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Does China's low-carbon city pilots policy stimulate green development? Evidence from a multiple mediating effect model

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Abstract

Low-carbon city pilot (LCCP) policy is a progressive pollution regulation policy. Besides its role in carbon emission reduction, it has a profound impact on green growth performance and green innovation efficiency. Based on the data of 12 pilot cities and 14 non-pilot cities in the Yangtze River Delta (YRD), this study applies the PSM-DID and spatial mediating model to investigate the multi-dimensional policy effects of LCCP policy on green growth performance and green innovation efficiency. First, the direct effect of LCCP policy on green growth performance has reached 1.46%, ever since its implementation in 2017. Second, considering the intercity innovation cooperation in YRD, LCCP policy has influenced green innovation efficiency by an increase of 12.6%. Furthermore, the time-spatial DID model and multiple mediating effect model identify that LCCP policies have significantly improved green innovation cooperation. Such policies act on the industrial structure upgrading path to achieve the ultimate objective of carbon emission reduction and green growth performance. Third, the green innovation cooperation and substantial transformation of industrial structure upgrading played an important role in realizing the LCCP policy’s effect, with its mediating effect reaching 33.63%.

Keywords: *Low-carbon City Pilot Policies, Green Growth Performance, Green Innovation Efficiency, Time-Spatial DIDModel, Mediating Model*

JEL Classification: C54, L16, O11, O17

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1. INTRODUCTION

Air pollution is the most severe challenge facing the sustainable development of economy and society (Cui et al., 2023). To deal with the pressure of emission reduction, both national and local governments have issued a series of environmental regulatory policies to pursue both environmental protection and economic growth (Jahanger et al., 2022). China has taken efforts to conduct carbon reduction practices at the national, regional and industry levels to explore effective models and paths for different cities to achieve green and low-carbon development. Specifically, China has issued low-carbon city pilot policies (LCCP) for several Chinese cities since 2017. LCCP is the implementation of low-carbon economy in the city, including low-carbon production and low-carbon consumption to establish a resource-saving and environmentally friendly society, and build a benign and sustainable energy ecosystem. Such policies are progressive and have a profound impact on city collaborative innovation and green development (Yu & Zhang, 2021; Wen et al., 2023). Empirical evidence suggests that LCCP policy implemented cities have supported an average annual GDP growth of 5.8% with an average annual carbon dioxide emission rate of 1.3% between 2017 and 2022. Concerning the direct policy effect of LCCP policies, the carbon dioxide emission control effects of pilot cities were remarkable. Specifically, LCCP policies have led to a decline in growth rate of total carbon dioxide emission for 95% of the implemented cities; and they have further stabilized and decreased the total carbon dioxide emissions for 38% of the implemented cities (Ministry of Ecology and Environment of the People's Republic of China)

Literature has provided evidence that environmental regulation could result in both short-term environmental performance and long-term technological innovation (Yue et al., 2023; Zeng et al., 2022). Similarly, besides the instant controlling effect of carbon dioxide emissions, LCCP policies could stimulate green technology innovation with low carbon dioxide emissions and reach a more sustainable green growth performance and internal green innovation for high-carbon industries (Yue et al., 2023). Moreover, LCCP policies can stimulate industrial structure upgrading to achieve an increased carbon dioxide emissions reduction, promote healthy urbanization and restore urban ecosystems (Yang et al., 2023). The emission reduction effect resulting from industrial upgrading has recently been increasing (Lu et al., 2020; Zhou & Liu, 2020). Even though LCCP policies have been generally accepted as an effective way to control carbon dioxide emissions, their role in green innovation efficiency and role in green growth development through the intermediate path of industrial structure upgrading is unclear.

The Yangtze River Delta (YRD) has taken a leading position in the practice of air pollution control and has unique advantages in innovation cooperation and green development (Zeng et al., 2023); it strives to achieve the world's most advanced green development by 2035 (Wu et al., 2020). YRD belongs to the regions that implemented LCCP policies at the beginning of 2017. Besides its performance in the environmental arena, YRD has received widespread attention in terms of technological innovation and industrial structure upgrading. However, in the process of analyzing the impact of LCCP policies on urban development in YRD, few studies have considered technological innovation and industrial structure as the actual channels through which LCCP policies exert positive effects. It is crucial to identify the LCCP policies' role in technological innovation and industrial structure upgrading in green development. Therefore, this study takes YRD as the research area and poses the following questions concerning the effects of LCCP policies. First, do LCCP policies exert a direct effect in stimulating green growth performance for YRD cities? Second, what is the extensive effect of LCCP policies in promoting green innovation efficiency, both in innovation cooperation and innovation efficiency, for enterprises in the pilot cities? Third, under the background of strengthening innovation cooperation, do the green innovation efficiency improvement and transformation of industrial structure upgrading stimulated by LCCP policies work as mediating paths to achieve green growth performance in YRD cities?

To answer these questions, this study applies both PSM-DID and a spatial mediating model method to investigate the comprehensive effect of LCCP policies on green growth performance and green innovation with sample data from 26 YRD cities. YRD has carried out the co-integration development plan since 2019, and the cities in YRD have cooperated in multiple areas such as technological innovation, environmental regulation, and sustainable growth. The cities influence each other in regulation policy, environmental reaction behaviors, and also innovation imitations. In this sense, the study introduces the spatial PSM-DID method to measure the effects of LCCP policies on green growth performance and innovation efficiency. Moreover, both the industrial structure upgrading and innovation behavior could push green growth performance. The study employs the spatial mediating model to further investigate the mediating role of green innovation efficiency and industrial structure upgrading in LCCP policies. YRD is chosen as the pilot demonstration region because of the similarities in its wealth and sustainable development. The measure of LCCP policies' direct and indirect effects on YRD could have significant implications on the environmental governance for other regions. Moreover, the study introduces the spatial PSM-DID and mediating model for analysis according to the economic reaction modes, which could influence future related studies.

The remainder of this paper is organized as follows. Section 2 clarifies the literature review and theoretical hypothesis. Section 3 presents the research methodology, data specification, and related green development illustration for 26 YRD cities. Section 4 measures the effect of LCCP policies on green growth performance and green innovation efficiency. Section 5 identifies the mediating effect of green innovation improvement and industrial structure upgrading on LCCP policies. Section 6 concludes and remarks.

2. LITERATURE REVIEW AND THEORETICAL HYPOTHESIS

2.1. Literature review

Environmental regulation is regarded as one of the most important means for a government to conduct environmental supervision. Green growth performance is the main indicator to measure cities' green development. Some scholars believe that environmental regulation has a positive effect on green economy (Zhu et al., 2022). The Porter hypothesis proposed that environmental regulation is conductive to improving production efficiency with the gain brought by long-term technological innovation (Porter, 1991). Through encouraging enterprises to innovate (Shah, 2022), environmental regulation can reduce the cost burden of enterprises and pollution emissions (Samour et al., 2023). Some scholars have also proposed that environmental regulations have a negative effect on green economy (Gollop & Roberts, 1983). The high administrative penalties force enterprises to increase production costs and reduce R&D investment in technological innovation (Yin & Wu, 2021), which will inhibit the development of green economy in the short term. In addition, the high intensity of environmental regulations in this region will also force polluting enterprises to turn to other cities with lower regulations, thus inhibiting the development of green economy in neighboring regions (Li et al., 2020; Ren et al., 2020). Some scholars believe that the impact of environmental regulations on green economy is non-linear (Wang et al., 2022c). Environmental regulation promotes the growth of green economy in the short term, but long-term unchanged regulation policies cannot promote the continuous improvement of green economy, thus presenting a U-shaped feature (Dong et al., 2022).

Scholars hold different views on the relationship between regulatory policies and green innovation. Some scholars regard green innovation as the dependent variable in discussing the regulatory role of the marketization process, financial constraints (Xie et al., 2023), enterprise size and other variables in environmental regulation and green innovation. Mazaheri et al.

(2022) and Sterlacchini (2020) believe that the strictness of incentive-based environmental regulations will have a positive impact on green innovation. Du et al. (2022) calculated low-carbon city performance scores and determined that industrial structure optimization is the weak link in northeastern and western cities in China. The adjustment of energy structure and the improvement of carbon sink levels are the weak links of northern cities, while low energy efficiency is the problem of central and western cities.

Green innovation can improve environmental quality while promoting green economy (Wu et al., 2022). However, many scholars have found that technological progress would improve the local pollution problem significantly (Hu & Liu, 2022), but it is not conducive to the improvement of environmental pollution in surrounding areas (Qi et al., 2015; Li & Gong, 2021). Other scholars have also studied the influencing factors of green innovation spillover, including environmental regulation (Zhao & Zhang, 2022; Xie et al., 2023), international trade (Wang et al., 2022a), foreign direct investment (Behera & Sethi, 2022), and industrial structure (Gao et al., 2023).

Industrial structure is the main transmission channel through which environmental constraints affect economic growth. It plays an important role in upgrading industrial structure (Wu et al., 2023) and improving regional competitiveness (Sun et al. 2022). Mandatory control tools in environmental regulation may cause heavy polluters to invest more of their pollution control budget and use weak competitiveness to influence the allocation of human resources (Troilo, 2023; Ogunrinde, 2022), thus inhibiting industrial structure upgrading and affecting the green economy growth negatively. Some scholars have proposed that the implementation of environmental regulation is conducive to the decline of industrial energy intensity (Ajayi & Reiner, 2020) and the improvement of economic openness and foreign investment (Ding, et al., 2022). These factors promote industrial transformation (Wang et al., 2022d), which drives the green economy growth. It has been found that environmental regulation can promote high-quality industrial development significantly (Lu et al., 2022) and high-grade structure (Huang & Qi, 2022) to promote the development of green economy. Wang et al. (2022b) believe that environmental regulations play a relatively high role in promoting the rationalization and upgrading of industrial structure. Song et al. (2022) believe that environmental regulation stimulates the generation of innovation activities, and innovation further leads to the industrial structure upgrading (Qiu et al., 2023).

