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Neighbor's profit or Neighbor's beggar? Evidence from China's low carbon cities pilot scheme on green development

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A R T I C L E I N F O

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A B S T R A C T

China has implemented three sets of low-carbon city pilot policies (LCCP), making it the world's most extensive low-carbon and green development program. Many studies have examined the impact of this policy on green development. However, studies rarely discuss spillover effects. This deficiency can lead to biased policy evaluations. This study employs a quasi-experimental approach to investigate the spillover effects of LCCP on the green total factor productivity (GTFP) of neighboring non-pilot cities and identify the underlying mechanisms. Using panel data from 283 cities in China spanning from 2004 to 2020, this study employs the time-varying difference-in-difference method. The empirical evidence suggests that LCCP can significantly enhance the GTFP growth of non-pilot cities located within 100 km, with an average annual increase of approximately 1.43%. Mechanism analysis indicates that increasing technological innovation and learning from the pacesetter play crucial intermediary roles in promoting GTFP improvements in neighboring cities. Furthermore, the spillover effects exhibit noticeable heterogeneity, particularly among cities in the eastern region, middle region, and large cities. These findings provide empirical evidence regarding the spillover effects of China's largest carbon pilot policies, contributing to a comprehensive assessment of policy impacts and offering fresh insights for climate policy tools.

1. Introduction

Green development, which involves achieving economic growth through environmental sustainability, has long been considered a critical aspect of global sustainable development (Zhang and Wen, 2008). The concept emphasizes integrated management, scientific allocation, and comprehensive conservation and recycling of resources, effectively resolving the conflict between economic growth and environmental conservation. With carbon emissions increasing dramatically since the turn of the century, China has actively promoted green development as climate change has become an urgent global issue(Mi and Sun, 2021). China's 20th National Congress in 2022 once again elevated green development as a priority for achieving a low-carbon transition and high-quality economic development. In this context, green development has garnered unprecedented attention in China's academia.

Cities make significant contributions to national economic development, but they are also major sources of pollution. In 2021, the "Opinions on Promoting Green Development of Urban and Rural Construction" issued by the central government underscored the importance of green development in cities to reduce emissions. China's government has devoted considerable efforts towards city-based green growth, including the large-scale and pioneering Low-carbon City Pilot (LCCP) policy.

According to Tobler's First Law of Geography, everything is interconnected, but closer things are more related than further away (Tobler, 2004). This phenomenon is especially evident in the context of environmental regulation. Due to externalities, a city inevitably benefits from the environmental policies of neighboring cities or incurs additional costs from such policies (Case et al., 1993; Ertmer, 1996). For example, local governments may adopt similar environmental standards from other regions to capitalize on external benefits, such as access to foreign markets and attracting foreign investments (Faber and Gerritse, 2012). Environmental policies also have negative externalities. Strict environmental regulations can improve green development in one pilot city, while the inflow of polluting industries and the outflow of innovation resources (siphoned off from the pilot city) may cause green development in surrounding cities to decline (Chen and Wang, 2022). Our research objective is to identify whether and how LCCPs affect neighboring non-pilot cities' green development. Our focus is on the

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List of abbreviations:

LCCP	Low-carbon City Pilot
SBM-DDF	Slack-based measured directional distance function
GTFP	Green total factor productivity
SDID	Spatial difference-in-differences
FYP	Five-Year Plan
NDRC	National Development and Reform Commission
GLPI	Global Luenberger productivity indicator
DMU	Decision-making unit
BPC	Best practice change
PEC	Pure efficiency change
SEC	Scale efficiency change
SDM	Spatial Durbin model

non-pilot cities in this issue, which explores the externalities of China's pilot reform.

Academics have extensively studied the impact of the LCCP policy on urban green development since its nationwide implementation. Most studies have revealed that LCCP policies have contributed to green development in pilot cities (Cheng et al., 2019; Fu et al., 2021; Qiu et al., 2021; Wang et al., 2023c; Zhang et al., 2022a). For example, Qiu et al. (2021) used a quasi-natural experiment approach and found that LCCP policies increased green total factor productivity (GTFP) by approximately 5.5%. Zhang et al. (2022a) demonstrated that the LCCP policy could increase GTFP by decreasing the scale effect, enhancing the structural effect, and promoting innovation. Fu et al. (2021) and Wang et al. (2023a) found that the effects of the LCCP policy on GTFP in pilot cities were heterogeneous across city types (such as size, location, and resource endowment). Additionally, GTFP in pilot cities improved through various mediating mechanisms, such as innovation, enhancement of industrial structure, and optimization of industrial structure and resource allocation. There are also several studies contend that the LCCP failed to reduce carbon emissions due to unclear development objectives (Lo, 2014; Zhou and Zhou, 2021).

