Atmospheric Administration (NOAA). Airflow speed is a parameter commonly used in environmental regulation research. The carbon dioxide diffusion rate is related to wind speed and the height of the atmospheric boundary layer. The faster the wind speed, the quicker the pollutants diffuse to neighboring areas. The higher the atmospheric boundary layer, the greater the degree of pollutant diffusion. The speed of air circulation is the product of wind speed and the height of the atmospheric

boundary layer. That is to say, the higher the IV, the lower the carbon dioxide concentration, and the less likely the city is to be included in the low-carbon pilot city. That is, the correlation assumption of the instrumental variable is met. Geographical and meteorological conditions determine the airflow speed, which is not a city characteristic variable that determines the number of employees in the labor market, thus meeting the homogeneity assumption of the instrumental variable. In addition, to control the impact of the sample selection bias of low-carbon cities, this paper refers to the research of Lu et al. (2017) and Edmonds et al. (2010) [56,57]. It adds the interaction term of urban attributes and time trend term to the baseline model to control the impact of the inherent attribute differences between cities on urban employment over time. This paper selects three types of variables as proxy variables for urban attributes: whether the city is a city in the two control zones in 1998, whether it is a city in the special economic zone, and whether it is a city on the right side of Hu Huanyong. The estimation results are listed in Table 3. Model (1) shows that, after adding the instrumental variable urban airflow speed, the low-carbon city policy still significantly impacts the number of employed people. Models (2)–(4) are the results after adding the interaction term of the low-carbon pilot city and the three cities' historical characteristic value dummy variables. The results show that the coefficients of the core explanatory variables are still significantly positive, indicating that, after considering the possible impact of inherent differences between cities, the estimation results are still robust.

Table 3. Results of the endogenous problem of low-carbon city policies affecting total employment.

	(1)	(2)	(3)	(4)
	IV	Add the Interaction Term		
Variable	Labor	Labor	Labor	Labor
LCCP	0.044 *	0.097 ***	0.083 ***	0.188 *
	(0.027)	(0.029)	(0.028)	(0.102)
Two control zones	/	Yes	No	No
Special economic zone	/	No	Yes	No
Hu Huanyong	/	No	No	Yes
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Constant	/	−0.612 ***	−0.104	0.365 ***
Over-identification test	/	(0.155)	(0.151)	(0.024)
Chi-sq(1) *p*-value	0.000	/	/	/
Weak instrumental variable-F	19.602	/	/	/
Observations	4512	4512	4512	4512
City numbers	282	282	282	282
R-squared	0.398	0.454	0.519	0.511

Standard errors in parentheses. *** $p < 0.01$, * $p < 0.1$.

4.2.2. Parallel Trend Test

Since this article uses a multi-time-point DID model of panel data, that is, the implementation of low-carbon pilot city policies are not carried out in all treatment group cities at the same time, this article uses Jacobson et al.'s (1993) proposed event study method to conduct parallel trend testing and refers to the practices of Beck et al. (2010) to use an improved form of parallel trend hypothesis testing [51,58]. This method visually displays the changing trends in the treatment and control groups before and after the intervention by drawing graphs. The parallel trends hypothesis is supported if the coefficient before the intervention occurs is insignificant. The test results are presented in the form of graphs. We plot the change trends of the treatment and control groups before and after the intervention

to visually demonstrate whether the parallel trends hold true. The specific model settings are as follows:

$$citylabor_{it} = \beta_0 + \alpha_k \sum_{-5}^{6} \Psi_{ck} + \beta_2 X_{it} + \beta_3 Z_{ct} + \delta_i + \varphi_t + \mu_{it} \quad (2)$$

In Formula (2), the settings of the explained variables, control variables, and fixed effects are consistent with the benchmark regression model setting Formula (1). The difference is the core explanatory variable Ψ_{ck} in the parallel trend test model setting Formula (2). This group of treatment variables represents dummy variables of whether to implement low-carbon pilot city policies defined at different time points: dummy variables for the first three periods of implementation and dummy variables for the three periods after implementation. Expressly, if time t is the kth period before the policy is implemented, the value of the treatment variable Ψ_{ck} ($k < 0$) in the city where the low-carbon pilot policy is implemented is set to 1; otherwise, it is set to 0. If the time t is the policy in the kth period after implementation, the value of the treatment variable Ψ_{ck} ($k > 0$) in the city where the low-carbon pilot policy is implemented is set to 1; otherwise, it is set to 0.

As seen in Figure 2, the estimated coefficient of the low-carbon pilot city policy fluctuates around zero before the implementation of the policy (95% confidence interval includes the zero value). That is, the estimated coefficient of the dummy variable before the policy's implementation is insignificant (statistics are not significantly different from 0). That is, before the low-carbon set-point city policy implementation, there is no significant difference between the total labor market volume of the treatment group and the control group city, but the coefficient is significant from the first year after the policy is implemented is positive (95% confidence interval is above the abscissa). This shows that the difference between the treatment and control groups before implementing the low-carbon pilot city policy is not apparent and can be compared. That is, the premise assumption of the parallel trends is met.