The existing research has contributed to the understanding of the relationship between environmental regulation, green growth performance, green innovation efficiency, and the role of industrial structure upgrading. However, notable defects still exist in previous studies concerning the effects of LCCP policies on green growth performance and green innovation efficiency. First, few studies have focused on the working mechanism of environmental regulation on green innovation efficiency and green growth performance. Even fewer studies have examined the detailed effects of LCCP policies on green innovation efficiency for YRD cities with consideration for the innovation cooperation network, which is increasingly important in the regional co-integration development for the whole society. Secondly, the implementation of LCCP policies has brought out both the promotion of green innovation efficiency and industrial structure upgrading. There is a mutual synergy among industrial structure upgrading, green innovation efficiency and carbon dioxide emission reduction targets.

Few studies have clarified the relationship between industrial structure upgrading, green innovation efficiency, and green growth performance in the long term for YRD, China, which is of vital importance for future environmental regulation and green development. Finally, the YRD cities have conducted the regional co-integration plans in both environmental and economic growth. Limited studies have included the geographical proximity and cooperation features when investigating how intercity cooperation of green innovation efficiency works on green growth performance with the impact of LCCP policies.

2.2. Theoretical hypotheses development

Both central and local governments have the common objectives of green economic growth and carbon emission reductions through the dynamic improvement of green innovation efficiency and industrial structure upgrading. On the one hand, the enterprises tend to directly reduce carbon emissions through a decrease in production in the short term. On the other hand, the implementation of environmental regulations could indirectly lead to the industrial structure upgrading and green innovation improvement in the long term. Also, green innovation improvement and industrial structure upgrading could serve as two possible paths to reach the balance between reduction in carbon oxide emissions and green growth performance.

This study develops the theoretical framework and hypotheses involving the conduction mechanism from environmental regulations, carbon emissions reduction, industrial structure upgrading, green innovation improvement, and green growth performance, which is illustrated in Figure 1.

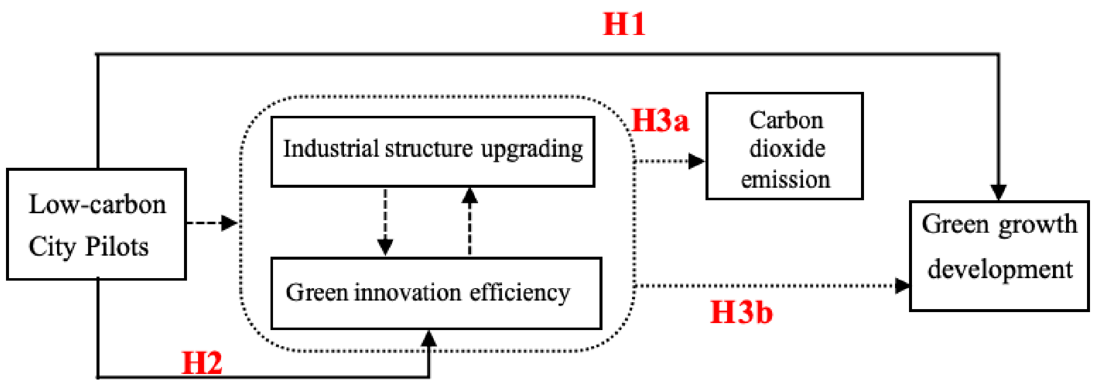

Fig. 1 – Conduction mechanism of LCCP on green development Source: own research

The ultimate objective of every environmental regulation is to reach a healthier development mode for the regional and national industries. In this sense, green growth performance is the common pursuit for LCCP policies. In this sense, the study proposes the overall hypothesis H1 concerning LCCP policies as follows:

H1: LCCP policies can promote green growth performance in the YRD region.

Indirectly, scholars hold that environmental regulations will have a positive impact on green innovation (Maryam et al., 2022; Sterlacchini, 2020). And the YRD region is also under implementation of the regional co-integration plan. The innovation cooperation in the YRD has been strengthening. Moreover, the intercity innovation cooperation of environment-friendly patents has valuable merits for environmental regulation efficiency and effects. In this sense, with consideration of the intercity innovation cooperation of patents, the study proposes hypothesis H2 concerning the effect of LCCP policies on innovation efficiency as follows:

H2: LCCP policies can promote the cooperative weighted green innovation efficiency in the YRD region.

Besides the instant controlling effect of carbon emissions, LCCP policies could indirectly accelerate the enterprises and the region to seek out suitable industrial structure upgrading and innovation efficiency improvement paths to reach a balance between reduction in carbon oxide emissions and green growth performance (Yue et al., 2023). In this sense, the research proposes Hypothesis H3 concerning the conduction paths of LCCP policies as follows:

H3a: LCCP policies can achieve carbon emissions reduction through the mediating paths of green innovative cooperation and industrial structure upgrading.

H3b: LCCP policies can achieve green growth performance through the mediating paths of green innovative cooperation and industrial structure upgrading.

3. METHODOLOGY, DATA SPECIFICATION, AND RELATED GREEN DEVELOPMENT RESULTS

3.1 Methodology

The research employs and establishes the following methodology framework to validate the listed hypotheses.

(1) DDF-GML method

Data envelopment analysis (DEA) has been widely applied to measure green growth performance. The directional distance function (DDF) expands both expected and unexpected outputs along the maximum and minimum frontiers, meeting the requirements of GDP growth and pollution emissions reduction with fewer resource inputs (Hickel & Kallis, 2020). Additionally, the Global Malmquist Luenberger productivity index (GML index) has been proposed to address transitivity and comparability issues over time in GTFP measurements. Therefore, the research employs the DDF-GML method to measure GTFP, representing green growth performance in the YRD.

Specifically, the GML technology set under global settings is $P^G = P^1 \cup P^2 \cup \cdots P^T$ global DDF is $D^G\left(\mathrm{x}, y, b, g\right) = \sup\left\{\beta : \left(\left(x, y, b\right) + \beta g\right) \in P^G\left(\mathrm{x}\right)\right\}$. The GTFP productivity calculation is given by:

$$GML_i^{t,t+1}\left(x^t, \mathrm{y}^t, b^t;\ x^{t+1}, y^{t+1}, x^{t+1}\right) = \frac{1 + D^G(x^t, \mathrm{y}^t, b^t, g^t)}{1 + D^G(x^{t+1}, \mathrm{y}^{t+1}, b^{t+1}, g^{t+1})} \tag{1}$$

The GTFP productivity index represents the efficiency change from t to $t+1$. Its value is compared with 1, where greater than 1 and less than 1 indicate the increase and decrease of green growth performance. The GTFP index can be further broken down into technical efficiency and technological progress.

(2) Propensity Score Matching and staggered difference-in-differences

Normally, the performance evaluation of LCCP policies could encounter the endogenous problems that may be caused by external factors. First, the impact of the implementation of pilot policies of LCCP on green growth performance may be attributable to the "policy effect" produced by the pilot policies of LCCP and to the "time effect" caused by other factors or developmental inertia in the process of economic development. The primary issue needed to be addressed is how to eliminate interference from other factors during policy implementation to separate the net effect of the policy. Second, the unobservable variables such as regional culture, green conception, and traditional values in each city may potentially affect the observation values for each pilot city, which could further influence the green growth performance.

The research takes LCCP cities in the YRD as the experimental group and other cities as the control group to identify the effect of LCCP policies. Considering that the LCCP-implemented cities are under regulation at varying times, this research applies the staggered DID for analysis:

$$Y_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \beta_2 control_{i,t} + A_i + T_t + \varepsilon_{i,t} \tag{2}$$

The selection of the LCCP cities involves various factors, such as the level of economic development, industrial structure, and infrastructure improvements. The approval of a city as a low-carbon pilot city can be influenced by the government's intention, resulting in the non-random grouping of "pilot" and "non-pilot" cities. Propensity score matching (PSM) matches each object in the experimental group with the best control sample using the corresponding matching method. The subsequent application of the difference-in-differences (DID) estimation helps overcome the problem of sample self-selection and addresses the issue of failing to meet the parallel trend, resulting in more accurate and reasonable estimation results. Therefore, the research proposes the PSM-DID model to explore the actual effect of LCCP policies on green growth performance.

$$GTFP_{i,t}^{PSM} = \beta_0 + \beta_1 DID_{i,t} + \beta_2 \sum control_{i,t} + A_i + T_t + \varepsilon_{i,t} \tag{3}$$

where $GTFP_{i,t}^{PSM}$ is the explained green growth performance for city i in year t. The key variable $DID_{i,t} = treat_{i,t} \times time_{i,t}$ is the cross term between the LCCP dummy variable and pilot time dummy variable.

$time_{i,t}$ is the dummy variable of time, and $time_{i,t} = \begin{cases} 0, if\ t \geq 2017 \\ 1, if\ t < 2017 \end{cases}$, else $time_{i,t} = 1$. $treat_{i,t}$ is the dummy variable of the LCCP policy of a YRD city, $treat_{i,t} = \begin{cases} 0, if\ city\ i\ isn't\ under\ the\ LCCP \\ 1,\ otherwise \end{cases}$. β_1 is the estimated coefficients for the impact of LCCP policies on green growth performance.

$control_{i,t}$ refers to the collected control variable. A_i an T_t are the variables of the control area effect and time effect. $\varepsilon_{i,t}$ is the random disturbance terms.

(3) Super-SBM with undesirable outputs

Studies concerning environmental regulation have applied the improved Super-SBM model to estimated efficiency (Guo & Yuan, 2020). Similarly, the research employs the Super-SBM model to measure green innovation efficiency of 26 cities in the YRD.