However, these studies focused primarily on the direct impact of LCCPs on green development in pilot cities, with few examining the spatial spillover effect. To our knowledge, only a few previous studies in the literature have examined the spillover effects of LCCP on green development by using spatial difference-in-difference (SDID) model (Chen and Wang, 2022; Wang et al., 2023a). These studies evaluate the average spillover effect (both on pilot and non-pilot cities) and failed to provide conclusive evidence about the influence of the LCCP on the green development of neighboring non-pilot cities. Moreover, selecting the optimal matrix remains an unresolved issue in the SDID model, and inappropriate decision-making can result in biased coefficient estimations.

To reveal the spillover effect of the LCCP on non-pilot cities' green development, this paper utilizes panel data for 283 Chinese cities from 2004 to 2020 and employs a time-varying difference-in-differences (DID) model. The contribution is threefold. Firstly, we extend the concept of policy evaluation to the perspective of the spillover effect, thereby overcoming the limitations of existing research, which largely focuses on local effects. Secondly, we contribute to empirical research by employing the time-varying DID model to estimate the spillover effect, which can capture the effect to neighboring non-pilot cities. Compared to the SDID model, this study not only allows a more refined analysis of policy spillovers, but also mitigates the selection bias associated with the optimal matrix methodologically. The third contribution of this study is to identify a new mechanism of spillover effect. Compared to innovation development levels, innovation factor flows can offer a more reasonable explanation of policy effect that across administrative boundaries.

This study is organized as follows: Section 2 discusses the research background and hypotheses, Section 3 describes the research methodology, and Section 4 reports the empirical results and conducts robustness analysis. Section 5 delves into the mechanism analysis and heterogeneous analysis, and the final section is the conclusion and policy recommendations.

2. Policy background and research hypothesis

2.1. China's low-carbon city pilot policy

Due to accelerated urbanization and industrialization, which have increased fossil fuel consumption, cities have assumed greater responsibilities in transitioning to a green economy and addressing climate change (Wang et al., 2018). In the 11th Five-Year Plan (FYP), carbon reduction was initially established as a binding target for performance evaluation. To achieve this goal, China launched three batches of LCCP policies to meet its carbon reduction targets in 2010, 2012 and 2017.

In 2010, the National Development and Reform Commission (NDRC) initiated the first set of pilot areas, encompassing five provinces, two municipalities and six prefecture-level cities (see Appendix A), which collectively accounted for 54.16% of the nation's carbon emissions (Chen et al., 2021). The CO_2 emissions of pilot cities decreased by 88.9% in 2010–2011 compared with other cities in the same province (Chen et al., 2021). In the subsequent two years, green development was elevated to a national strategy for building a "Beautiful China", and 29 additional areas extended the second batch of pilot regions. Following the success of the first two pilot batches, a third batch was launched with a focus on innovation. An additional 45 pilot areas were included as part of the policy framework of the National Plan to Address Climate Change (2014–2020) and the 13th FYP to control greenhouse gas emissions. These pilot cities were tasked with providing practical experiences and developing replicable and scalable practices for non-pilot cities.

The government conducted low-carbon city pilots in several key areas. First, it aimed to achieve industrial restructuring and the upgrading of cities by transforming the functions of urban industrialization into low-carbon, circular development models. A second objective was to encourage pilot regions to adjust their energy structure by replacing coal with green and renewable energy sources, thereby enhancing green productivity. The third aim was to promote public transportation, especially electric buses, to develop a low-carbon urban transportation system. Fourth, it encouraged the construction of green buildings that consider the need to provide people with healthy, suitable, and energy-efficient spaces. Additionally, a greenhouse gas statistics system was established to support macro-environmental regulation.

