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Research on the Impact of Low-Carbon Pilot Policies on the Upgrading of China's Urban Industrial Structure

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Abstract: The construction of low-carbon cities in China represents a profound socio-economic transformation. This study investigates whether the implementation of low-carbon city pilot projects facilitates industrial structure adjustment. Utilizing panel data from 297 prefecture-level cities spanning 2001 to 2020, this research treats the low-carbon city pilots as a quasi-natural experiment to examine their impact on industrial structure upgrading and the underlying mechanisms. The findings indicate that low-carbon city initiatives positively contribute to the optimization of the industrial structure but have a limited effect on its rationalization. Mechanism analysis reveals that green technological innovation driven by pilot projects plays a crucial role in promoting industrial structure upgrading. Regional heterogeneity analysis shows that the impact of low-carbon city pilots is more pronounced in central and western regions compared to the eastern region, with no significant effect observed across all three regions collectively. This study offers valuable insights for integrating low-carbon city development with industrial structure upgrading.

Keywords: low-carbon pilot; industrial structure upgrading; industrial structure rationalization; differentially differential method; green technology innovation

1. Introduction

China's reform and opening-up has brought elements of a market economy, attracted domestic and foreign investment, and promoted industrial upgrading and the rise of export-oriented manufacturing. The period saw rapid development in light industry, electronics and information technology, but the extensive industrial development model also led to environmental problems such as climate change. Since the beginning of the 21st century, in the context of the global response to climate change, China, as a major carbon emitter, has gradually adjusted and upgraded its industrial structure, focusing on the development of high-tech industries such as electronics, semiconductors and biotechnology, service industries such as finance, e-commerce and the Internet, and cultural and creative industries. In order to achieve the goal of "achieving carbon peak before 2030 and carbon neutrality before 2060" (referred to as "double carbon"), the National Development and Reform Commission launched the pilot work of low-carbon provinces and cities in 2010, and further expanded the scope of the pilot in 2012 and 2017.

Environmental policies play an important role in solving environmental problems and promoting industrial restructuring. China has entered the stage of high-quality development, and after the rapid industrialization process, the rapid rise of high-carbon industries and become the leading economic development, so there is an

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urgent need to adjust the industrial structure and promote industrial transformation and upgrading. Undoubtedly, the low-carbon pilot policy proposed by China will impose constraints on urban economic growth, industrial structure and population development mode. Is the low-carbon pilot policy, an important means in environmental improvement policies, capable of facilitating the upgrading of industrial structure and realizing the integrated development where low-carbon cities and industrial structure upgrading go hand in hand? On the one hand, the public is worried that the "dual carbon" goal will have a negative effect on urban economic growth, restrict the realization of corporate profit goals, and thus delay industrial transformation and upgrading. On the other hand, according to Porter's hypothesis, appropriate environmental regulation can stimulate the impetus of innovation of enterprises and promote their research and development of green technologies, processes and products. In order to cover the cost of environmental compliance either to some degree or entirely, so as to increase the technological innovation potential and competitiveness of enterprises [1]. From this perspective, low-carbon pilot policies will promote the upgrading of industrial structure. In addition, under the constraints of environmental regulations, enterprises' pollution management strategies will reduce investment in high-energy-consuming and high-polluting production, which will lead to the transfer of production resources from high-polluting and high-energy-consuming areas to low-polluting and low-energy-consuming areas [2].

There exist two principal challenges in evaluating the influence of environmental regulation on the upgrading of industrial structure. First, there are endogenous problems in environmental regulation and industrial structure upgrading. On the one hand, the implementation of regional environmental policies may be affected by the level of industrial structure and have mutual influence. On the other hand, unobservable individual heterogeneity and macroeconomic trends may also have an impact on economic performance. These unaccounted factors can lead to model estimation errors [3]. Secondly, most of the existing studies use proxy indicators, like the release of pollutants, discharge cost, environmental pollution expenditure, etc. These indicators are not only related to the intensity of environmental supervision, but also affected by many factors such as enterprises' pollution behavior and local environmental supervision. It is often challenging, therefore, to link the changes in these indicators to the adjustment of environmental regulations.