Suppose the prefecture-level cities in the YRD as DMUs. Each of them has the inputs, desirable outputs and undesirable outputs indicators, and they are represented by three vectors respectively: $x \in R^m$, $y^g \in R^{s1}$, $y^b \in R^{s2}$. The definition for matrices of X, Y^g, Y^b is expressed as follows:

$$\begin{gathered} X = [x_1, x_2, \ldots, x_n] \in R^{m \times n} \\ Y^g = [y_1^g, y_2^g, \ldots, y_n^g] \in R^{s_1 \times n} \\ Y^b = [y_1^b, y_2^b, \ldots, y_n^b] \in R^{s_2 \times n},\ X > 0, Y^g > 0, Y^b > 0 \end{gathered} \tag{4}$$

The production possibilities set (P) is defined as the following equation:

$$P = \left\{ (x, y^g, y^b) \middle| x \geq X\lambda,\ y^b = Y^b\lambda,\ \lambda \geq 0 \right\} \tag{5}$$

where λ represents the non-negative intensity vector.

The SBM model with undesirable outputs is expressed by the following equation:

$$\begin{gathered} \rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{\bar{s}_i}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{l=1}^{s_2} \frac{s_l^b}{y_{r0}^b} \right)} \\ s.t. \quad x_0 = X\lambda + s^-,\ y_0^g = Y^g\lambda - s^g,\ y_0^b = Y^b\lambda + s^b \\ \sum_{i=1}^{n} \lambda_j = 1,\ \lambda \geq 0,\ s^- \geq 0,\ s^g \geq 0,\ s^b \geq 0 \end{gathered} \tag{6}$$

where ρ^* is the efficiency value for $DMU(x_0, y_0^g, y_0^b)$. $s = (s^-, s^g, s^b)$ and (m, s_1, s_2) represent the slack variables and the number of factors for inputs, desirable outputs and undesirable outputs. The objective function is strictly decreasing about s^-, s^g and s^b. If and only if $s^- = 0$, $s^g = 0$ and $s^b = 0$, $\rho^* = 1$.

However, the SBM model with undesirable outputs may experience the inconvenient difficulty of sorting the multiple DMUs when they are valid simultaneously. The Super-SBM model with undesirable outputs can truly reflect the efficiency of DMUs and is more appropriate for further estimation for the multiple DMUs. The Super-SBM is expressed by the following equation (Guo & Yuan, 2020):

$$\delta^* = \min \frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{i0}} \Bigg/ \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\overline{y_r^g}}{y_{r0}} + \sum_{l=1}^{s_2}\frac{\overline{y_l^b}}{y_{l0}^b}\right)$$

$$s.t.\quad \bar{y} \le \sum_{j=1,\ne 0}^{n}\lambda_j \bar{y}_j,\ \overline{y^g} \le \sum_{j=1,\ne 0}^{n}\lambda_j \overline{y_j^g},\ \overline{y^b} \le \sum_{j=1,\ne 0}^{n}\lambda_j \overline{y_j^b} \tag{7}$$

$$\bar{x} \ge x_0,\ \overline{y^g} \le y_0^g,\ \overline{y^b} \le y_0^b,\ \overline{y^g} \ge 0,\ \sum_{j=1,\ne 0}^{n}\lambda_j = 1,\ \lambda \ge 0$$

In the research, δ^* refers to the green innovation efficiency for the investigated YRD city. The green innovation efficiency for the investigated city is inefficient if $0<\delta^*<1$; and efficient if $\delta^* \ge 1$. The higher the δ^* value refers to the more effective state of transforming the green innovation input into effective output.

(4) Time- spatial weight matrix

To take consideration of spatial impact of LCCP policies on green growth performance, the research employs the spatial weight matrix in equation (6) :

$$W = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix} \tag{8}$$

A well-accepted weight matrix in spatial econometrics is the adjacent weight matrix, which is composed of matrix elements 0 and 1 as follows:

$$w_{ij} = \begin{cases} 0, \text{city } i \quad and \text{ city } j \quad are \quad not \quad spatially \quad adjcent \\ 1, \text{city } i \quad and \quad \text{city } j \quad are \quad spatially \quad adjcent \end{cases} \tag{9}$$

In order to capture the policy effect of LCCP policies considering the innovation cooperation background in the YRD, the research constructs the time-spatial weight matrix based on the annual global Geary's C statistics of the betweenness centrality of innovation cooperation of green patents in the YRD as follows:

$$T = \begin{bmatrix} c_1/c_1 & 0 & \cdots & 0 \\ c_2/c_1 & c_2/c_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ c_T/c_1 & c_T/c_2 & \cdots & c_T/c_T \end{bmatrix} \tag{10}$$

The row standardization form of matrix T is given by T' :

$$T^{'} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ c_2/A & c_1/A & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 1/c_1C & 1/c_2C & \cdots & 1/c_TC \end{bmatrix} \tag{11}$$

where $A = c_1 + c_2, C = \sum_{i=1}^{T} 1/c_i$.

Finally, the time-spatial weight matrix is obtained through the combination of Kronecker deduction in a matrix (10).

$$T'W' = \begin{bmatrix} W' & 0 & \cdots & 0 \\ (g_2/A)W' & (g_1/A)W' & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ (1/g_1C)W' & (1/g_2C)W' & \cdots & (1/g_TC)W' \end{bmatrix} \tag{12}$$

(5) Time-spatial DID model

The time-spatial DID model with consideration of time-spatial weight matrix is given by equation (11):

$$har_{it} = \sum_{it}^{NT} r\left(q \otimes W\right)_{it} har_{it} + b_0 \times DID + j \times \left(q \otimes W\right)_{it} DID_{it} + \sum_{k=1}^{k} b_k X_{it,k} + m_t + g_t + e_t \tag{13}$$

where q and W represent the standardized time weight matrix and spatial weight matrix in the equation. har represents the capacity of green innovation cooperation between cities. DID is the core cross term between LCCP dummy variable and pilot time dummy variable. X refers to the control variables. r is the spatial correlation coefficient, and b represents the regression coefficients of DID and control variables.

(6) Multiple mediating effect model

The theoretical hypotheses of our study aim to test whether LCCP policies could bring about a carbon dioxide emissions reduction by improving green innovation efficiency and industrial structures upgrading for the policy-treated cities. Furthermore, LCCP policies could stimulate green growth performance through the fact that green innovation efficiency promotion plays a pivotal role in industrial structure upgrading. In this sense, the research employs the multi-channel mediating effect model (Dong et al., 2020) to investigate the extensive conduction mechanism by equations (12-14):

$$Ind_{it} = \gamma_0 + \gamma_0 DID_{it} + \gamma_1 \delta_{it} + \gamma_2 \sum contorl_{i,t} + A_i + T_t + \varepsilon_{i,t} \tag{14}$$

$$C_{it} = \eta_0 + \lambda_0 DID_{it} + \lambda_1 \delta_{it} + \lambda_2 Indit_{it} + \lambda_3 \sum contorl_{i,t} + A_i + T_t + \varepsilon_{i,t} \tag{15}$$

$$GTFP_{i,t}^{PSM} = \varphi_0 + \varphi_1 DID_{i,t} + \varphi_2 \delta_{i,t} + \varphi_3 Indit_{i,t} + \varphi_4 C_{it} + \varphi_5 \sum contorl_{i,t} + A_i + T_t + \varepsilon_{i,t} \tag{16}$$

The multi-channel mediating effect model measures the multi-conduction effects among LCCP policies, green innovation efficiency, industrial structures upgrading, carbon dioxide emissions reduction, and green growth performance. Equation (12) examines the impacts of LCCP policies and green innovation efficiency on the drive for industrial structure upgrading. *Ind* encompasses both industrial structure supererogation ($Ind-sh$) and industrial structure rationalization ($Ind-sr$). Equation (13) assesses the impacts of LCCP policies, green innovation efficiency, and industrial structure upgrading on carbon dioxide emissions reduction. Equation (14) investigates the impacts of LCCP policies, green innovation efficiency, industrial structure upgrading, and carbon dioxide emissions reduction on green growth performance.

3.2. Data Specification

(1) Data source

The green patent data in the research originates from the Incopat database, and the data is directly collected from the Chinese National Intellectual Property Office (CNIPA). The green invention patent data identifies the green patents of enterprises according to the classification index list of the "IPC Green Inventory," which was issued by the World Intellectual Property Organization (WIPO) in September 2010. The research selects 413,414 green patent data from YRD cities during the period from 2013 to 2020. Other related data are collected from Chinese Statistical Yearbook 2014-2021.

(2) Core variables

With regard to the existing literature and the theoretical relationship between LCCP policies, carbon dioxide emission reduction, green growth performance, and green innovation efficiency, this study includes the following 3 core variables.

– Carbon dioxide emissions (C_{it})

The research takes the logarithmic treatment variable of carbon dioxide emissions levels of the city as the indicator of carbon dioxide emissions for each city(C_{it}). The data is collected from China Emission Accounts and Datasets (CEADs).

– Green growth performance ($GTFP$)

The research employs the green total factors production ($GTFP$) as a substitution variable for green growth performance, since the calculation attribute of $GTFP$ could represent "energy saving and emission reduction promote economic growth" (Li & Xu, 2018). And, GTFP satisfies the intrinsic attribute of green economy growth (Wei et al., 2022) and is provided by equation (1).

Considering the calculation principle of DEA and data availability features, this study includes urban employment and urban area coal consumption as input indicators, economy development as an expected output indicator, and three industrial wastes as unexpected output indicators (Jiang et al., 2021).

Tab. 1 – Green growth performance indicators system

Index type	Indicators	Data processing
Input index	Urban employment	The number of employees in urban each city
	Urban area	The area of each city

	Coal consumption	City gas, liquefied petroleum gas and electricity consumption are converted into standard coal based on the energy conversion coefficient table
Expected output index	Economy development	Capital stock based on 2006
Unexpected output index	Three Industrial Wastes	Industrial sulfur dioxide emissions, industrial wastewater emissions and industrial smoke and dust emissions (Statistical consistency adjustment for industrial smoke and dust emissions)

Source: own research

– Green innovation efficiency (δ)

Green innovation efficiency involves many aspects and is subjected to several uncertain factors. Green innovation efficiency is estimated by the Super-SBM approach in equation (5) based on the collected indicators with references to existing studies and environmental situations. As environmental pollutants are the accepted unfavorable outputs, the research integrates previous literature and constructs a green innovation efficiency index system with expected inputs, expected outputs, and unexpected outputs in Table 2.