Cities in this study include municipalities and prefectural-level cities. Fig. 1 displays the geographical distribution of the three pilot city batches. Among our sample of 283 cities, 27 pilot cities were located in the eastern region, 18 pilot cities in the central region, 20 pilot cities in the western region, and 4 pilot cities in the northeastern region, representing 39%, 26%, 29%, and 6% of the total number, respectively. Furthermore, we can conclude that the number of pilot cities in the eastern region exceeds that in other regions. Possible reasons for this discrepancy may include higher levels of production activities and greater population densities in the eastern part. Moreover, some cities in the pilot provinces are excluded from the pilot group because they aren't on the pilot list and haven't adopted low-carbon pilot strategies as the pilot cities.

2.2. Research hypothesis

The LCCP can influence local green development and simultaneously impact the green development of neighboring non-pilot cities. This mechanism connects these cities' efficiency performance. A possible demonstration effect is that, the surrounding non-pilot cities may be

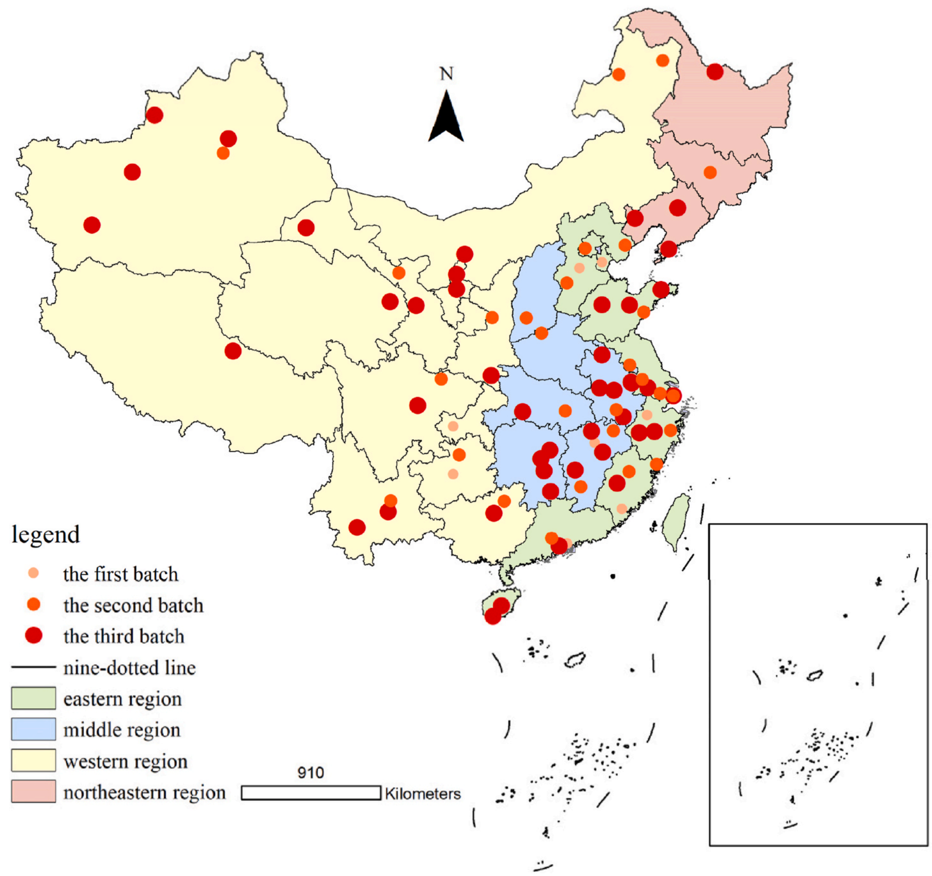

Fig. 1. Geographical distribution of the pilot area in three batches of LCCP policy.

influenced by the pilot policy by political and economic linkages, subsequently affecting the green development(Sun et al., 2022). Additionally, the "First Law of Geography" emphasizes the critical role of geographic proximity; that is, spillover effects are subject to a distance threshold. The first explanation is that greater geographical distance increases learning and communication costs and results in information asymmetry, thereby reducing the spillover effects of the LCCP (Zhu and Lee, 2022). Secondly, resource flow is limited due to administrative barriers, transaction costs, and local protectionism (Liu et al., 2022), which further contribute to spillover thresholds.