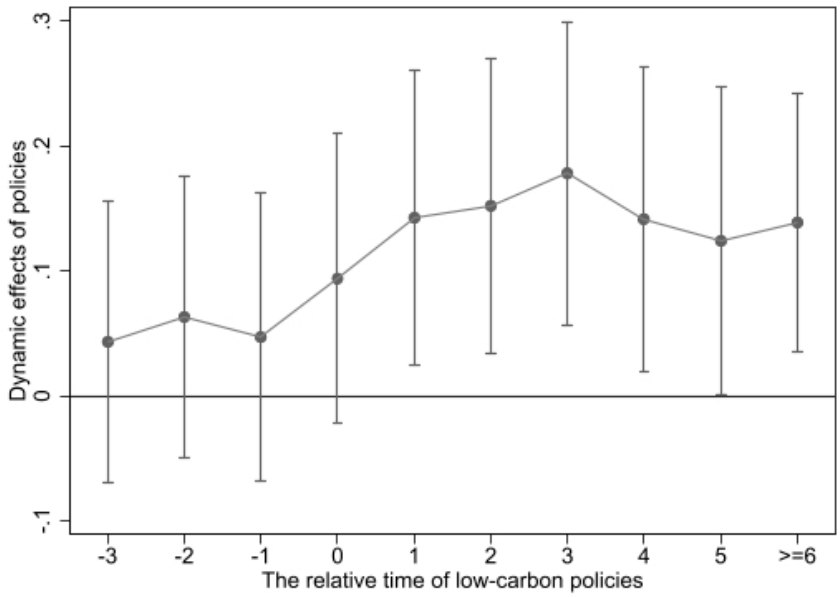


Figure 2. Parallel trend test on the impact of low-carbon city policies on total employment.

4.2.3. Placebo Test

The core idea of the placebo test is that, if the effect of low-carbon urban policies on total employment found in this study is accurate, no significant effects should be observed when the policy implementation or the treatment group's definition is artificially changed. In other words, the placebo test tests whether the estimated results are robust by

constructing false policy scenarios. The DID model assumes that the underlying trends in the treatment and control groups are parallel, except for policy shocks.

This article refers to the approach of Cai et al. (2016) by randomly setting the implementation time of low-carbon pilot city policies in the treatment group cities, conducting multiple placebo tests on the treatment effects, and using a basic regression model to set Equation (1). Using regression estimation for the treatment effect, randomly setting the policy implementation time and estimating the treatment effect, this testing process was repeated 500 times in total [55]. Figure 3 shows the distribution of the estimated coefficients of the treatment effects for 500 placebo tests under different policy implementation times. The placebo test's estimation results show apparent anomalies in the randomly generated treatment effects compared to the estimated coefficients of the actual low-carbon pilot city policy implementation. This analysis shows that low-carbon urban policies have a significant objective and credible positive treatment effect on the overall benefits of employment rather than an accidental result obtained from an unexpected observation.

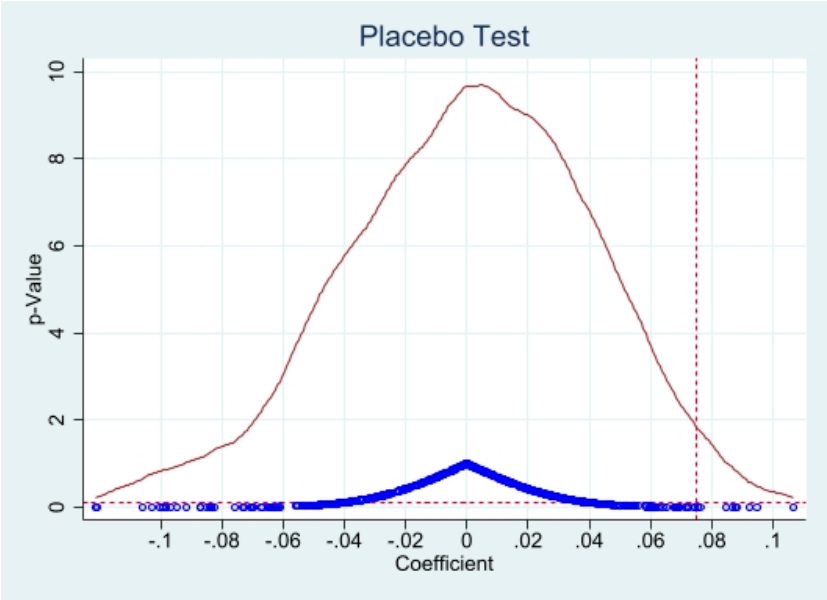


Figure 3. Placebo test on the impact of low-carbon city policies on total employment.