To solve the above problems, Hering L and Poncet S, Greenstone M and Hanna R., Guo X and Zhang P and other scholars used natural experiment methods to build a differentially based model [4–6]. In addition, the intermediary effect model under the framework of causal inference is one of the most popular methods for analyzing policy mechanisms. Zhou and other scholars expanded the relationship between multiple influencing mechanisms on the basis of the traditional intermediary effect and solved the problem of biased estimation caused by missing variables [7]. In this paper, the above two methods will be adopted to evaluate the effects of environmental policies and analyze the mechanism of policy action.

In this research, the implementation of the low-carbon city pilot program in China is treated as a quasi-natural experiment. The difference-in-differences (DID) approach is employed to assess how this pilot initiative affects the upgrading of China's industrial structure. This article selects 297 prefecture-level cities nationwide as samples. Among them, 116 cities were granted permission to construct low-carbon cities prior to 2012, offering us an eminently appropriate quasi-natural experimental object. Within these samples, these 116 low-carbon pilot cities constitute the experimental group, while the remaining 181 prefecture-level cities naturally form the control group. On one hand, applying the DID method can rule out the impacts of non-time-varying unobservable regional factors (such as the economic foundation and natural conditions). on the other hand, a series of annual macroeconomic indicators of cities before and after the pilot can be controlled through detailed geographic location information to further reduce the estimation error caused by missing variables. The second part is the construction of the econometric model, the third part is the empirical analysis, including benchmark regression, parallel trend test, robustness test, heterogeneity analysis and mechanism analysis, and the last part is the research conclusions and suggestions.

2. Econometric Model

2.1. Data Sources

From 2001 to 2020, data of 297 Chinese cities is used in this paper to investigate the impact of low-carbon pilot cities. The list of 116 low-carbon cities comes from the "Notice on carrying out the pilot work of low-carbon provinces and regions and low-carbon cities" document and the second and third batch of notification documents of pilot cities in this category released later. The economic data of prefecture-level cities are derived from the China City Statistical Yearbook, including per capita GDP, informatization level, human capital level, urbanization degree, openness degree, etc. The economic data of prefecture-level cities are derived from the "China Urban Statistical Yearbook" and the statistical yearbooks of various provinces. After obtaining the initial data, the prefecture-level cities with severely lacking data were eliminated, and some missing data were completed through the interpolation method.

2.2. Model Construction

The difference-in-differences (DID) methodology, widely utilized in recent years for evaluating policy impacts, is particularly suitable for the research topic addressed in this paper. This approach effectively addresses variations at two key levels: inter-city differences and year-to-year disparities. By controlling for these dual dimensions of variation, it can accurately assess changes in industrial structure within China's pilot and non-pilot cities before and after the introduction of the low-carbon city pilot policy. The low-carbon city pilot policy was implemented in 2010 and 2012, with an additional implementation in 2017. However, due to the significant time gap between 2017 and the earlier implementations, only the data from 2010 and 2012 were selected to ensure accuracy. To operationalize this, we created a binary variable, "treat", indicating whether a city was affected by the pilot policy in 2010 or 2012. Cities designated as pilots were assigned a value of 1, while those that were not were assigned a value of 0, forming the control group. This resulted in a sample of 116 cities in the experimental group and 181 cities in the control group. Additionally, we introduced a binary variable, "period", based on the timing of policy implementation. If the observation occurred during or after the policy year, it was coded as 1; otherwise, it was coded as 0. Consequently, a two-way fixed effects model was employed to estimate the policy impact. The DID model is structured as follows:

$$Upgrading_{i,t} = \alpha_0 + \alpha_1 treat_i + period_t + \gamma X_{i,t} + \mu_t + \phi_i + \varepsilon_{i,t} \tag{1}$$