Therefore, this paper proposes the central hypothesis of spatial spillover (H1).

Hypothesis 1. LCCP impacts the green development of non-pilot cities within a certain distance threshold.

The environmental policies impact the green development of neighbors, as institutional differences trigger the flow of spatial factors (Álvarez et al., 2018; Sun et al., 2022). According to the LCCP policy, pilot cities should disseminate innovative experiences and measures nationwide, implying that the innovation factor can transfer from pilot cities to surrounding non-pilot cities (Song et al., 2018b). Empirically, innovation is often rooted in other carriers (e.g., capital, labor, knowledge), and the free flow of these carriers due to market signals can explain spatial innovation spillovers (Almeida and Kogut, 1999; Los and Verspagen, 2000). For example, Bottazzi and Peri (2003) found that a region's innovation performance is affected by nearby R&D investments. Peri (2005) and Cabrer-Borrás and Serrano-Domingo (2007) demonstrate that the diffusion of knowledge and ideas enhances the innovation of less developed regions in proximity. This finding is further reinforced by Zhai and An (2021) and Gao and Yuan (2022), who use China as a case study to prove that technology commercialization exerts significant positive effects on green transformation efficiency in neighboring provinces and the spillover effect conforms to the distance attenuation law. Shang et al. (2012) contend that exchanging labor and capital between regions enhances the knowledge of differentiated green products, resulting in endogenous development. In short, spatial spillovers occur when neighboring non-pilot cities absorb innovative capital, labor, knowledge, and ideas from pilot cities.

Given the realities of indigenous development in China, this study includes two major carriers to measure the innovation spillover effect (Shang et al., 2012). These are R&D capital and R&D labor. For one thing, R&D capital was positively related to innovation capability, alleviating financial stress for high-tech enterprises and stimulating technological progress. Another reason is that high-skilled R&D immigrants can explain China's innovation development in the post-reform years because skilled workers, such as scientists and engineers, are equipped with the knowledge to conduct innovative research and production (Fei, 2017). Therefore, this study identifies the mechanism of spatial spillover as the innovation effect.

Hypothesis 2-a. The LCCPs promote the flow of R&D capital factors, creating positive innovation spillovers and contributing to green development.

Hypothesis 2-b. The LCCPs promote the flow of R&D labor factors, creating positive innovation spillovers and contributing to green development.

LCCP policies reduce energy consumption by adjusting the industrial structure. They will gradually phase out traditional pollution-intensive industries in favor of emerging green and low-carbon industries. These emerging industries are high-tech, low-polluting, and low-energy-intensive, reducing carbon emissions, enhancing urban productivity, and improving regional green development. This will also impact the structural transition of surrounding non-pilot cities (Chen and Wang, 2022). Therefore, this study formulates the mechanism of spatial spillover (H3) of LCCP.

Hypothesis 3. The LCCPs promote neighboring green development through the industrial structure effect.

The spatial correlation also reveals that LCCPs influence the surrounding cities' green development through policy learning. With the inclusion of green development in the performance evaluation system for government officials, local policy learning is crucial to reduce costs of low-carbon development, and the governors of non-pilot cities have an enormous incentive to learn from the pilot cities about carbon regulation(Irwin and Klenow, 1994). This is because policy success in pilot cities is a legitimacy signal that prompts other cities to adopt and imitate the successful experience of pioneers with fewer costs and risks. For instance, it is documented that officials adopted Huzhou's innovative "Hezhang" policy following significant improvements in water quality during water pollution control (Liu and Richards, 2019). Several studies have shown that local learning may be interactive, involve proximity, require tacit knowledge, and be supported by a strong local experience base. Additionally, the role of spatial proximity in local policy learning is emphasized, along with face-to-face communication, networks, knowledge spillover, and pooled resources(Roper and Love, 2018). Therefore, this study formulates the mechanism of spatial spillover of LCCP.

Hypothesis 4. The LCCPs promote neighboring green development through the learning effect.

Based on the above discussion, Fig. 2 illustrates the four underlying hypotheses.