4.2.4. Propensity Score Matching PSM-DID

When using a multi-time-point DID model, the treatment group and the control group may not only differ at one time point. Still, they may also show systematic differences in different periods between multiple periods. This complexity further exacerbates the effects of selection bias, and endogeneity issues may not be addressed simply through the fixed effects of time or the treatment effects. Propensity score matching (PSM) is used to deal with selection bias. It matches individuals in the treatment group and the control group by estimating the probability that each individual or unit is assigned to the treatment group, that is, the propensity score, so that the two groups have similar characteristics before treatment, thereby reducing the impacts of systemic differences. This article uses the k-nearest neighbor matching method (one-to-one matching), kernel matching, and radius matching methods to conduct robustness testing. The results are shown in Table 4. The coefficients (treatment effects) of $lowcarbon_{it}$ under the three methods are all significant at the 1% level, and the t values of the treatment effect ATT all exceed the critical value of 1.96, so the ATT is also significant.

Table 4. PSM-DID method test on the impact of low-carbon city policies on total employment.

Variable	(1) k-Nearest Neighbor Matching Method	(2) Radius Matching Method	(3) Kernel Matching Method
_treated	0.922 ***	0.922 ***	0.922 ***
	(0.049)	(0.049)	(0.049)
Constant	0.777 ***	0.777 ***	0.777 ***
	(0.024)	(0.024)	(0.024)
ATT	0.284	0.212	0.366
t-ATT	3.05	2.57	4.66
Observations	4512	4512	4512
R-squared	0.073	0.073	0.073

Standard errors in parentheses. *** $p < 0.01$.

4.2.5. Eliminate Interference from Other Policies

To avoid the possible bias of basic regression caused by the impacts of other policies on the total urban employment during the sample period, this paper collects three policies from 2012 to 2017, "Notice of the National Development and Reform Commission on Promoting the National Innovative City Pilot Work", "Three-Year Action Plan for Winning the Blue Sky Defense War", and "National Smart City (District, Town) Pilot Index System (Trial)",[2] and constructs virtual variables, $innovate_{it}$, $blue_{it}$, and $clever_{it}$, based on the documents of these three policies.

These three virtual variables are added to the regression model, and the results are presented in Table 5. The regression coefficients of low-carbon pilot cities in Table 5 are close to the basic regression results, indicating that the basic regression results are still robust after eliminating other policy interferences.

Table 5. Test on the impact of low-carbon city policies on total employment, excluding interference from other policies.

Variable	(1) Labor	(2) Labor	(3) Labor
LCCP	0.074 ***	0.077 ***	0.309 ***
	(0.029)	(0.028)	(0.035)
innovate	−0.110 ***		
	(0.042)		
blue		0.102 ***	
		(0.028)	
clever			0.429 ***
			(0.050)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Observations	4512	4512	4512
City numbers	282	282	282
R-squared	0.519	0.523	0.222

Standard errors in parentheses. *** $p < 0.01$.

4.2.6. Other Robustness Tests

In addition to the above robustness test methods, this paper will, in addition, use the techniques of replacing the core explanatory variable, the explained variable, and data tailing, which have been used more frequently in previous studies for robustness tests.

1. Replace the core explanatory variable

This paper uses the virtual variable of whether a "low-carbon pilot city" policy is implemented in the city as a proxy variable for the low-carbon city policy. The advantage of this is that it can clearly distinguish whether a low-carbon city has been constructed. The time node and city division of constructing a low-carbon city are apparent. There is no need to consider the differences between cities regarding whether or not the policy is implemented. The operation process is relatively simple and conducive to clearly drawing the differential impact of whether the city carries out low-carbon construction on the total labor force in the analysis. However, the disadvantage of this method is that the proxy variable of whether the "low-carbon pilot city" policy is implemented only has two values, 0 and 1, and the conclusion may have an unexplainable "black box". In addition, in real applications, cities that have not implemented a "low-carbon pilot city" policy may also have some policy constraints conducive to the city's low-carbon development, or the city's development environment may be relatively low-carbon. This paper refers to the evaluation index system constructed and released by the Institute of Urban Development and Environment of the Chinese Academy of Social Sciences [59], constructs the evaluation index of the city's low-carbon development level, and conducts a robustness test.

2. Replace the explained variable

This paper refers to the practice of [60,61], which replaces the explained variable urban labor employment with the proportion of urban jobs to the city's population at the end of the year and conducts a robustness test.

3. Data truncation

Taking into account the vast differences between the data and the cities, this paper also performs a 5% bilateral truncation on each variable's data and re-regresses the processed data in Section 4.1 for a robustness test.

The econometric results after replacing the core explanatory variables are shown in Table 6. Models (1) and (2) are the econometric results of the robustness test model after replacing the core explanatory variables with and without adding control variables. Models (3) and (4) are the econometric results of the robustness test model after replacing the explained variables with and without adding control variables. Models (5) and (6) are the econometric results of the robustness test model after 5% bilateral tailing of the variable data with and without adding control variables, respectively. The results show that, regardless of whether control variables are added or not and which robustness test method is used, low-carbon city policies still have a significant positive impact on the total urban employment at the 1% level, indicating that the conclusion that low-carbon city policies can bring significant incremental effects to the total urban labor force in the previous basic regression is accurate and robust.