In Equation (1), $Upgrading_{i,t}$ serves to represent the upgrading level of the urban industrial structure in the *i* city during the *t* year, measured by the two dimensions of industrial structure upgrading AIS and industrial structure rationalization TL. $treat_i = 1$ indicates that city *i* in *t* year is a low-carbon city. $treat_i = 0$ means city *i* is not a low carbon city in t years. $period_t = 0$ indicates before the implementation of the project, and $period_t = 1$ indicates during or after the implementation of the project. $X_{i,t}$ represents a set of control variables at the annual city-level. These variables incorporate the economic development level, informatization level, human capital level, urbanization degree, openness degree, and so on. ϕ_i Represents the fixed effect of the city, controlling factors such as geographical location that do not change over time. μ_t Represents fixed effects in time, controlling for features that do not vary with region, such as changes in macroeconomic conditions. In the aforementioned formula, if the estimated value $\alpha_1 > 0$, it demonstrates that the pilot policy is beneficial for the upgrading of the industrial structure in Chinese cities. If the estimated value $\alpha_1 < 0$, it implies that the pilot policy has an inhibitory effect on the industrial structure.

2.3. Description of Variables

2.3.1. Explained Variables

In this paper, the variable to be explained is industrial structure upgrading, which can be broken down into two aspects: the advancement of the industrial structure and the rationalization of the industrial structure. The rationalization of the industrial structure is a dynamic progression where the coordination capabilities within industries are increasingly strengthened. It reflects the degree of coupling between the allocation of factor inputs and output distribution [8]. The degree of industrial structure rationalization is measured by some scholars using the degree of structural deviation [9]. Yet, this technique fails to consider the relative importance of the industry and puts the absolute value into the calculation process.

By surmounting the deficiency of structural bias, the TL index can maintain its theoretical basis and economic significance [10]. The TL index, therefore, is picked by this paper to be a proxy index for the rationalization of the industrial structure in prefecture-level cities. The equation is expressed as:

$$TL = \sum_{m=1}^{3} y_{i,m,t} \ln(y_{i,m,t}/l_{i,m,t}), m = 1, 2, 3 \quad (2)$$

In Equation (2), $y_{i,m,t}$ represents the proportion of m industry in region i in year t. $l_{i,m,t}$ Represents the proportion of employees in m industry in region i in year t. The industrial structure index of these regions mirrors the production and employment structures of China's three main industries. When the value of this index is 0, it implies that the industrial structure has reached an equilibrium state. Conversely, if the value is non-zero, it suggests that the industrial structure is departing from equilibrium, meaning that the industrial structure is irrational. Industrial structure upgrading is the process through which the industrial structure, in accordance with the historical and logical order of economic development, evolves step-by-step from a lower-tier state to a higher-tier state [11]. Usually, following Clark's Law, the upgrading of industrial structure is defined as the growth in the share of non-agricultural industries. It can be measured using indicators like the coefficient of industrial structure level, the Mole structure variation index, and the percentage of high-tech industries [12]. Using the industrial structure level coefficient, the evolution process of the three industries is quantitatively described from the relative change of the proportion. The equation is as follows:

$$AS_{i,t} = \sum_{m=1}^{3} y_{i,m,t} \times m, m = 1, 2, 3 \quad (3)$$

In Equation (3), $y_{i,m,t}$ represents the proportion of m industries in region i in the GDP of the region in t year. The index shows that China's leading industries have gradually shifted from the primary industry to the secondary and tertiary industries, which is the connotation of industrial structure upgrading.

2.3.2. Explanatory Variables

This article takes the dummy variable treat as the explanatory variable. According to the document "Notice on the pilot work of low-carbon provinces and low-carbon cities" and the list of low-carbon cities and the establishment time in the first and second batch of notice documents of pilot cities in this category released later, the key independent variable treat*period is derived by us.

2.3.3. Control Variables

By referring to previous literature, this paper selects the following control variables:

(1) Economic Development Level (Pergdp). Per capita GDP is a more precise indicator of economic development compared to aggregate GDP. Higher per capita GDP generally signifies greater potential for industrial structure upgrading, as it reflects more comprehensive infrastructure and higher population quality, both of which are conducive to economic advancement.

(2) Informationization Level (Inform). This study calculates this variable as the ratio of per capita postal and telecommunications service volume to per capita GDP. Informationization level measures the extent to which modern communication and Internet technologies are integrated into daily life and production activities. In the era of technological revolution, higher levels of informationization can significantly facilitate industrial structure upgrading by enhancing productivity and innovation.