3. Research design and methodology

3.1. Green development

One of the challenges is measuring green development. The earliest measurement involves constructing a comprehensive index that can analyze green development from various perspectives (Ge et al., 2023; Hu and Zhou, 2014). The second and most widely used approach employs the concept of productivity, calculated using the data envelopment analysis (DEA) methodology. For instance, Qiu et al. (2021) utilized the slack-based measured directional distance function (SBM-DDF) and Luenberger productivity index method to calculate GTFP, while Wang et al. (2021a) employed the undesired output-super-efficiency SBM model. A third approach describes green development based on some of its core drivers. As an example, Wang et al. (2023c) asserted that digital economy growth can serve as a measure of green development because it drives green public affairs, green production activity, resulting in innovative approaches and feasible pathways. As stated by Zhang et al. (2021) green credit is one of the most significant green financial instruments, as it can reduce pollution emissions and facilitate the financing of green enterprises.

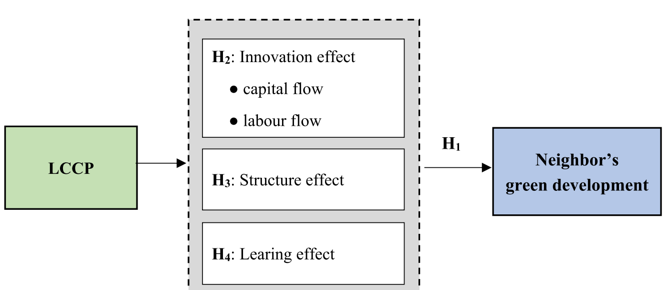

Fig. 2. Hypothesis framework of the spillover effect of the LCCP on green development. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

This study uses the second method of the productivity concept for several reasons. First, GTFP is a vital index for evaluating the synergistic effect of economic growth and carbon reduction. It aims to maximize output while minimizing emissions based on the required input factors, aligning with the requirements of sustainable development (Young, 2003). Second, instead of relying on the single input that generates GDP, GTFP incorporates multiple factors, such as capital, labor, and energy, providing more accurate estimates than a single indicator measure (Sun et al., 2022). Third, it is widely recognized that GTFP is a critical engine for green development in macro planning. As indicated at the 20th National Congress of the Communist Party of China, increasing GTFP is the most crucial solution for developing a low-carbon, sustainable, and environmentally friendly economic system.

1. Green total factor productivity growth estimation

(1) Directional distance function approach

This study estimates GTFP growth for each city using the DEA method, a nonparametric frontier method proposed by Charnes et al. (1978) and Banker et al. (1984). The DEA approach can estimate production frontiers considering various inputs and outputs without making any prior assumptions about the production function's form. The efficiency of each decision-making unit (DMU) is evaluated based on the relative distance (i.e., inefficiency) from the estimated production frontier to each DMU (Ogata et al., 2023).

The DEA-type directed distance function (DDF) approach, which can account for undesirable outputs that traditional DEA models cannot, is suitable for GTFP growth estimation (Nakaishi et al., 2023). The vector of inputs, desirable inputs, and undesirable outputs in a city's production activities are $x = (x_1, \ldots, x_k) \in \Re_+^K$, $y = (y_1, \ldots, y_l) \in \Re_+^L$, and $b = (b_1, \ldots, b_m) \in \Re_+^M$, respectively. The production technology $P(x)$ is defined as:

$$P(x) = \{(y, b) : x \; can \; produce \; (y, b)\}. \tag{1}$$

The DDF $\vec{D}(x, y, b)$, the inefficiency of each city, is defined based on the distance (β) from the production frontier formed by the efficient DMUs (i.e., cities) as:

$$\vec{D}(x, y, b) = Sup\left\{\beta : \left(y + \beta g_y, b - \beta g_b\right) \in P(x)\right\}, \tag{2}$$

where g_y and g_b are the directional vectors of desirable and undesirable outputs, respectively.