Tab. 2 – Green innovation efficiency index system

Grade 1	Grade 2	Grade 3	Grade 4
Evaluation index system of green innovation efficiency	Expected inputs	Financial investment	Internal expenditure of R&D founds R&D full-time equivalent staff
		Material investment	Industrial energy consumption
		Capital investment	Fixed-asset investment
	Expected outputs	Economic growth	Patent application and granted Industrial added value
	Unexpected outputs	Pollution discharge	Industrial sulfur dioxide Industrial wastewater discharge Industrial smoke and dust emissions

Source: own research

This study employs social network analysis to quantify the innovation cooperation of the green patents for 26 cities in the YRD. The social network of the innovation cooperation is mainly expressed by closeness centrality and betweenness centrality.

Closeness centrality is a measure of centrality concerning the proximity and distance between nodes in a network. It calculates the sum of the distances between a node and all other nodes in the network. The primary distinction between closeness centrality and degree centrality lies in the consideration of indirect relations.

Betweenness centrality characterizes a node's capacity in the network to control the transmission of information and resources by positioning itself in the middle of the shortcut paths connecting other node pairs. Higher betweenness centrality values indicate that the node plays a more significant role in controlling the flow of various key elements within the network.

(3) Control variables

Opening degree (fdi). Some scholars indicate that foreign direct investment can enhance green development (Adikari et al., 2021). In this sense, the study chooses the proportion of foreign direct investment to total fixed asset investment to reflect the degree of openness of a city, taken as fdi in the estimation.

Government intervention degree (gid). This study uses the proportion of government fiscal expenditure to regional GDP.

Infrastructure ($\inf$). This study collects the urban road area per capita for each investigated city in the YRD for analysis.

Total number of population (tp). The study collects the total number of population for each investigated city in the YRD for analysis.

Science and technology investment (sti). The study uses the logarithm of the cities' government expenditure on science in each year.

GDP per capita (gdp). Economy is an inevitable factor in all development. The improvement of economic level can indirectly enhance the awareness of enterprises to better maintain the environment and can allow for the investment of more funds to improve traditional industrial technology and improve green innovation capacity.

Education investment (edu). There is an important relationship between regional education and environmental governance. This study chooses the ratio of education expenditure to local public budget expenditure to measure education investment.

In addition, this study applies the average annual exchange rate between China and the United States from 2006 to 2019 to convert the FDI. To eliminate the interference of price factors, all indicators related to price factors are reduced to constant prices in 2006. The control variables are collected from the China Statistical Yearbook, the China Science and Technology Statistical Yearbook, and the China Urban Statistical Yearbook during 2014-2021.

3.3. Measurement of green development in YRD cities

(1) Green growth performance identification

Figures 2 shows the fluctuation trend of green growth performance (GTFP) for all YRD cities during the period from 2013 to 2020. The overall estimated GTFP demonstrates a fluctuating upward trend through the whole period. It experienced a surge from 0.9683 to 1.0432 and witnessed a rapid development stage before 2017. The fact is that local governments have introduced a series of new policies to support green growth. The conception of environmental protection has gradually developed into a self-governance for the whole system.

In contrast, LCCP policies focus more on achieving a win-win scenario for economic development and green sustainability. Consequently, GTFP experienced a significant decline after 2017, but a gradual resurgence began after 2018. The YRD is distinguished by its excellent environmental pollution remediation and high enterprise innovation vitality. Even under the influence of LCCP policies, the Global Malmquist Luenberger (GML) index consistently remains above 1, indicating that the development of green growth performance continues to exhibit a positive trend.

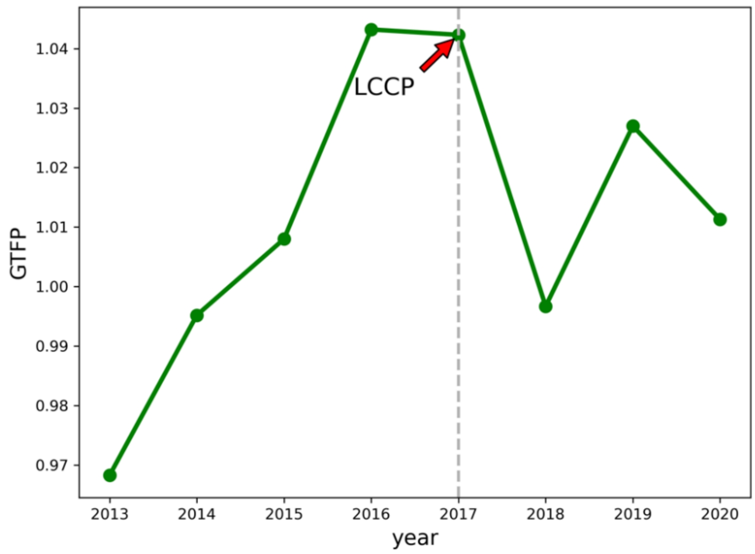

Fig. 2 – The trend of GTFP from 2013 to 2020. Source: own research

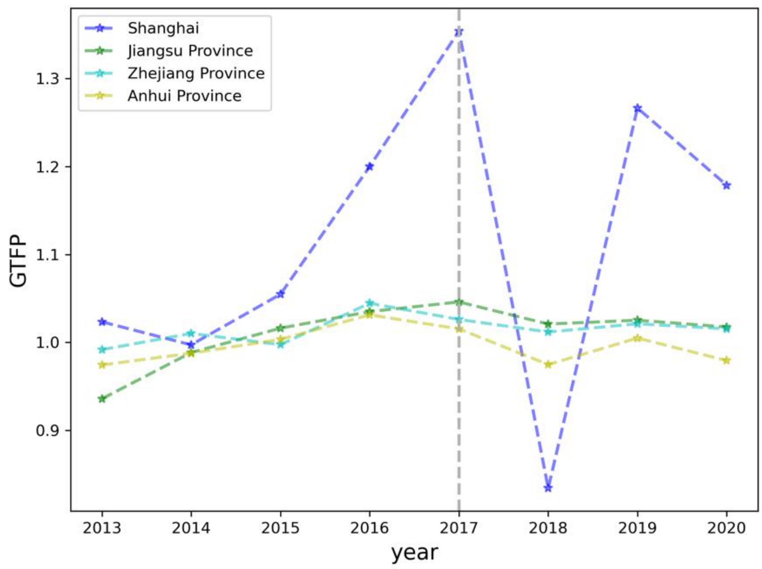

Fig. 3 – The trend of GTFP in YRD areas. Source: own research

Figure 3 shows the growth trend of green growth performance for Zhejiang, Jiangsu, Anhui and Shanghai during the period from 2013 to 2020. It shows that green growth performance in Shanghai largely fluctuated from 2013 to 2020. Shanghai's green growth performance reached the highest level of green growth performance in the YRD, while it quickly dropped to the lowest level after the implementation of LCCP policies in 2017. This indicates that although green growth performance in Shanghai is at a leading level, it is subjected to more impacts by LCCP policies. Green growth performance in Jiangsu Province, Zhejiang Province and Anhui Province are mostly maintaining at 1. The green growth performance in these three provinces exhibited a gradual upward trend before 2017, and the development of green growth performance gradually stabilized from 2018 to 2020.

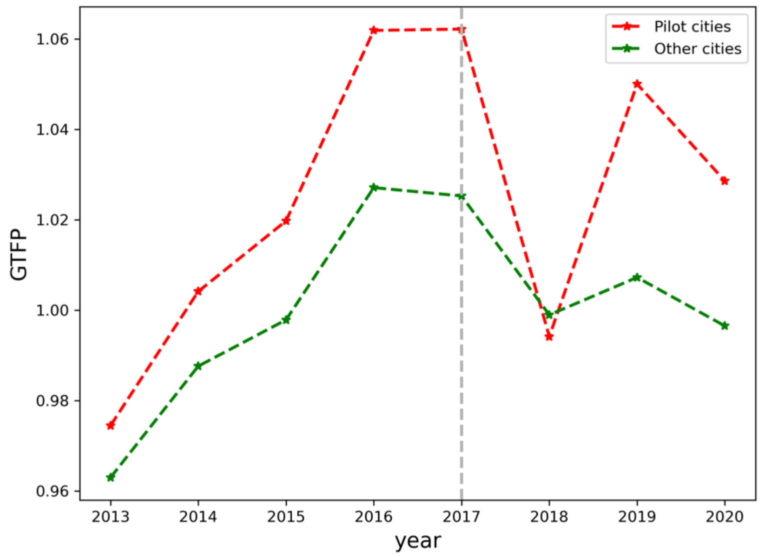

Fig. 4 – The trend of GTFP of pilot cities and other cities. Source: own research

Figure 4 shows that there is a significant difference in green growth performance between LCCP cities and other cities. The green growth performance of all cities experienced a rapid upward trajectory before 2017, which reflects the rapid development of green economy in various cities. However, the green growth performance of LCCP cities declined rapidly after 2017, and the average level of GTFP was even lower than that of other cities in 2018. This indicates that the policies did have an impact on the development of green growth performance. However, LCCP cities quickly adapted to the policies and still maintained a high level of development after 2018. The green growth performance of other cities always fluctuates about 1. Although the implementation of LCCP policies temporarily inhibits the increase of green growth performance, it also effectively stimulates the development effect of green economy and brings long-term maintenance effects.

(2) Green innovation efficiency identification

Table 3 lists the estimated green innovation efficiency in the YRD during 2013-2021. This study regards green innovation efficiency in the YRD as a long-term development trend, and the evolution is shown in Table 4 and Figure 5. From the overall perspective, green innovation efficiency shows a trend of fluctuation and increase.