Table 6. Other robustness tests on the impact of low-carbon city policies on total employment.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Labor		Labor		Labor	
LCCP	0.162 ***	0.056 ***	0.006 ***	0.005 ***	0.250 ***	0.227 ***
	(0.019)	(0.015)	(0.002)	(0.002)	(0.072)	(0.026)
Controls	No	Yes	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4512	4512	4512	4512	4512	4512
City numbers	282	282	282	282	282	282
R-squared	0.184	0.523	0.239	0.273	0.246	0.558

Standard errors in parentheses. *** $p < 0.01$.

5. Spatial Spillover Effect

Previous studies on the impact of low-carbon city policies on total employment at the city scale were mainly based on the traditional multiple linear regression (OLS) model. However, the implicit assumption of OLS is that the city where the event occurs is spatially homogeneous. Different sample points are assumed to have the same regression coefficient. If the relationship between the explanatory variables and the explained variables of each sample point is spatially non-stationary, the global regression model that does not consider spatial correlation, such as the OLS model, cannot measure the differentiated impact of the explanatory variables on the dependent and explained variables in different regions, and the econometric model may have endogeneity problems [62–64].

5.1. Model Settings

In the double difference method used in the basic regression of this article, the "low-carbon pilot city" policy is used as a policy variable. In the actual processing, the low-carbon policy implemented by the treatment group not only affects the labor market of the city, but also may have spillover effects on other neighboring or related cities, so the assumption of spatial homogeneity cannot be fully met, and spatial econometrics needs to be added for further analysis. In the actual application of spatial measurement, the treatment effect of the treatment group will not have the same spillover effect on all cities in the whole region. A common spillover effect is that the closer the economic connection between the two places, the shorter the distance or geographical distance between the city centers and the stronger the spatial spillover effect of the policy [65]. According to the actual situation of policy implementation and the experience of spatial weight matrices in previous studies in the relevant literature, this paper selects an economic geography nested matrix, which is composed of an economic matrix formed by the per capita GDP gap and a geographic matrix formed by the geographic distance between the longitude and latitude of the cities. The weight matrix is defined as follows.

The geographic distance weight matrix is defined as follows: Assuming there are E spatial units, use m and n to represent any two spatial units. If the longitude and latitude coordinates (lat_m, lon_m) and (lat_n, lon_n) of each spatial unit are known, the geographical distance d_{mn} between them can be calculated using the following formula:

$$d_{mn} = acos[sin(lat_m) \times sin(lat_n) + cos(lat_m) \times cos(lat_n) \times cos(lon_m - lon_n)] \times R \quad (3)$$

In Formula (3), d_{mn} is the geographical distance between spatial units m and n; lat_m, lon_m are the latitude and longitude of spatial unit m, respectively; lat_n and lon_n are the latitude and longitude of spatial unit n, respectively; and R is the radius of the earth (usually 6371 km).

The economic distance weight matrix is defined as

$$W_{eco} = Q_{mn}, \ Q_{mn} = 1/Y_m - Y_n, \ (i \neq j) \quad (4)$$

In Formula (4), Y_m is the GDP per capita of the selected spatial unit m. The spatial weight matrix is standardized.

In addition, within the study scope from 2006 to 2021, the global Moran's I index of the spatial autocorrelation test in each year was significantly positive, indicating that observations with similar attributes are clustered in space from the overall perspective. In other words, there is an apparent positive correlation in the spatial distribution of the total employment in each city in China, and there is a significant positive spatial dependence between the total employment in adjacent areas. Combined with the mutual influence effects that may exist in the labor markets of various cities due to economic connections

and geographical proximity, this paper uses a spatial econometric model further to explore the impact of low-carbon city policies on employment. The general spatial panel model can be expressed as follows:

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \rho w_i' y_t + x_{it}'\beta + d_i' X_t \delta + \mu_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda m_i' \varepsilon_t + \nu_{it} \end{cases} \quad (5)$$

In Formula (5), $y_{i,t-1}$ is the first-order lag of the explained variable y_{it}, that is, the dynamic panel. If there is no dynamic panel, $\tau = 0$; $d_i' X_t \delta$ represents the spatial lag of the explanatory variable, d_i' represents the i-th row of the spatial economic geography nested matrix W; γ_t is the time effect; and m_i' represents the i-th row of the spatial weight matrix M of the disturbance term. Based on the LM, LR, and Hausman tests, this chapter selects the double-fixed space Durbin model for spatial econometric analysis.