Setting the direction vector $g\left(g_y, g_b\right)$ to $g\left(g_y, g_b\right) = (y, -b)$, the DDF for city i $\vec{D_i}(x, y, b)$ can be estimated by solving the following linear programming problem:

$$\vec{D_t}\left(x_i, y_i, b_i; g_y, g_b\right) = Maximize \; \beta_i,$$

s. t.

$$\sum_{n=1}^{N} \lambda_n x_{kn} \le x_{ki}, k = 1, 2, \ldots, K$$

$$\sum_{n=1}^{N} \lambda_n y_{ln} \ge y_{li}(1 + \beta_i), l = 1, 2, \ldots, L$$

$$\sum_{n=1}^{N} \lambda_n b_{mn} \le b_{mi}(1 - \beta_i), m = 1, 2, \ldots, M$$

$$\lambda_n \ge 0, n = 1, 2, \ldots, N, \tag{3}$$

where x_{ki}, y_{li}, and b_{mi} refer to the k th input, l th desirable output, and m th undesirable output of city i, respectively. n denotes the number of cities ($N = 283$). λ_n is the weight variable for the n th city. Eq. (3) assumes constant returns to scale. Adding constraint ($\sum_{n=1}^{N} \lambda_n = 1$) to the equation, this can be converted to a model assuming variable returns to scale (VRS).

(2) Global Luenberger productivity indicator

The GTFP growth in a given city was measured based on changes in DDF over the two periods. The global Luenberger productivity indicator (GLPI) proposed by Wang et al., 2016 can overcome the infeasibility problem of traditional Luenberger productivity indicators (LPI). Therefore, GLPI was adopted in this study as an indicator of GTFP growth in cities. The GTFP growth of city i from years t to s ($GTFP_i^{t,s}$) is defined by the following equation:

$$GTFP_i^{t,s} = \overrightarrow{D}_i^G(x^t, y^t, b^t) - \overrightarrow{D}_i^G(x^s, y^s, b^s), \tag{4}$$

where $\overrightarrow{D}_i^G(x^t, y^t, b^t)$ and $\overrightarrow{D}_i^G(x^s, y^s, b^s)$ are the DDFs of city i in year t and year s, respectively, which are measured based on a "global" frontier formed from all observations in all time periods. Specifically, $\overrightarrow{D}_i^G(x, y, b)$ can be estimated using Eq. (3) by considering observations from 2003 to 2020 for 283 cities (a total of 5096 samples) as different DMUs.

Following Wang et al. (2021b), GTFP growth ($GTFP_i^{t,s}$) can be further decomposed as the sum of the three sources of efficiency change: best practice change ($BPC_i^{t,s}$), pure efficiency change ($PEC_i^{t,s}$), and scale efficiency change ($SEC_i^{t,s}$), as follows:

$$GTFP_i^{t,s} = BPC_i^{t,s} + PEC_i^{t,s} + SEC_i^{t,s}. \tag{5}$$

Specifically, $BPC_i^{t,s}$ represents the frontier shift effect, $PEC_i^{t,s}$ represents the catch-up efficiency effect, and $SEC_i^{t,s}$ represents the scale optimization effect. The $BPC_i^{t,s}$, $PEC_i^{t,s}$, and $SEC_i^{t,s}$ can be estimated from each of the following equations:

$$BPC_i^{t,s} = \left[\overrightarrow{D}_i^G(x^t, y^t, b^t) - \overrightarrow{D}_i(x^t, y^t, b^t)\right] - \left[\overrightarrow{D}_i^G(x^s, y^s, b^s) - \overrightarrow{D}_i(x^s, y^s, b^s)\right], \tag{6}$$

$$PEC_i^{t,s} = \overrightarrow{D}_i^{VRS}(x^t, y^t, b^t) - \overrightarrow{D}_i^{VRS}(x^s, y^s, b^s), \tag{7}$$

$$SEC_i^{t,s} = \left[\overrightarrow{D}_i(x^t, y^t, b^t) - \overrightarrow{D}_i^{VRS}(x^t, y^t, b^t)\right] - \left[\overrightarrow{D}_i(x^s, y^s, b^s) - \overrightarrow{D}_i^{VRS}(x^s, y^s, b^s)\right], \tag{8}$$

where $\overrightarrow{D}_i^{VRS}(x^t, y^t, b^t)$ and $\overrightarrow{D}_i^{VRS}(x^s, y^s, b^s)$ are the DDFs for city i in years t and s, respectively, calculated using the VRS model mentioned in the previous subsection.