(3) Human Capital Level (human). The human capital level is measured by the ratio of students enrolled in higher education institutions to the total regional population. A higher educational attainment within a region implies a more skilled labor force, which increases the likelihood of generating transformative technologies. Technological innovation is a key driver of industrial structure transformation and upgrading.

(4) Urbanization Level (Urban). Urbanization is quantified by the proportion of urban residents to the total population. Urbanization is closely linked with industrialization, as higher urbanization levels typically indicate

more efficient industrial production. Accelerated urbanization suggests that rural areas are transitioning towards urban development, thereby enhancing regional development levels and facilitating industrial structure upgrading.

(5) Degree of Openness (Open). The degree of openness is measured by the ratio of actual foreign direct investment (FDI) to regional GDP. Greater openness can attract more foreign investment, leading to industrial transfer and technology spillover effects. These phenomena not only stimulate economic growth but also influence industrial structure adjustment through increased competition and knowledge diffusion. As shown in Table 1, these are the descriptive statistical results of variables.

Table 1. Descriptive statistics.

Variables	Observed Values	Mean Value	Standard Error	Minimum	Maximum
Rationalization of industrial structure	5698	0.318	0.256	0.001	1.964
Upgrading the industrial structure	5698	2.154	0.161	1.164	2.866
Level of economic development	5698	0.387	0.316	0.081	5.331
Informatization level	5698	0.302	0.417	0.003	6.025
Human capital level	5698	0.152	0.212	0.002	1.810
Level of urbanization	5698	0.362	0.166	0.075	1.001
Openness	5698	0.038	0.061	0.000	0.886

3. Empirical Analysis

3.1. Baseline Regression

Table 2 (1–2) shows the benchmark regression results of the pilot project's impact on the rationalization of industrial structure. Model (2) is based on model (1) by adding the cross-fixed effects considering region and year. The results show that the treat*period is negative and does not have statistical significance, that is, low-carbon city pilot can not promote the rationalization of industrial structure. The reason is that the pilot did not take into account the location advantage and targets in the development of industries, causing improper resource allotment and a feeble relationship between industries. This has had an adverse impact on the rationalization of local industrial structure. Therefore, the impact of the pilot on the rationalization of industrial structure is not significant.

Table 2. Impacts of low-carbon city pilot policies on industrial structure upgrading.

Variables	Industrial Structure Rationalization TL	Industrial Structure Rationalization TL	Upgrading of Industrial Structure AS	Upgrading of Industrial Structure AS
Models	**(1)**	**(2)**	**(3)**	**(4)**
Treat×period	−0.047 (0.115)	−0.051 (0.198)	−0.032 (0.013)	0.021 (0.004)
Control variable	yes	yes	yes	yes
City, year fixed effect	no	yes	no	yes
Observed values	5698	5698	5698	5698
R^2	0.288	0.368	0.287	0.408

Note: robust standard errors are in parentheses.

Table 2 (3) to (4) shows the baseline regression results of the impact of low-carbon city pilot on the upgrading of industrial structure. Model 4 adds the region-year cross-fixed effect on the basis of model 3. The results show that the treat*period is 0.021, which is significant at 1% level, which proves that the low-carbon city pilot significantly promotes the upgrading of industrial structure, and indicates that the low-carbon city pilot speeds up the evolution of the leading industry transfer from agriculture to industry and service industry. In the process of building a low-carbon city, it is necessary to vigorously eliminate those contaminating processes, apparatuses and enterprises, and actively promote the development of strategic emerging industries, so as to promote the optimization and upgrading of local industrial structure.

3.2. Parallel Trend Test

The key prerequisite of the DID model is the parallel trends assumption, which posits that the trends in enterprise employment changes in pilot cities and non-pilot cities should be parallel prior to policy implementation. This study rigorously tests the parallel trends between the experimental group and the control group to ensure the validity of the low-carbon city pilot policy impact assessment. Given that policies typically require a substantial period from formulation to effective implementation, and policy adjustments also demand considerable time, policymakers need sufficient time to accurately convey their intentions. Additionally, it takes time for stakeholders to fully comprehend the policy information and make appropriate responses, gradually adapting to the new policy environment [13].