5.2. Results of Spatial Spillover Effect Analysis

From the results of the spatial Durbin model in Table 7, it can be seen that the interaction term between the spatial weight matrix and the explanatory variables, the direct effect, the indirect effect, and the total effect core explanatory variable coefficients are all significantly positive, indicating that there is a significant positive effect on the total urban employment. After considering the spatial weight matrix, low-carbon pilot cities still significantly affect the total urban employment at the 1% level. The impact coefficient is similar to the basic regression impact coefficient. The results confirm Hypothesis 2. The indirect effect coefficient is significantly positive at the 5% level, indicating that the construction of low-carbon cities in surrounding areas will substantially promote improvements in employment levels in the region. When neighboring governments improve low-carbon urban policies, their employment-boosting effects will spill over positively, and large-scale labor flows between cities will benefit employment growth in neighboring cities. This is because, when local governments adopt a race-to-the-bottom or race-to-the-top competition strategy, the local government's low-carbon city construction intensity is consistent with other local governments, which will not lead to large-scale cross-regional flows of labor or pollution-intensive enterprises or investment. Instead, this strategy tends to cause changes in total employment in neighboring areas to become more consistent, however, when local governments choose differentiated competition, that is, when the local government increases the intensity of low-carbon construction. At the same time, other local governments have lower policy intensity, and high-skilled and advanced labor may flow into the local area in large numbers, causing a decline in employment in neighboring cities [66].

Furthermore, to further explore the geographical scope of the spillover effect of low-carbon city policies on employment promotion in surrounding cities, referring to the methods of Liu et al. (2022) and Liu et al. (2024), the inverse distance spatial weight matrix of Formula (6) was constructed on the basis of the spatial Durbin model Formula (5), and stepwise regression was performed with a step size of 100 km [67,68].

$$w_{ij}^{d} = \begin{cases} \frac{1}{d_{ij}}, d_{ij} \geq d, d = 100, 200, 300, \ldots, 1000 \\ 0, other \end{cases} \quad (6)$$

Based on Equations (5) and (6), we estimate 100 km in steps, record the spatial spillover effects (indirect effects) and 95% confidence intervals produced by low-carbon pilot city policies, and draw Figure 4.

Table 7. Spatial Durbin model of the impact of low-carbon city policies on total employment.

	(1)	(2)	(3)	(4)	(5)
Variable	**Main Labor**	**W*x Labor**	**Direct Labor**	**Indirect Labor**	**Total Labor**
LCCP	0.018 ***	0.009 *	0.018 ***	0.015 **	0.034 ***
	(0.002)	(0.005)	(0.002)	(0.006)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes
Spatial rho			0.207 ***		
			(0.025)		
Variance sigma2_e			0.001 ***		
			(0.000)		
Observations	4512	4512	4512	4512	4512
R-squared	0.838	0.838	0.838	0.838	0.838
City numbers	282	282	282	282	282

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

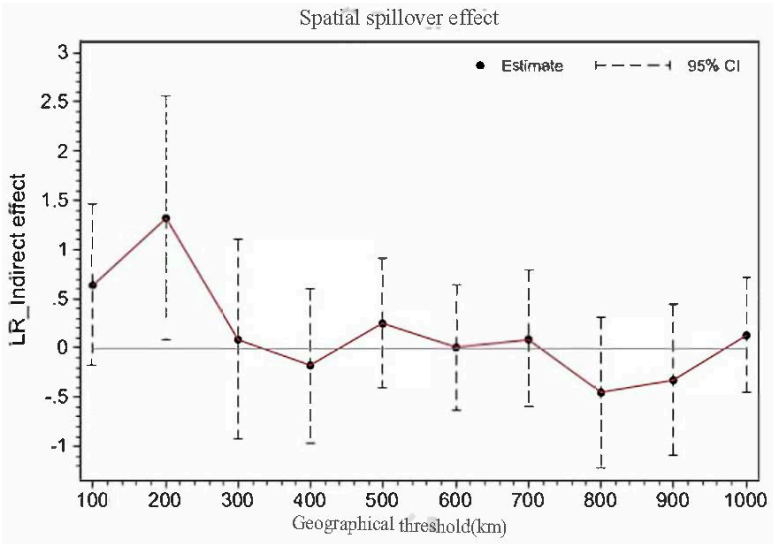


Figure 4. Spatial spillover effects vary with geographic distance.

The results in Figure 4 show that the spatial spillover effect of low-carbon urban policies on total employment is not significant within 100 km, is significantly positive within the 100–200 km range, and is not substantial beyond 200 km. Adjacent areas within 100 km of cities that implement low-carbon policies may be more susceptible to the "siphon effect" of cities that implement policies due to their closer distance. Low-carbon pilot cities have substantial advantages in technological innovation, green industry agglomeration, and resource attraction, which may attract high-quality labor and green industries to the pilot cities, causing surrounding areas within 100 km to face the pressure of resource and brain drain. This "competition effect" weakens the positive spillover effect of low-carbon construction on total employment in surrounding cities within a short distance, so the spatial spillover effect within 100 km is insignificant. Within a range of 100–200 km, due to the moderate distance, the low-carbon construction achievements of the pilot cities (such as technological innovation and industrial chain expansion) will have a specific radiating effect on these areas. Still, they will not inhibit local development due to the siphoning effect. Enterprises and labor in these areas may benefit from the low-carbon development of pilot cities through industrial chain linkages or technology diffusion. For example, green industries and technological innovation in pilot cities may drive related industries' growth through supply chain cooperation or market expansion within 100–200 km, increasing employment demand. Therefore, within this medium-distance range, the spatial spillover