Tab. 3 – The trend of green innovation efficiency in YRD. Source: own research

	2013	2014	2015	2016	2017	2018	2019	2020	2021
Shanghai	1.075	1.071	1.082	0.840	1.346	1.374	1.384	1.389	1.425
Suzhou	1.363	1.369	1.350	1.239	1.172	1.240	1.232	1.237	1.275

Nantong	1.013	1.004	0.804	1.015	1.046	1.086	1.074	1.063	1.125
Hangzhou	1.122	1.098	1.073	1.092	1.157	1.183	1.181	1.180	1.247
Jiaxing	0.572	0.586	0.664	1.009	0.710	1.009	1.004	0.993	1.058
Wuxi	1.001	0.659	0.536	0.477	0.423	0.369	0.364	0.372	0.406
Hefei	1.098	1.039	1.115	1.234	1.199	1.174	1.167	1.156	1.244
Nanjing	0.588	0.524	0.521	0.595	1.019	1.003	1.008	1.005	1.048
Ningbo	1.156	1.401	1.129	1.256	1.024	1.023	1.009	1.002	1.065
Jinhua	0.742	1.009	0.800	1.032	1.049	1.054	1.045	1.038	1.100
Changzhou	1.093	1.092	1.046	0.561	0.540	0.508	0.499	0.486	0.533
Taiizhou	1.059	1.096	1.092	1.052	1.085	1.077	1.067	1.078	1.118
Taizhou	0.597	1.066	1.043	1.054	1.059	1.063	1.052	1.060	1.115
Wuhu	0.761	1.094	0.747	1.024	0.684	1.026	1.026	1.016	1.082
Huzhou	1.030	1.039	1.054	1.026	1.013	0.697	0.700	0.695	0.736
Yangzhou	1.007	1.039	1.004	1.012	1.008	0.697	0.699	0.714	0.754
Shaoxing	1.174	1.035	1.106	1.090	1.079	1.137	1.139	1.126	1.186
Yancheng	0.600	0.602	0.573	0.586	0.645	0.674	0.676	0.680	0.746
Chizhou	1.018	1.012	1.028	1.012	1.078	1.038	1.033	1.041	1.109
Zhenjiang	0.626	1.027	1.032	1.001	1.057	1.003	0.992	0.984	1.060
Zhoushan	1.051	1.012	1.041	1.087	1.070	1.214	1.203	1.206	1.269
Anqing	1.186	1.146	1.264	1.267	1.311	1.018	1.017	1.029	1.089
Maanshan	0.502	0.472	0.483	0.472	1.004	0.424	0.421	0.435	0.489
Chuzhou	1.096	1.084	1.074	1.069	1.086	1.028	1.032	1.037	1.076
Xuancheng	0.545	0.533	0.514	0.537	0.549	0.430	0.429	0.431	0.482
Tongling	0.498	1.018	1.016	1.023	0.457	1.140	1.140	1.133	1.190

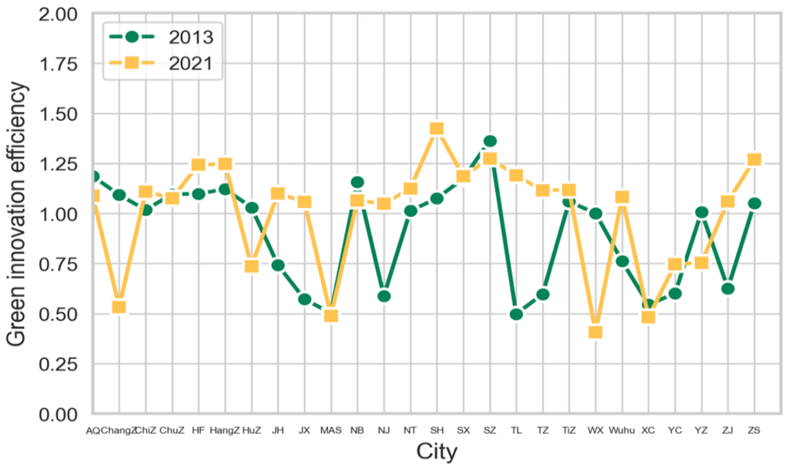

Fig. 5 – Comparison of green innovation efficiency in YRD. Source: own research

Tab. 4 – Green innovation efficiency of LCCP cities and other cities in YRD

	2013	2014	2015	2016	2017	2018	2019	2020	2021

LCCP cities	0.916	0.980	0.946	0.951	0.992	1.003	0.999	0.995	1.054
Other cities	0.898	0.955	0.917	0.947	0.927	0.904	0.901	0.903	0.956

Source: own research

The average green innovation efficiency of LCCP cities had a significant upward trend, but then became basically stable at about 1 after 2017. In contrast, the green innovation efficiency of other cities has always remained at about 0.9. The comparison shows that LCCP policies have played a role in application with the continuous construction. In addition, there are certain differences in green innovation efficiency among different LCCP cities. Xuancheng has slowly improved in green innovation efficiency, while other LCCP cities, such as Shanghai, Suzhou, and Hangzhou have developed rapidly. Their green innovation efficiency are all higher than 1 after 2017. It shows that there is still significant potential for green innovation in LCCP cities. However, a few cities exhibit less evident long-term trends in green innovation efficiency.

(3) Green innovation cooperation network identification

Considering that LCCP policies would restrict urban carbon dioxide emissions, industrial structure can be adjusted by improving green innovation to reduce carbon dioxide emissions, thus affecting the development of urban green economy. Due to the development gap of various cities in the YRD (Dong & Han, 2021), internal green innovation and external technological cooperation will also lead to differences in urban green development.

Tab. 5 – Cities included in YRD

	City
Shanghai	Shanghai
Jiangsu Province	Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, Yancheng, Taizhou
Zhejiang Province	Hangzhou, Ningbo, Huzhou, Jiaxing, shaoxing, Jinhua, Zhoushan, Taiizhou
Anhui Province	Hefei, Wuhu, Maanshan, Tongling, Anqin, Chuzhou, Chizhou, Xuancheng

Source: own research

A. Construction of green innovation cooperation network in the YRD

The study refers to the construction of a cooperative network matrix (Li et al., 2020). From the authorized invention patents of 26 cities in the YRD from 2013 to 2020, this study selects 26,742 invention patents that allow for cooperation between cities. The data was used to digitize the technological innovation cooperation network between provinces, and this study involves the 26*26 matrix from 2013 to 2020. Subsequently, Gephi software was employed to compute the overall network characteristics and assess the position of each city within the network structure. In Figure 6, the network density between cities in the YRD shows an upward trend from 2013 to 2014, accompanied by a gradual increase in the number of network nodes. It indicates that the total amount of cooperation between cities has increased significantly, and the cooperation relationship between cities has increased significantly. The cooperation relationship between various cities became increasingly intense from 2019 to 2020. Shanghai, Nanjing, Suzhou, Hangzhou, Hefei and other cities have taken the lead in the number of patents, and the cooperation network density has increased significantly. It shows that the frequency of cooperation between cities is growing rapidly, and the leading cities are gradually fixed.

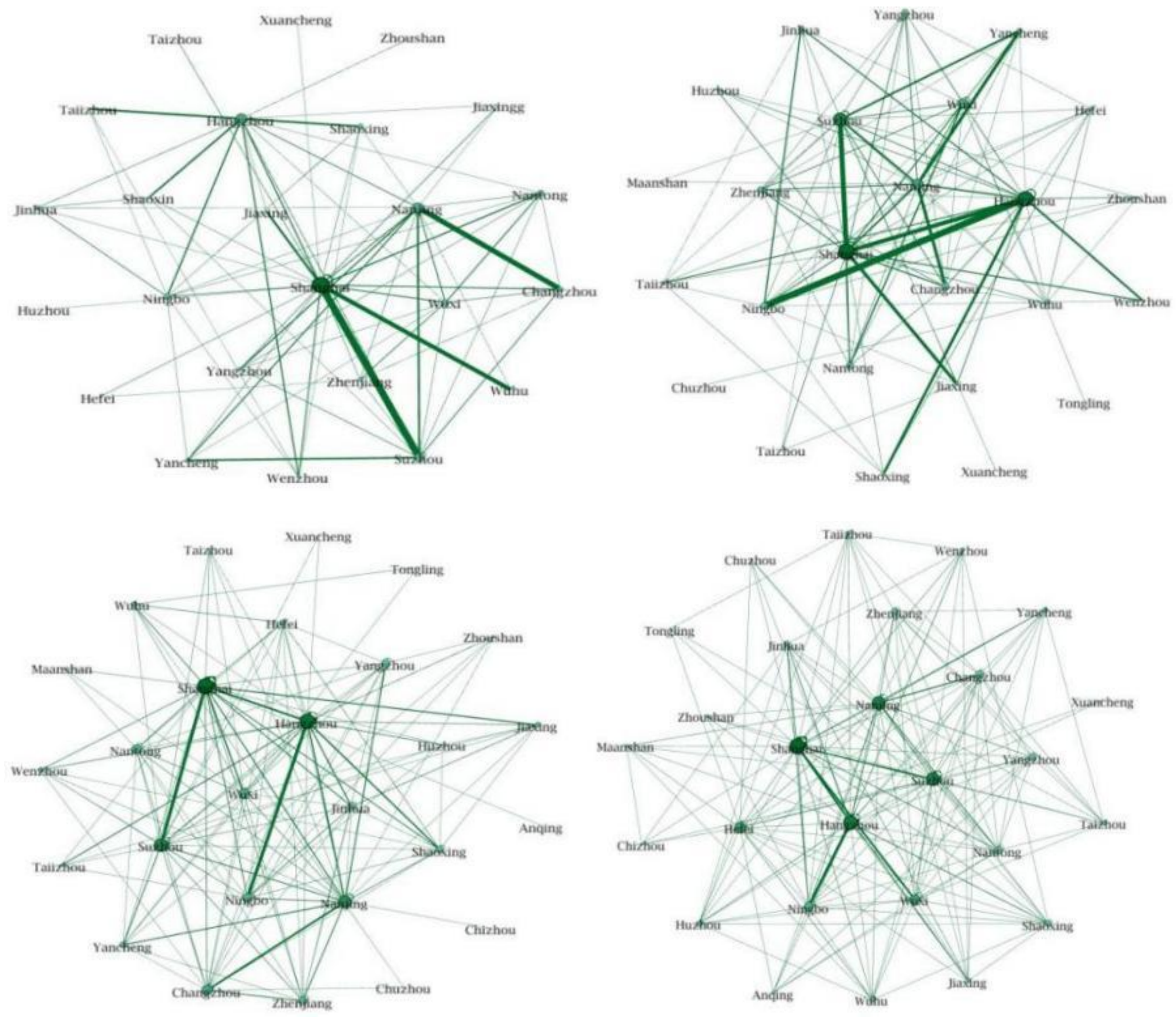

Fig. 6 – Green patent cooperation network map of YRD during 2013 to 2020
(from left to right, from top to bottom, 2013-2014, 2015-2016, 2017-2018, 2019-2020)
Source: own research