3.2. Model establishment and variable description

To test H1, based on the research by Cao (2020), this study employs a two-step empirical approach as follows. First, it estimates the distance threshold for spillovers, which involves identifying the geographic range within which non-pilot cities are affected by LCCPs. Using overall Chinese city-level data, we utilize a time-varying DID model because the pilot cities were not exposed to the regulations at the same time. Compared to SDID, traditional DID can refine spillovers to non-pilot cities. The specific model is as follows:

$$GTFP_{it} = \alpha + \beta_0 DID_{it} + \sum_{50}^{400} \delta_s D_{it}^s + \lambda Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{9}$$

where i represents 283 cities, and 69 pilot cities are in the treatment group,[1] while 214 cities are in the control group. s represents different distance intervals within 400 km, and 50 km is the attenuation distance. Specifically, s=(0,50], (50,100], (100,150], (150,200], (200,250], (250,300], (300,350], (350,400]. D_{it}^s is a interaction term of the city and time dummy variables, and we construct eight D_{it}^s according to s. Taking s=(0,50] as an example, if there is a pilot city within 50 km of city i, then $D_{it}^{0\text{-}50}$ takes the value of 1 after implementing the LCCP policy and 0 otherwise. DID_{it} is a dummy variable set to 1 when the LCCP policy is implemented in year t by city i, and 0 otherwise. The dependent variable $GTFP_{it}$ is described in Section 3.1. Z_{it} contains all control variables, and ν_t is the year fixed effect that captures all time-varying factors. μ_i is the individual fixed effect that captures all variables that change with the city but are time-invariant. ε_{it} is the error term.

Second, we estimate the spillover effects of LCCPs. More specifically, our focus is on non-pilot cities, and we consider the spillover shock as a "quasi-natural experiment." In the DID model, non-pilot cities within a certain distance are in the treatment group and those beyond the certain distance are in the control group. The analysis compares the differences in *GTFP* before and after the spillover shock between non-pilot cities exposed to the spillover shock and those that were not. The specific model is as follows:

$$GTFP_{jt} = \alpha_1 + \beta_1 DID_{jt}^s + \gamma Z_{jt} + \mu_j + \nu_t + \varepsilon_{jt} \tag{10}$$

where j represents 214 non-pilot cities, and 70 cities are in the treatment group, while 144 cities are in the control group. DID_{jt}^s is a spillover dummy that takes the value of 1 when non-pilot city j is subject to LCCPs' spillover in year t and 0 otherwise. The other variables are the same as in (9); the only difference is that the study in (10) is for non-pilot city j.

3.3. Variables and data

3.3.1. Dependent variable

In line with previous studies, input-output data for GTFP growth estimation were constructed as follows (Song et al., 2018a; Xia and Xu, 2020; Xie et al., 2021). The three inputs are capital stock, labor, and energy consumption, and the two outputs are GDP (desirable output) and carbon emissions (undesirable output). For the input variables, the labor force data were based on the annual total number of employees in a city. According to Zhang et al. (2004), the perpetual inventory method is used to calculate capital stock: $K_t = I_t + (1\text{-}\delta)\cdot K_{t\text{-}1}$, in which $K_{t\text{-}1}$ and K_t are capital stock in year t and t-1. I_t is added fixed asset investment. δ is the depreciation rate of fixed assets, defined as 9.6% (Zhang, 2008). Our energy consumption data were based on the total electricity consumption of prefecture-level cities because of a lack of prefecture-level energy consumption data (Cheng et al., 2019). The desirable output is the GDP, whereas the undesirable output is the carbon emissions of each city.

3.3.2. Independent variables

As previously mentioned, the core independent variable is the DID variable, defined as the LCCPs spillover shock. The second phase batch was scheduled for December 2012. Considering the time lag of the policy's effects, this study regards 2013 as the actual year of

[1] Based on the definition of city in this paper (municipalities and prefecture-level cities) and the availability of statistical data (there are no statistics for Tibet Autonomous Region, and Lhasa City is not included), 69 cities were selected as pilot cities.

implementation.