effect of low-carbon construction on total employment is significantly positive. In areas 200 km away from the pilot city, the spatial spillover effect of low-carbon policies will gradually weaken as the geographical distance increases, showing a typical spatial attenuation effect. Since the economic ties between areas 200 km away and the pilot cities are relatively loose, the policy radiation effect they receive is significantly weakened, and the positive economic benefits and employment promotion effects brought by low-carbon construction are too complex to affect further areas sustainably. This spatial attenuation effect makes the spillover effects of low-carbon policies gradually less significant beyond 200 km. In addition, although the low-carbon pilot city policy has an agglomeration shadow area within 100 km, it is significantly positive within the range of 100–200 km. Combined with the spatial Durbin model results in Table 7, it shows that, among the driving effects of low-carbon pilot cities on regional employment, the significant net growth effect is greater than the spatial reallocation of existing resources. Research on the employment effects of past low-carbon-related policies also provides similar evidence [69].

6. Heterogeneity Analysis

Due to the significant differences in the development of cities in China, low-carbon city policies have different impacts in different cities or regions. This paper conducts a heterogeneity analysis from different angles and levels to form a more comprehensive and accurate conclusion.

6.1. Threshold Effects

Given the varying stages and characteristics of urban development in China, this paper employs a threshold effect model to examine the differential impacts of low-carbon city policies on total urban employment, segmented by industrial structure, government innovation preference, and urbanization rate. These three factors were chosen as threshold variables for the following reasons: (1) Optimizing industrial structure reduces the proportion of high-energy-consuming and high-emission industries, facilitating the transition to low-carbon and green industries, thereby lowering overall urban carbon emissions. Industrial restructuring is a key pathway to achieving urban low-carbon goals and lays a solid foundation for sustainable urban development. (2) Government innovation preference: Cities with stronger government innovation preferences can reduce the initial costs and risks of technological innovation by increasing fiscal support for low-carbon technology research and infrastructure, thereby promoting the development and dissemination of green technologies. Following Wang Yuqin et al. (2024) [69], this paper uses government expenditure on science and technology as a proxy variable for innovation preference. (3) Urbanization rate: Cities with higher urbanization rates tend to have better infrastructure, stronger environmental awareness among residents, and higher demand for green products and services. These cities also attract more highly skilled labor and technical talent, aligning with low-carbon construction's technological demands.

The basic form of the threshold model is as follows:

$$regional_{it} = \alpha_0 + \beta digital_{it} + \gamma_n Z_{nit} + \beta_1 \tau \times I(thv \leq \varphi) + \beta_2 \tau \times I(thv > \varphi) + \mu_i + v_t + \varepsilon_{it} \quad (7)$$

In Equation (7), where thv represents the threshold variable, and φ is the threshold value to be estimated. Z_{nit} includes control variables that are not used as threshold variables. τ is the explanatory variable interacting with the threshold variable, and ε_{it} is the random disturbance term. $I(\cdot)$ is an indicator function, defined as $I_{it}(\gamma) = \{thv \leq \varphi\}$, where $I = 1$ if $thv \leq \varphi$ and $I = 0$ otherwise. The threshold effect model assumes the following:

$$H_0 : \gamma_1 = \gamma_2, \quad H_1 : \gamma_1 \neq \gamma_2 \quad (8)$$

In Formula (8), rejecting the null hypothesis (H_0) suggests a non-linear model with a threshold value. The presence of a threshold effect is determined by examining the *p*-value of the threshold effect. If the p-value is significant, the null hypothesis is rejected, confirming the existence of a threshold effect. The number of thresholds is then further tested until the null hypothesis can no longer be rejected. Using Hansen's threshold model, this paper employs regional GDP and the logarithm of the secondary industry's share of GDP as threshold variables, where GDP is adjusted to 2006 constant prices using a price index.

The regression results of the threshold effect model are shown in Table 8. Model (1) presents the results with industrial structure as the threshold variable. Testing indicates that setting the number of thresholds to two or more yields p-values more significant than 0.1. Thus, a single threshold is selected for this model. The threshold value is 1.58, which is higher than China's national industrial structure value of 1.43 in 2023 and close to the target value of 1.63 specified in China's 14th Five-Year Plan (2025) [70], where the tertiary sector is expected to account for 58% and the secondary sector 35.5% of GDP.

Table 8. The threshold effect of low-carbon city policies on total employment.