In 1993, Jacobson et al. utilized event analysis to study parallel trends and lagging periods. The equation can be written as:

$$upindustry_{i,t} = \alpha_0 + \sum_{k=-8}^{k=3} a_k \times treat_i \times period_k + \gamma X_{i,t} + \mu_t + \phi_i + \varepsilon_{i,t} \quad (4)$$

In Equation (4), “Period” is a dummy variable, indicating the years of the low-carbon city pilot program. The coefficient represents the disparity in industrial structure upgrading between the experimental group and the control group in the kth year since the initiation of the pilot. If the trend of a_k undergoes a marked increase or decrease during the period when $k > 0$, it implies that the experimental group and the control group were dissimilar prior to the policy implementation, not complying with the parallel trend assumption. If the trend of $a_k$is relatively smooth, it is in line with the parallel trend assumption.

The results are depicted in Figures 1 and 2. The coefficient estimates for each period prior to the implementation of the low-carbon city pilot policy were insignificant. The research sample passed the parallel trend test, indicating that there were no significant disparities between the enterprises in the pilot and non-pilot cities before the policy was implemented.

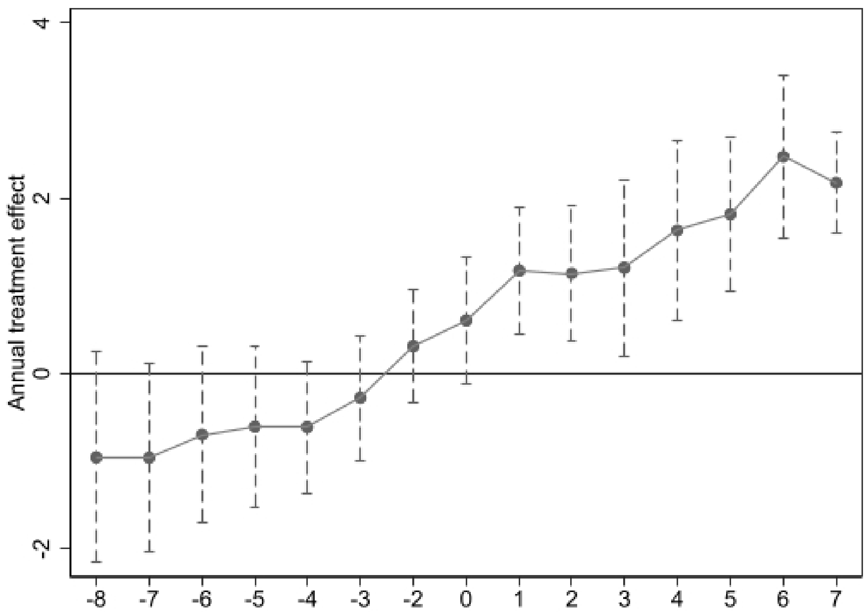

Figure 1. Annual treatment effect of AS.

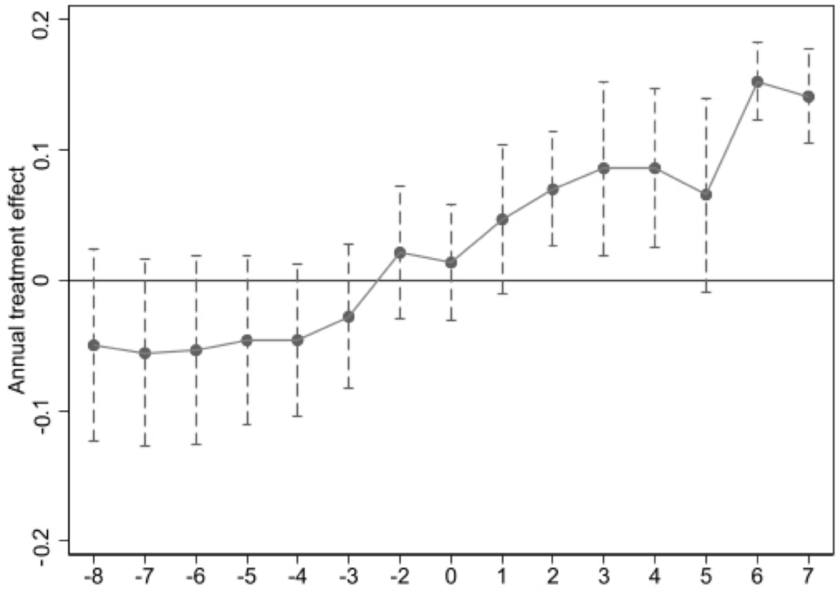

Figure 2. Annual treatment effect of TL.