B. Overall structural characteristics of green innovation cooperation in the YRD

Table 6 shows that from 2013 to 2020, the number of non-isolated activity nodes in the green innovation cooperation network of the YRD gradually increased. This pattern suggests that more than half of the cities have started to establish cooperative relationships, and the scale of the cooperation network has expanded significantly. Network density describes the closeness of patent cooperation between node cities within a network. The network density reached 0.405 from 2013 to 2014 but slightly decreased in 2015. Nevertheless, from 2018 to 2020, the network density showed a steady increase to 0.729. This indicates that with the increasing frequency of intercity research and development cooperation, the phenomenon of network density dilution has improved. Such a trend reflects that there is still considerable potential for further cooperation.

Tab. 6 – Overall characteristics of green patent cooperation network

	2013	2014	2015	2016	2017	2018	2019	2020
Number of non-isolated nodes	22	21	23	24	24	25	26	26
Network density	0.359	0.405	0.375	0.486	0.444	0.61	0.553	0.729

Source: own research

C. Individual characteristics of the green innovation cooperation network in the YRD

– Closeness Centrality

Table 7 shows that Shanghai always occupies the highest position and has a core influence in green innovation cooperation network in the YRD from 2013 to 2020. Hangzhou, Suzhou, Nanjing, Wuxi and other cities are gradually rising to core cities. This indicates that the degree of centralization in multi-core cities is gradually weakening, and the network shows the trend of multi-center and diversification.

– Tab. 7 – Closeness centrality of green innovation cooperation cities in YRD

	2013	2014	2015	2016	2017	2018	2019	2020
Shanghai	0.840	0.870	0.846	0.852	0.813	0.889	0.765	0.929
Suzhou	0.656	0.645	0.667	0.793	0.722	0.800	0.839	0.839
Nantong	0.568	0.571	0.524	0.590	0.605	0.615	0.634	0.684
Hangzhou	0.700	0.690	0.710	0.793	0.743	0.857	0.788	0.813
Jiaxing	0.500	0.476	0.524	0.511	0.520	0.558	0.565	0.591
Wuxi	0.618	0.625	0.629	0.697	0.634	0.686	0.667	0.743
Hefei	0.467	0.488	0.489	0.575	0.542	0.632	0.619	0.765
Nanjing	0.656	0.714	0.647	0.697	0.703	0.706	0.765	0.839
Ningbo	0.525	0.606	0.579	0.639	0.619	0.667	0.650	0.703
Jinhua	0.525	0.465	0.449	0.548	0.531	0.615	0.619	0.591
Changzhou	0.553	0.541	0.550	0.622	0.634	0.632	0.634	0.667
Taiizhou	0.420	0.455	0.500	0.561	0.448	0.533	0.473	0.619
Taizhou	0.467	0.476	0.489	0.511	0.510	0.522	0.553	0.578
Wuhu	0.404	0.476	0.564	0.575	0.520	0.571	0.578	0.619
Huzhou	0.467	0	0.512	0.500	0.510	0.545	0.553	0.634
Yangzhou	0.525	0.526	0.537	0.590	0.634	0.571	0.634	0.605
Shaoxing	0	0.588	0.500	0.523	0.578	0.615	0.634	0.591
Yancheng	0.525	0.541	0.524	0.575	0.578	0.571	0.553	0.591
Chizhou	0	0	0	0	0.419	0	0.481	0.542
Zhenjiang	0.420	0.556	0.550	0.575	0.553	0.632	0.605	0.619
Zhoushan	0.420	0.417	0.449	0.535	0.456	0.500	0.456	0.553
Anqing	0	0	0	0	0.456	0.480	0.448	0.578
Maanshan	0	0	0.400	0.451	0.464	0.490	0.491	0.578
Chuzhou	0	0	0.367	0	0.426	0	0.441	0.553
Xuancheng	0	0.476	0	0.451	0.426	0.490	0.464	0.510
Tongling	0	0	0	0.418	0.394	0.369	0.464	0.542

Source: own research

– Betweenness Centrality

Betweenness centrality is a metric that can be utilized to assess a city's ability to control and transfer information resources within a network. Table 8 indicates that the betweenness centrality of Shanghai, Hangzhou, and other cities has exhibited a continuous decline from 2013 to 2020. This suggests that the original monopolistic mode of operation has gradually been replaced by a cooperative mode, with their cooperation resources and control abilities being dispersed to other cities.

Tab. 8 – Betweenness centrality of green innovation cooperation cities in YRD

	2013	2014	2015	2016	2017	2018	2019	2020
Shanghai	100.073	103.689	96.251	55.513	86.252	76.543	32.792	58.753
Suzhou	20.918	5.215	15.993	62.100	45.274	29.735	84.194	31.950
Nantong	2.112	0	0	0.183	7.065	1.248	1.188	4.309
Hangzhou	55.900	38.423	43.613	45.811	47.976	50.366	69.835	27.844
Jiaxing	0	0	2.882	0	0.682	0.516	0.171	0.771
Wuxi	4.777	2.342	5.645	26.629	29.031	10.408	3.214	9.186
Hefei	0	0	0	1.535	0.894	1.504	4.339	30.200
Nanjing	26.107	15.157	28.299	8.942	35.301	9.453	44.930	25.873
Ningbo	0.700	6.021	7.852	5.615	6.678	6.855	9.477	4.947
Jinhua	0.143	0	0.111	0.700	1.777	1.531	9.341	1.203
Changzhou	2.084	0	0.433	1.345	20.508	0.896	1.876	2.189
Taiizhou	0	0	0	0.864	0	0.067	0	2.821
Taizhou	0	0	0	0	0	0	0.114	0
Wuhu	0	0	23.306	0.273	7.293	23.056	0.040	0.343
Huzhou	0	0	0	0	0.167	0	0	0.844
Yangzhou	0	0	1.372	0.105	10.863	0.216	1.301	1.214
Shaoxing	0	1.977	0	0.333	0.683	1.364	2.602	0.334
Yancheng	0	0.200	0.111	0.053	3.002	0.000	0.111	0.077
Chizhou	0	0	0	0	0.000	0	0.000	0.202
Zhenjiang	0	1.643	0.798	0	0.320	1.241	0.473	1.504
Zhoushan	0	0	0.333	0	0.125	0	0	0
Anqing	0	0	0	0	0	0	0	0.490
Maanshan	0	0	0	0	0	0	0	0.475
Chuzhou	0	0	0	0	0.111	0	0	0
Xuancheng	0	0	0	0	0	0	0	0
Tongling	0	0	0	0	0	0	0	0.118

Source: own research

It was found that Shanghai has experienced a decrease in both network centrality and network media degree. However, it continues to play a leading role in the patent cooperation network, guiding the green innovation cooperation development of the YRD. The influence of Shanghai and Hangzhou on green innovation cooperation resources and relations is gradually declining, while the innovation ability of other cities is on the rise. As a result, there have been increased technology spillovers from dominant cities.

– Small-world effect

The small-world effect can be characterized by the average path length and clustering coefficient. The average path length represents the average shortest path between two points in a network. Table 9 shows that the average path length of the green innovation cooperation network in the YRD decreased from 1.922 to 1.515 from 2013 to 2020. This suggests that the information flow and transmission among cities in the region was relatively smooth.

On the other hand, the clustering coefficient measures the degree of clustering among nodes in a network. The clustering coefficient of cities in the YRD has remained around 0.7. This indicates that the degree of agglomeration within the green innovation cooperation network is not excessively high.

Tab. 9 – Clustering coefficient and average path length of green innovation cooperation network in YRD

	2013	2014	2015	2016	2017	2018	2019	2020
Clustering coefficient	0.727	0.718	0.729	0.743	0.744	0.764	0.754	0.742
Mean path coefficient	1.922	1.801	1.822	1.761	1.741	1.687	1.608	1.515

Source: own research

Table 9 shows that the global effect of green innovation cooperation in the YRD is not small, and the possibility of cooperation is reduced. This indicates that although cooperation between cities has become frequent, core cities have not formed effective monopolies. The green innovation cooperation between cities is not random, but strong cities are more likely to form partnerships with other cities.

4. OVERALL EFFECT OF LCCP POLICIES

4.1. Effect of LCCP policies on green growth performance

To verify the direct impact of LCCP policies on green growth performance (GTFP), this study conducts an analysis based on panel data from 26 cities in the YRD from 2013 to 2020 and applies PSM to search for qualified control samples for low-carbon pilot cities. In this study, the low-carbon pilot cities are designated as the dependent variable, while other variables serve as co-variates. The low-carbon pilot cities in the experimental group are matched using the nearest kernel matching method, followed by a balance test on the matched samples.

(1) Test of matching quality

Table 10 and Figure 7 show the propensity score and bias degree for each variable before and after matching. The average standard bias of all variables in the control group and the experimental group are relatively large before matching. The absolute value of the average standard bias of permanent population and fiscal science expenditure in the control group and the experimental group are all above 50%, indicating that there are significant differences among variables.