	(1)	(2)	(3)
	Industrial Structure	Government Innovation Preference	Urbanization Rate
Variable	Labor	Labor	Labor
Threshold	1.5804	80,339.00	0.6772/0.7361
Threshold-*p* value	0.0000	0.0000	0.0000/0.0047
Controls	Yes	Yes	Yes
Less than the first threshold	0.015 ***	−0.002	−0.002
	(0.005)	(0.002)	(0.003)
Greater than the first threshold	0.057 ***	0.056 ***	0.031 ***
	(0.017)	(0.011)	(0.009)
Greater than the second threshold			0.073 ***
			(0.016)
Observations	4512	4512	4512
City numbers	282	282	282
R-squared	0.229	0.267	0.268

Standard errors in parentheses. *** $p < 0.01$.

The results show that low-carbon city policies positively impact total urban employment at the 1% significance level, both below and above the threshold. When the ratio of tertiary to secondary industry output is below 1.58, the regression coefficient is 0.015, smaller than the overall effect observed in the base regression. Conversely, when the ratio exceeds the threshold, the coefficient increases to 0.057. This suggests that cities with a higher proportion of tertiary industries experience a more significant positive impact of low-carbon policies on employment. In contrast, cities dominated by secondary industries may face declines in employment within energy-intensive sectors, mitigating the overall employment growth.

Model (2) uses government innovation preference as the threshold variable, with a threshold value of 80,339. This value is higher than all cities' median science and technology expenditure (54,344) in 2022, but lower than the third quartile (142,554.5). When science and technology expenditures exceed the threshold, indicating higher government innovation preference, low-carbon policies positively and significantly impact urban employment at the 1% level, with an effect more significant than the base regression. Below the threshold, the impact is negative and statistically insignificant. This suggests that cities with low government innovation preference face inefficiencies in policy implementation, delaying the impact on employment growth.

Model (3) reports the results for urbanization rate as the threshold variable, with two thresholds identified at 0.6772 and 0.7361. When urbanization rates are below 0.6772,

the impact of low-carbon policies on employment is insignificant. For urbanization rates between 0.6772 and 0.7361, the effect is significantly positive with a coefficient of 0.031. When urbanization rates exceed 0.7361, the positive impact on employment increases further, with a coefficient of 0.073. As of 2021, China's national urbanization rate was 64.72%, approximately equal to the first threshold. This indicates that low-carbon policies significantly positively affect employment only in cities with urbanization rates above the national average. Moreover, the higher the urbanization rate, the stronger the positive impact of low-carbon policies on total employment, assuming that other factors remain constant.

6.2. Heterogeneity of Urban Characteristics

6.2.1. Impact of Low-Carbon City Policies on Cities with Different Resource Endowments

The type of resource endowments determines a city's dominant industries, with resource-based cities typically relying more heavily on high-energy-consuming industries. Based on the National Sustainable Development Plan for Resource-Based Cities (2013–2020), this study divides the sample of 282 prefecture-level cities into 113 resource-based cities and 169 non-resource-based cities to explore the differing effects of low-carbon city policies on employment across these two groups.

Table 9 presents the regression results for the impact of low-carbon city policies on total employment in resource-based cities (Model 1) and non-resource-based cities (Model 2). The findings reveal notable differences in how these policies influence employment based on resource type. Low-carbon city policies significantly negatively affect total employment, although the magnitude of the effect is relatively small. This suggests that, in resource-based cities, such policies lead to short-term unemployment due to their impacts on high-energy-consuming industries. In contrast, low-carbon city policies significantly positively affect total employment. This indicates that such policies generate apparent job-creation effects in non-resource-based cities. Moreover, the positive impact of low-carbon urban policies on employment is greater, while the negative impact coefficient is smaller in non-resource-based cities. A potential explanation for this disparity lies in the higher constraints faced by resource-based cities due to their resource endowments, which limit their ability to innovate and flexibly upgrade industries in the short term. On the other hand, non-resource-based cities benefit from more diversified industrial structures and favorable environments for innovation and business operations, making the employment effects of low-carbon policies more pronounced in the short term.

Table 9. Heterogeneity analysis of the impact of low-carbon city policies on total employment in different cities.

	(1)	(2)	(3)	(4)
	Resource-Based Cities	Non-Resource-Based Cities	Capital Cities	Non-Capital Cities
Variable	Labor	Labor	Labor	Labor
LCCP	−0.003 *	0.024 ***	0.030 **	0.009 ***
	(0.002)	(0.003)	(0.012)	(0.002)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Observations	1808	2704	496	4016
City numbers	113	169	31	251
R-squared	0.243	0.258	0.390	0.217

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2.2. Impact of Low-Carbon City Policies on Cities with Different Administrative Levels

Cities at different administrative levels may exhibit policy implementation strength and efficiency variations. This study divides the 282 target cities into 31 provincial capitals or municipalities and 251 other prefecture-level cities to investigate these differences. Table 9 presents the regression results for the impact of low-carbon city policies on total urban employment in cities of different administrative levels (Model 3 and Model 4). The results demonstrate that low-carbon city policies significantly positively affect total employment in both categories of cities. The impact coefficient is 0.030, indicating a more substantial effect compared to non-capital cities. The impact coefficient is 0.009, significantly smaller than the overall effect seen in the baseline regression.