3.3. Robustness Test

3.3.1. Placebo Test

To circumvent the potential influence of unobservable omitted variables on the benchmark regression results and thereby confounding the hypotheses, Chetty et al. resorted to an indirect placebo test [14]. In this vein, this paper emulates the previous approaches and implements a city placebo test. Among the 297 sample cities, 116 cities were randomly selected as low-carbon pilot cities, with the remainder classified as non-pilot cities. This procedure was replicated 500 times, yielding 500 regression coefficients and their corresponding *p*-values. Evidently, the estimated coefficients from the random samples are distributed approximately around 0 and adhere to a normal distribution, conforming to the expectations of the placebo test. Accordingly, it can be excluded that the benchmark estimation results of this paper are attributed to unobservable factors. The distribution of the regression coefficients is depicted in Figure 3.

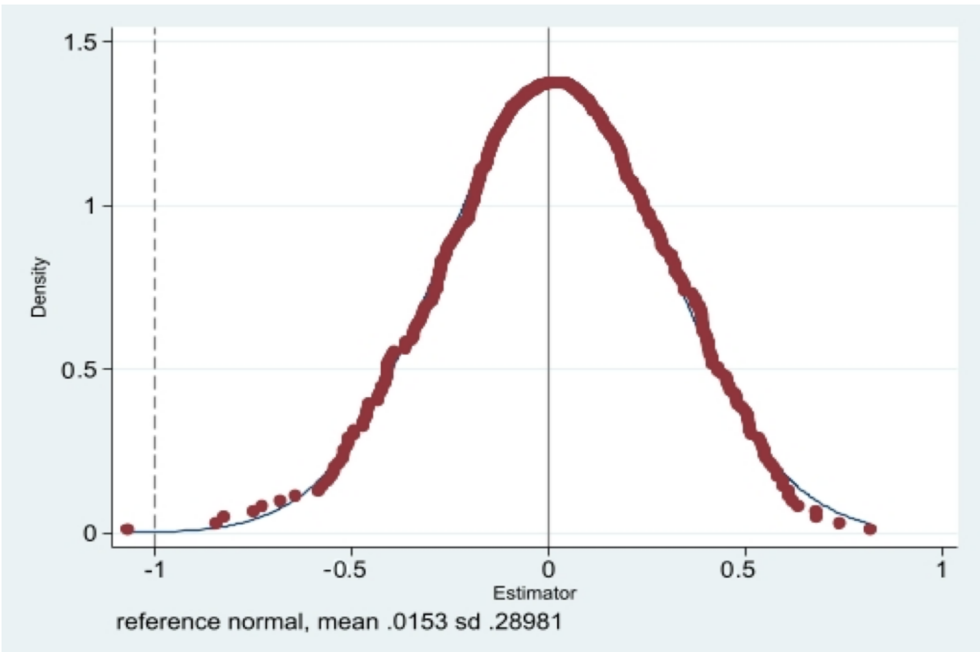

Figure 3. Kernel density distribution.

3.3.2. Re-Select Experimental Group and Control Group

The upgrading of the industrial structure in a region is not merely associated with pilot policies but also with differences in aspects such as the level of economic development. Consequently, leveraging the Regression Discontinuity methodology, this study establishes comparable treatment and comparison cohorts through a phased implementation strategy. Municipalities designated as low-carbon pilot zones were systematically categorized into three implementation waves: an initial cohort of 85 urban centers commencing in 2010, followed by 31 municipalities in 2013, and a subsequent cohort of 42 cities initiated in 2015. The analytical framework specifically designates the 2010 cohort (n = 82) as the treatment group, while utilizing the 2017 cohort (n = 42) as the counterfactual baseline.

Our econometric analysis employs panel data spanning 2000–2017, with regression outputs detailed in Table 3 (Columns 1–2). The empirical findings reveal a statistically significant negative correlation between policy implementation and industrial structural transformation, contrasted by a positive association with industrial structural rationalization. Crucially, the robustness of these estimates demonstrates insensitivity to geographical selection bias in control group construction.