However, the experimental group and the control group are roughly balanced, and the differences of each variable decreased significantly after matching. The ATT value of nuclear matching is 1.42, which passes the 10% significance test. The deviation of each variable after matching is basically less than 10%, and the t-value indicates that there is no systematic difference between the experimental group and the control group. This shows that the experimental group and the control group are similar in all aspects after pairing, and there is no significant systematic difference. Consequently, the matched samples are appropriate for an analysis using the DID model.

Tab. 10 – Homogeneity test of variables

Variables		Mean		Deviation	Deviation reduction	t
		Experimental group	Control group			
Opening degree	Before matching	0.0287	0.0301	-12.8	50	-0.73
	After matching	0.0297	0.0308	-6.4		-0.27
Degree of government intervention	Before matching	0.1457	0.1439	3.7	171.6	0.22
	After matching	0.1427	0.1475	-10.1		-0.44
Per capita road area	Before matching	2.994	3.0944	-21.6	65.2	-1.45
	After matching	3.1243	3.0894	7.5		0.38
Permanent population	Before matching	6.4617	6.0897	52.5	94.5	3.29^{***}
	After matching	6.1881	6.1677	2.9		0.12
Fiscal science expenditure	Before matching	12.982	12.073	76.7	98.3	5.20^{***}
	After matching	12.424	12.409	1.3		0.06

Source: own research

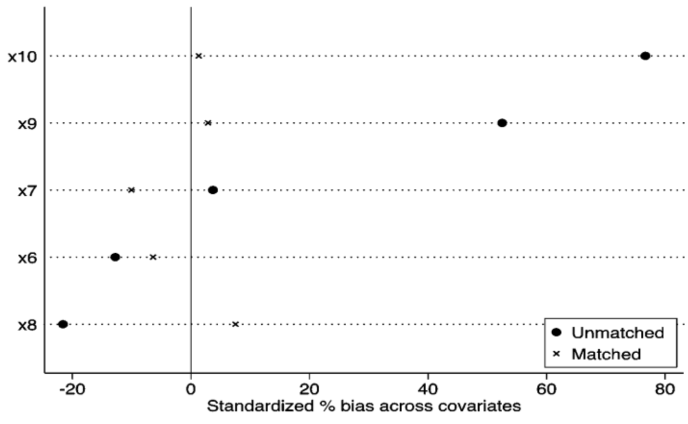

Fig. 7 – The diagram of matching deviation. Source: own research

(2) DID regression results on green growth performance

Based on the data after PSM matching, this study applies the fixed effect to examine the influence of LCCP policies on the green growth performance of cities in the YRD. This approach is employed for the purpose of differential analysis.

Tab. 11 – The regression results of LCCP on green growth performance

Variables	Model (1) DID	Model (2) DID	Model (3) PSM+DID	Model (4) PSM+DID
DID	0.0246***	0.0135*	0.0079	0.0146**
	(0.0084)	(0.0082)	(0.0083)	(0.0071)
Opening degree		-0.1500		-0.1493
		(0.1758)		(0.1541)
Degree of government intervention		0.1186		-0.0058
		(0.0742)		(0.0625)
Per capita road area		-0.0236***		-0.0260***
		(0.0090)		(0.0078)
Permanent population		-0.0009		-0.0069
		(0.0090)		(0.0078)
Fiscal science expenditure		0.0141**		0.0176***
		(0.0063)		(0.0056)
Time effect	YES	YES	YES	YES
Urban effect	YES	YES	YES	YES
Constant	1.0058***	0.9001***	1.0062***	0.8580***
	(0.0051)	(0.0697)	(0.0029)	(0.0621)
Within R2	0.2150	0.2719	0.0870	0.5336

Source: own research

Model (1) and model (2) represent the regression results of DID conducted prior to propensity score matching. Model (3) and model (4) present the DID regression results post-matching. The results show that LCCP policies have a positive impact on green growth performance (GTFP). After matching, the GTFP of LCCP policies in the YRD has increased by 1.46% compared with that of cities without approval. Although the effect is not obvious enough, it may be because LCCP policies still need long-term development to be effective. Nonetheless, the results also show that the policy dividend has brought the momentum of GTFP to LCCP cities and promoted the improvement of urban GTFP. The incentive effect and demonstration effect of LCCP policies will encourage market players to improve their technologies and adjust their structure, thus enhancing the internal growth impetus for GTFP. However, the sustainability of these pilot initiatives remains a question, necessitating further exploration into the operational aspects of their effects. Therefore, the effect of LCCP policies on GTFP through patent cooperation and efficiency optimization should be researched in more detail.

4.2. Effect of LCCP policies on green innovation efficiency

(1) LCCP policies' effect on green innovation efficiency

This study believes that after the promulgation of LCCP policies, LCCP cities may implement a series of short-term measures aimed at controlling pollution emissions to meet the standards of green pilot cities. This initial effort is expected to lead to a brief increase in green total factor productivity (GTFP). However, the sustainability of controlling pollution emission through regulatory policies is not high. The study further explores the long-term trend impact of LCCP policies on green innovation efficiency. Based on PSM matching data, the study adopts the city year dual fixed effect model for research, and the results are shown in Table 12.

Tab. 12 – The regression results of LCCP on green innovation efficiency

Variables	Model (5) DID	Model (6) DID	Model (7) PSM+DID	Model (8) PSM+DID
DID	0.0601** (0.0289)	0.0435 (0.0363)	0.0379* (0.0311)	0.0126** (0.0383)
Opening degree		0.6661 (1.4757)		0.8531 (1.4803)
Degree of government intervention		0.4222 (0.6426)		0.4807** (0.6578)
Per capita road area		0.0022 (0.0044)		0.0018 (0.0045)
Permanent population		0.1061 (0.1611)		0.1579 (0.1625)
Fiscal science expenditure		0.0216 (0.0387)		0.0324*** (0.0397)
Time effect	YES	YES	YES	YES
Urban effect	YES	YES	YES	YES
Constant	0.9347*** (0.0122)	-0.1149 (0.9350)	0.9261*** (0.0121)	-0.5685 (0.9447)
Within R2	0.2005	0.0337	0.075	0.3022

Source: own research

Model (5) and model (6) are regression results without and with control variables. Model (7) and model (8) are regression results of the DID model after PSM matching. LCCP policies have a significant positive impact on green innovation efficiency. Compared with other cities, green innovation efficiency of LCCP cities increases by about 12.6%. LCCP cities have better carried out green innovation activities.

With policy incentives, local governments actively promote market reform and industrial upgrading, and encourage green innovation in cities. In this sense, LCCP policies can not only promote the city to effectively carry out green emission reduction activities in the short term, but also guide the city to carry out green innovation in the long-term development to achieve sustainable green development.

(2) Placebo Test

500 random impacts of pseudo-LCCP pilot policies on 26 cities were constructed in this study. Each iteration involved the random selection of 19 cities as the experimental group, with the policy implementation time assigned randomly. The density of 500 cores and their p value distribution are presented in Figure 8.

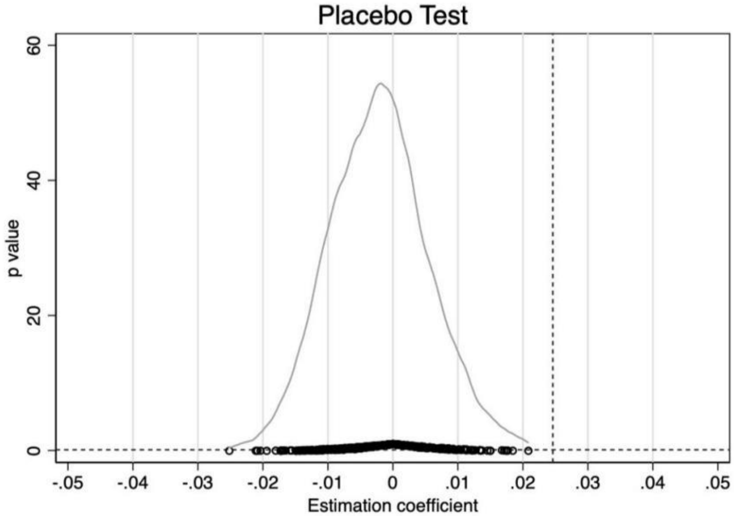

Fig. 8 – The result of placebo test. Source: own research

Figure 8 shows the estimated coefficients and the p value distributions of 500 LCCP virtual policy groups. On the horizontal axis, the size of the estimated coefficient of LCCP policies are represented. The vertical axis corresponds to the size of the p value. The curve represents the kernel density distribution of the estimated coefficient. The black circle corresponds to the p value of the coefficient. The vertical dashed line is the true reference regression 0.0246, and the horizontal dashed line corresponds to the significance level of 5%. The estimated coefficient of 500 policy groups is near 0, and the p value corresponding to the estimated coefficient is not significant at the level of 5%. Importantly, the real benchmark regression coefficient has no intersection with the estimated coefficient of virtual regression, which further verifies the reliability of the DID regression results.

5. THE MEDIATING EFFECT OF CONDUCTION PATHS

5.1 Independent mediating effect of conduction paths on LCCP

LCCP policies exert a significant influence on promoting green innovation. However, the estimation results may be biased due to the spatial correlation between regions. To address this issue, the existing studies have introduced the Spatial Durbin Model (SDM) to examine the impact of LCCP policies on not only the region itself but also its surrounding areas.

Additionally, this model allows for an assessment of the innovation spillover effects that arise during the implementation of LCCP policies.