This disparity highlights provincial capitals' and municipalities' advantages in resource allocation, administrative efficiency, talent and technology reserves, and economic structure. These cities possess excellent government execution and policy coordination capabilities, concentrate more fiscal resources and infrastructure, and face fewer financial and technological barriers during policy implementation, resulting in higher execution efficiency. Furthermore, the more advanced and complete economic structures of provincial capitals and municipalities, including well-developed industrial chains, enable these cities to adapt and respond to adjustment policies quickly. They are also better positioned to achieve economies of scale in high-energy-consuming industries, amplifying the effectiveness of low-carbon policies. Consequently, the impacts of such policies are more pronounced in provincial capitals and municipalities compared to non-capital cities.

7. Conclusions

Based on an in-depth analysis of panel data from 2006 to 2021, this study examines the impact of low-carbon city policies on urban labor market employment. It derives the following conclusions with practical and policy significance:

Firstly, low-carbon city policies significantly promote urban labor employment levels. Low-carbon development is an effective means of combating climate change and an important driver of economic growth and social prosperity. The findings demonstrate that low-carbon city construction significantly increases urban employment opportunities, primarily through mechanisms such as promoting green technological innovation. This conclusion remains robust across various tests, underscoring the positive contribution of low-carbon policies to labor market development.

Secondly, low-carbon city policies exhibit significant spatial spillover effects. Against the backdrop of increasingly interconnected regional economies, low-carbon city policies benefit local economies and employment and exert spillover effects on neighboring cities. This study finds that these spillover effects display non-linear patterns with distance: within 200 km, the effects are initially positive but turn negative, while beyond 200 km, weak positive spillover effects are observed. This suggests that low-carbon development can enhance regional cooperation and elevate employment levels across broader areas. However, policymakers should also consider potential adverse spillover risks to avoid exacerbating regional economic imbalances.

Thirdly, low-carbon city policies enhance employment by green technological innovation, industrial structure optimization, and upgrading residents' green consumption concepts. The widespread adoption of green technologies reduces energy consumption and pollution emissions while fostering the creation and expansion of related industrial chains, generating numerous high-skilled job opportunities. Simultaneously, low-carbon development accelerates industrial transformation and upgrades, mainly promoting the growth of the tertiary sector and green industries. Additionally, low-carbon policies are pivotal

in reshaping consumer habits and encouraging sustainable lifestyles, further expanding emerging markets and creating new jobs.

Finally, our heterogeneity analysis reveals significant differences in the employment-promoting effects of low-carbon policies across different types of cities.

This study finds that the employment-promoting effects of low-carbon construction are particularly pronounced in non-resource-based cities, provincial capitals, cities with strong government innovation preferences, cities dominated by the tertiary sector, and cities with higher urbanization rates. These findings highlight the need for tailored policy tools that account for a cities' unique characteristics. Policymakers should design adaptive strategies based on variations in economic structures, administrative levels, and resource endowments to maximize employment benefits.

This study demonstrates the organic integration of low-carbon transition and employment growth. As global climate actions continue to intensify, low-carbon policies will play an increasingly crucial role in shaping the future of urban development. Our findings align with Wagner's (2003) estimates from German renewable energy policies and Harrison et al.'s (2014) French clean-tech subsidies analysis [42,43]. Like these studies, we observe skill-biased job creation concentrated in technical sectors (Figure 3), reinforcing the Porter Hypothesis's cross-cultural validity. But the proportion of low-skilled employment lost in China is lower than in other countries that have been studied. This may stem from differences in compensatory mechanisms: whereas U.S. regions relied on market-driven adjustments, Chinese municipalities actively retrained displaced workers through state-funded programs [8]. Governments at all levels should seize this opportunity by using the following means: (1) Investing in green technological innovation to reduce costs and risks while driving the development of green industries. (2) Optimizing industrial structures facilitates the transition toward sustainable economic models. Enhancing public environmental awareness to encourage the adoption of green lifestyles. (3) By fostering green employment growth. Governments can achieve economic, social, and environmental development synergy, paving the way for sustainable urban progress.

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

Notes

1 Data source: White Paper on Low-carbon Employment in China's Energy Transition, 2023.

2 Notice of the National Development and Reform Commission on Promoting the National Innovative City Pilot Work: National Development and Reform Commission (NDRC). Notice on promoting the pilot work of national innovative cities. Beijing: NDRC, 2010. Three-Year Action Plan for Winning the Blue Sky Defense War: State Council. Three-year action plan for winning the battle for blue skies. Beijing: State Council, 2018. National Smart City (District, Town) Pilot Index System (Trial): National Development and Reform Commission (NDRC). Pilot index system for national smart cities (districts, towns). Beijing: NDRC, 2014.

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