Table 3. Instrument variable.

Variable	**Industrial Structure Rationalization TL**	**AIS for Upgrading Industrial Structure**
Models	**(1)**	**(2)**
Treat×period	−0.061 (0.137)	0.038 (0.007)
Control variable	yes	yes
City, year fixed effect	yes	yes
Sample size	1637	1637
R^2	0.1367	0.2505

Note: robust standard errors are in parentheses.

3.3.3. Effects of Other Policies

Concurrent policy interventions during the study period necessitate rigorous confounding control. Our analysis specifically addresses two notable initiatives: (1) The Ambient Air Quality Standards reform enacted in 2012 through inter-ministerial collaboration between the Ministry of Environmental Protection and the General Administration of Quality Supervision, which mandated full deployment of monitoring infrastructure across 74 priority municipalities (including provincial capitals and direct-administered cities) by Q4 2012; (2) The Innovation-Driven City Pilot program initiated in 2017, targeting 61 urban centers characterized by technology-intensive development paradigms with significant spatial spillover potential. To mitigate confounding effects, our fixed-effects framework incorporates policy-time interaction terms following the approach of Goodman-Bacon (2021). As evidenced in Table 4 (Specifications 1–4), the coefficient stability on treat×period remains consistent with baseline estimates in Table 1, demonstrating robustness against contemporaneous policy shocks. This persistence in statistical significance ($p < 0.05$ across specifications) confirms the exclusion restriction's validity in our quasi-experimental design.

Table 4. Robustness test.

Variables	Industrial Structure Rationalization TL	Industrial Structure Rationalization TL	AIS for Upgrading Industrial Structure	Industrial Structure Upgrading AIS
Models	**(1)**	**(2)**	**(3)**	**(4)**
treat×period	−0.034 (0.124)	−0.027 (0.052)	0.034 (0.003)	0.029 (0.012)
Control variable	yes	yes	yes	yes
City, year fixed effect	yes	yes	yes	yes
Sample size	5698	5698	5698	5698
R^2	0.291	0.187	0.178	0.305

Note: robust standard errors are in parentheses.

3.4. Heterogeneity Analysis

To investigate spatial variation in policy efficacy, we stratified 297 prefectural-level municipalities into two cohorts: 102 industrialized urban centers (coastal regions) and 195 emerging economies (central-western regions). The industrialized cohort predominantly locates in eastern China, whereas the developing cohort clusters in central-western territories. Empirical outputs documented in Table 5 (Specifications 1–4).

The low-carbon city pilot policy exerts heterogeneous effects on industrial structure upgrading across regions, with significantly stronger impacts observed in central-western cities compared to eastern counterparts. This regional disparity likely stems from the central-western regions' heavier reliance on emission-intensive industries. The policy serves as a transformative catalyst in less-developed areas through concentrated deployment of low-carbon technologies, generating a 1.8× multiplier effect on local economic revitalization. Conversely, in developed eastern regions, marginal returns diminish significantly, functioning primarily as supplementary optimization mechanisms. Notably, industrial structure rationalization exhibits statistically insignificant coefficients across all regions, underscoring the need for region-specific policy calibration.

Table 5. Heterogeneity analysis.

Variables	Eastern		Midwest	
	Industrial Structure Rationalization TL	AIS for Upgrading Industrial Structure	TL for Rationalization of Industrial Structure	AIS for Upgrading Industrial Structure
Models	(1)	(2)	(3)	(4)
treat×period	0.232 (0.115)	0.015 (0.006)	−0.568 (0.146)	0.023 (0.004)
Control variable	yes	yes	yes	yes
City, year fixed effect	yes	yes	yes	yes
Sample size	180	180	335	335
R^2	0.4736	0.4865	0.2255	0.2568

Note: robust standard errors are in parentheses.