Tab. 13 – Spatial DID regression based on time-spatial weight matrix

Variable	(1) *har*	(2) *har*	(3) *har*	（4） *har*
DID	-0.049**	-0.064***	-0.049**	-0.032*
	（-2.21）	(-2.76)	(-2.21)	（-1.39）
gdp	-0.006*	0.002	-0.06*	-0.009***
	(-1.77)	(0.43)	(-1.77)	（-3.16）
edu	0.121	0.37	0.121	0.108
	(0.23)	(0.73)	(0.23)	（0.23）
fdi	0.435	0.34	0.435	1.027*
	(0.62)	(0.5)	(0.62)	(1.82)
r	0.411***	0.215***	0.411***	0.388
	(5.36)	(2.34)	(5.36)	(4.96)
Time effect	N	Y	Y	N
Urban effect	Y	Y	N	N
R^2	0.4376	0.4917	0.4376	0.4273

Source: own research

Table 13 presents the spatial spillover effect of low-carbon policy experiments on urban green cooperative innovation. Models (1), (2), (3), and (4) correspond to urban fixed effect SDM, bidirectional fixed effect SDM, time fixed effect SDM, and random effect SDM, respectively. Both the likelihood function value and the information criterion indicate that the SDM model with bidirectional fixed effect is the most appropriate, and the coefficients of all three are significantly negative at the level of 10%. The value of ρ of space spillover effect is also significantly positive. Low-carbon policies not only improve the local green cooperation and innovation capabilities and shorten the distance of green innovation cooperation but also have a spatial spillover effect on neighboring regions' green cooperation and innovation capabilities. In intercity green innovation cooperation, the utilization of innovative systems, strategic plans, and low-carbon technologies for internal management can facilitate mutual circulation of resources through cooperation. Consequently, this can promote the interests of neighboring enterprises. Remarkably, low-carbon policies enable enterprises to supervise and manage the entire process of cost reduction and efficiency improvement. By limiting various production behaviors that are non-environmentally friendly or non-low carbon, technical factors can be promoted to ensure fundamental low-carbon enterprise operation. These policies provide technical support for the long-term sustainable development of enterprises.

Table 14 presents the results of the analysis of direct effects, indirect effects, and total effects. The study utilized a time-space weight matrix DID model to calculate cross-effects, and the coefficient scores are as follows: 0.049, 0.007, 0.091, and 0.097 for models (1) to (4), respectively. Models (3) and (4) both passed the 10% significance test. Moreover, in Model (1), the indirect effect is even greater than the direct effect. This suggests that the pilot low-carbon policy not only improves the cooperation and innovation level of green innovation in this region, but also promotes the innovation level of neighboring regions, and the policy has a significant positive spillover effect. The possible reason is that low-carbon policies promote the flow of high-quality elements between cities and regions, which has a good spatial radiation effect, indicating the necessity of further promoting the diffusion of low-carbon policies between regions.

Tab. 14 – Decomposition of spatial Durbin effect of LCCP on green innovation

Model	(1)	(2)	(3)	(4)
	har	har	har	har
Direct effect	-0.042*	-0.063***	-0.042*	-0.024
	(-1.90)	(-2.67)	(-1.90)	(-1.04)
Indirect effect	0.049	0.007	0.091*	0.097**
	(0.392)	(0.12)	(1.74)	(2.11)
Total effect	0.049	-0.056	0.049	0.073
	(0.392)	(-0.89)	(0.86)	(1.32)

Source: own research

5.2 Multiple mediating effects of conduction paths on LCCP policies

Based on the analysis above, the GTFP of pilot low-carbon cities in the YRD is approximately 1.46% higher than that of unapproved cities. This highlights the significant impact of the LCCP policies on promoting green innovation cooperation in the region. The independent intermediary effect value of industrial structure upgrading in green innovation between cities is 0.3302, which suggests its crucial role in driving green innovation. In contrast, the independent intermediary effect value of industrial structure rationalization is -0.0467, which is not statistically significant, indicating its limited influence on green innovation. In general, the implementation of LCCP policies will promote the development of high-grade urban industrial structure. Urban green total factor productivity highlights the requirement for the quality of economic development, while the upgrading of industrial structure refers to the evolution from labor-intensive industries to technology-intensive industries, which helps to solve the problem of sustainable economic growth under the constraints of resources and environment, to promote the development of green economy.

Tab. 15 – Multiple mediating effect of LCCP

	Ind		C	$GTFP$
	$Indsh$	$Indsr$		
DID	0.0817**	-0.0168	0.0042*	0.0051*
	(0.0320)	(0.0131)	(0.0024)	(0.0066)
δ	0.3302***	-0.0467	0.0188***	0.0153**
	(0.0854)	(0.0349)	(0.0064)	(0.0214)

$Indsh$			0.0182***	0.0408***
			(0.0059)	(0.0113)
$Indsr$				
C				0.1169*
				(0.0772)
Opening degree	-1.9701*	-0.3550	0.1150	-0.0839
	(1.1558)	(0.5020)	(0.0997)	(0.1440)
Degree of government intervention	1.8263***	0.0094	-0.0348	0.0721
	(0.5083)	(0.2252)	(0.0473)	(0.0744)
Road area per capita	0.0003	0.0022	0.0005	-0.0004
	(0.0034)	(0.0016)	(0.0003)	(0.0004)
Permanent population	-0.0139	0.0342	0.0901***	-0.0078
	(0.0626)	(0.0293)	(0.0085)	(0.0071)
Fiscal scientific expenditure	0.1912***	-0.0500***	-0.0040	0.0129**
	(0.0356)	(0.0150)	(0.0031)	(0.0057)
Time effect	Y	Y	Y	Y
Urban effect	Y	Y	Y	Y
Constant	-1.6303***	0.5680***	-0.3982***	0.8840***
	(0.3761)	(0.1767)	(0.0564)	(0.0473)
Within R2	0.4809	0.1425	0.7937	0.7004

Source: own research

5.3 Analysis of mediating effect proportion

After conducting an evaluation of LCCP policies' impact on green innovation, industrial structure upgrading, and carbon dioxide emissions, the study further analyzes its direct and indirect effects. Table 16 reveals that LCCP policies primarily promote the development of the green economy in the YRD through direct effects, with an evaluation value of 51.47%. The number of chain intermediaries is relatively small. The results of the indirect effect evaluation indicate that the independent intermediary effect of industrial structure upgrading has reached 33.63%. This underscores the crucial role of industrial structure upgrading and transformation in promoting GTFP. Conversely, the independent intermediary effect of green innovation can potentially suppress GTFP, reaching 9.88%. However, in the pilot policies of LCCP, green innovation will promote the upgrading of industrial structure to a higher level. Therefore, it is believed that green innovation cooperation alone can play an important role in the growth of green economy only by promoting the advanced development of industrial structure. The independent mediating effect of carbon dioxide emission performance is only 4.95%, which is relatively small, indicating that after promoting green innovation cooperation and industrial structure upgrading, carbon dioxide emission performance does not have a strong influence on GTFP.

Tab. 16 – Multiple mediating effect of LCCP

	Mediating effect	Proportion
Direct effect	0.0051	51.47%

Indirect effect- innovation	-0.0009792	9.88%
Indirect effect- industrial structure supererogation	0.003333	33.63%
Indirect effect- industrial structure rationalization	-	-
Indirect effect- carbon dioxide emissions	0.00049098	4.95%
Multiple mediating	0.00000636	0.06%

Source: own research

6. CONCLUSIONS AND POLICY IMPLICATIONS

6.1 Conclusions

Based on the dynamic conduction mechanism among LCCP policies, carbon dioxide emissions reduction and green growth performance, the study employs the social network analysis, PSM-DID, and multiple spatial mediating models to measure the multi-dimensional policy effects of LCCP on green growth performance and green innovation efficiency for 12 LCCP pilot cities and 14 non pilot cities in the YRD. The main conclusions are as follows.

Firstly, the green growth performance for all investigated cities has witnessed an increase from 0.9683 to 1.0432 during 2013-2020. And, the direct effect of LCCP policies on green growth performance has reached 1.46% since its implementation in 2017.

Secondly, there is significant potential for green innovation efficiency in LCCP cities. Moreover, taken the intercity cooperation of green patents in the YRD for analysis, the research finds out that LCCP policies not only improve the green innovation cooperation capability and shorten the distance of green innovation cooperation, but also have a significant spatial spillover effect on the green cooperation innovation capability of surrounding areas.

Thirdly, considering the intercity innovation cooperation in the YRD, LCCP policies have exerted effects on green innovation efficiency with an increase of 12.6%. Among all the LCCP pilot cities, Shanghai, Nanjing, and Hangzhou are among the cities with greater promotion in innovation efficiency. These cities are pioneers in both green growth development and environmental-friendly growth mode.

Finally, the multiple mediating effect model identification results show that the industrial structure upgrading path is an important conduction path to achieve the ultimate objective of carbon emissions reduction and green growth performance. The substantial transformation of industrial structure upgrading has played an important role in realizing the LCCP policies' effect on green growth performance, accounting for 33.63% of its total effects.

6.2 Policy implications

Firstly, the implementation of LCCP policies can promote green growth performance, but the spatial effect of LCCP policies has not reached the ideal state. The government's innovation policy setting should involve multiple innovation subjects to achieve innovation improvement. According to different regions, policies suitable for local development should be proposed, focusing on regions with low innovation capacity, to achieve regional integrated development.

Secondly, the government should not only propose plans to stimulate green innovation, but also put forward policies to encourage green innovation cooperation. Moreover, each innovation cooperation city should give full play to its own advantages and strengthen cooperation and exchanges. Innovation output should provide direct impetus for industrial structure upgrading and form a relatively complete innovation transformation system. The government should encourage enterprises to improve the practicality of innovative products, improve the pollution problem, and improve the development of green economy through industrial structure upgrading.

6.3 Limitations and directions for the future

The study makes contributions to the mediating effect identification of LCCP policies on green growth performance. Despite these strengths, the study has some limitations, which may highlight possible directions for future study. First, there may be other indirect influence channels for LCCP policies. This study only selects green innovation and industrial structure as the positive influence channels, while government preference may also negatively affect the effect of LCCP policies. Second, the study focuses on the mediating effect of LCCP policies in the YRD region. The effect might be different for the varying samples in different industries, enterprises, and regions. To remedy this shortcoming, future research could deepen the theoretical argument and empirical identification on the mediating effects with various samples.

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