3.5. Mechanism Analysis

Empirical analysis has confirmed that the pilot policy for low-carbon cities significantly promotes industrial transformation. To explore its underlying mechanism, this section focuses on the key transmission channels through which policy intervention influences the industrial structure. Theoretical derivation and empirical testing jointly indicate that green technological innovation serves as the core mediating variable. Specifically, the pilot policy drives the dual processes of clean transformation in traditional industries and the cultivation of emerging environmental protection industries by establishing an incentive mechanism for low-carbon technology research and development. The mediation effect test confirms that technological innovation plays a crucial bridging role in the “policy incentive-structural upgrading” chain, with statistically significant transmission contributions.

This finding aligns with the theoretical expectations of innovation-induced environmental regulation: when policy design effectively stimulates enterprises’ investment in green technology R&D, it can break through the energy efficiency bottleneck of traditional industrial upgrading and foster a coordinated development path of pollution control and industrial high-end advancement. The results of the mechanism analysis reveal, from a technical and economic perspective, the internal logic by which the low-carbon pilot policy facilitates the optimization of the industrial structure.

The examination of the policy’s mechanism reveals that pilot cities can drive the optimization of industrial structure by leveraging the innovation of green technology paradigms. Specifically, the low-carbon technology research and development (R&D) system facilitates the clean transformation of traditional manufacturing and the strategic cultivation of energy conservation and environmental protection industrial clusters through a three-stage transmission path: “technology demonstration-process iteration-industrial diffusion”. To verify this transmission mechanism, the empirical analysis employs the number of authorized green invention patents as a proxy variable for technological innovation and uses the number of approved green utility model patents for multiple robustness checks. The econometric results from models (1)–(2) in Table 6 indicate that the low-carbon pilot policy has a significantly positive stimulating effect on urban green technological innovation.

The mechanism verification results demonstrate that policy intervention achieves ecological reconstruction of industries by stimulating green technological innovation. Notably, the regression coefficients obtained using the instrumental variable method remain highly consistent with those of the benchmark model, which aligns logically with the original intent of the policy design. Under carbon constraints, the technology-driven upgrading of industrial structure generates a synergistic effect of pollution reduction and total factor productivity improvement. This dual dividend effect underscores the pivotal role of green technological innovation in resolving the “decarbonization-growth” paradox.

Table 6. Mechanism analysis.

Variables	Number of Patent Applications for Green Inventions	Number of Green Utility Model Patent Applications
Models	**(1)**	**(2)**
treat×period	0.156 (0.068)	0.428 (0.164)
Control variables	yes	yes
City, year fixed effect	yes	yes
Sample size	5698	5698
R^2	0.293	0.461

Note: robust standard errors are in parentheses.

4. Research Conclusions and Recommendations

Empirical analysis reveals that the low-carbon pilot zones significantly enhance industrial structural advancement while demonstrating limited efficacy in structural rationalization. Regional heterogeneity examination indicates spatial variation solely exists in structural upgrading impacts, with central-western municipalities exhibiting greater responsiveness than eastern counterparts. Mechanistic investigation demonstrates that eco-innovative technological progress serves as the principal transmission channel, verifying the pilot program’s partial success in reconciling decarbonization and industrial modernization objectives.

The study's findings underscore the multifaceted implications of low-carbon urban initiatives on industrial transformation. To optimize policy effectiveness, the following evidence-based recommendations are proposed:

Enhancing Eco-Innovation Capabilities: Policy makers should establish comprehensive incentive mechanisms to accelerate green R&D investments. This involves transitioning industrial practices from end-of-pipe solutions to clean production paradigms through fiscal stimuli for eco-technologies. Concurrently, governments must strengthen intellectual property protection systems and cultivate innovation ecosystems through talent attraction programs and smart infrastructure development.

Differentiated Regional Implementation:

Central-Western Regions: Prioritize circular economy models in traditional industries through energy-efficient retrofitting and industrial symbiosis networks. Develop closed-loop industrial chains integrating resource recovery and emission minimization.

Eastern Coastal Areas: Leverage existing technological advantages to pioneer carbon-neutral industrial clusters, particularly in advanced manufacturing and digital service sectors.

Nationwide Coordination: Align local industrial planning with national strategic emerging sectors by implementing tiered environmental standards and green procurement policies. Special emphasis should be placed on nurturing renewable energy equipment manufacturing and smart grid infrastructure development.

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Data Availability Statement

Not applicable.

Conflicts of Interest

The author declares no conflict of interest.

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