Furthermore, this study incorporates two types of control variables. One consists of the economic variable, including the city's GDP per capita level (pergdp), economic openness level (open), fixed-asset investment (fixed), and fiscal decentralization (fiscal). The level of economic development (pergdp) is positively associated with productivity (Liu and Xin, 2019). Research on the impact of trade (open) on GTFP growth is inconclusive. The pollution haven hypothesis suggests that lax environmental regulations can lead to low-quality FDI and significant large-scale emissions, resulting in lower productivity efficiency (Cole, 2004). However, the pollution halo hypothesis argues that FDI can lead to technology spillover effects in host countries, leading to increased productivity efficiency (Antweiler et al., 2001). Given these opposing effects, its impact of trade on the non-pilot cities' GTFP growth remains ambiguous. Fixed-asset investment (fixed) is crucial for green development, as increasing investment in the green activities can promote high-quality development (Jin and Han, 2021). Logarithmic form was used for fixed. Fiscal decentralization (fiscal) reflects authorities' financial autonomy. A higher level of fiscal decentralization indicates that cities have greater authority to implement green development. It is calculated as fdc/(fdn + fdp + fdc), where fdn, fdp, and fdc represent budgetary expenditure per capita at the national, provincial, and city levels.

The second category is related to social development and includes urban population density (popd), urbanization (urban) and education level (educ). Population density (density) is the ratio of the city's population to its administrative land area. According to previous studies, population density has a dual effect on GTFP. On one hand, population clustering can lead to scale effects and enhance productivity through competition, exchange, and sharing activities, thereby bringing economic benefits (Kumar, 2006). On the other hand, population agglomeration increases energy consumption and emissions (Ohlan, 2015). Urbanization (urban) was measured as the ratio of the urban population to the total city population. This reflects labor force supply, influencing productivity (Chen et al., 2020). Regarding education level (educ), Jin et al. (2019) confirmed that increasing the level of education can accumulate high-level human capital and drive breakthroughs in green technology that boost green development. The total number of teachers enrolled in regular secondary and primary schools was displayed in logarithmic form to measure a city's educational level.

3.3.3. Mediation variable

There are three types of mechanism effects mentioned above.

The first mechanism is the innovation effect. According to Section 2.2, innovation flow manifests in scientific and R&D capital flow and R&D labor flow.

The gravity model was used to measure the factor flow based on Bai et al.(2017). It includes three parts: the evaluated factor (such as R&D capital and labor factors), the gravitational variables driving factor mobility, and the distance between regions. Regarding to the flow of capital, average corporate profitability and the level of financial market development level are essential drivers (Tellis et al., 2009). R&D capital flow, measured in a gravitational model format is given by Eq. (11):

$$cflo_{ijt} = ln\,C_{it} \times ln\left|Prof_{jt} - Prof_{it}\right| \times ln\left|Mark_{jt} - Mark_{it}\right| \times R_{ij}^{-2} \tag{11}$$

where $cflo_{ij}$ represents the quantity of R&D capital flow between cities i and j, and C_i represents R&D investment in city i. We employed the government's science and technology investment stock in city i following Bai et al. (2017). $Prof_i$ represents the average profit level of enterprises above the designated size in city i and $Mark_i$ represents city i's green market development index calculated by Wang and Wang (2021) and Wang and Wang (2023). R_{ij} is the distance from the center of the city, calculated using ArcGIS. Therefore, R&D capital flow in year t in city i is expressed as follows:

$$cflo_{it} = \sum_{j=1}^{n} cflo_{ijt} \tag{12}$$

According to Feng et al. (2023), wages and house prices are force variables for the labor factor flow. If the wage level in city i is higher or the house price level is lower than that in city j, then R&D labor flows in city j will flow to city i under the "utility maximization" theory. According to the gravity model, R&D labor flow is measured as follows:

$$lflo_{ij} = \ln L_i \times ln\left|Wage_j - Wage_i\right| \times ln\left|Hp_j - Hp_i\right| \times R_{ij}^{-2} \tag{13}$$

where $lflo_{ij}$ represents the quantity of R&D labor flow between cities i and j, and L_i represents the number of R&D laborers in city i. Due to the lack of city-level R&D labor data, this study uses the tertiary labor force. $Wage_i$ represents the average wage level of urban employees in city i, and Hp_i represents city i's housing price, measured by the average selling price of residential buildings. R_{ij} is the distance from the center of the city, calculated using ArcGIS. Therefore, the R&D labor flow in a certain year in city i can be expressed as follows:

$$lflo_{it} = \sum_{j=1}^{n} lflo_{ijt} \tag{14}$$

The second mechanism is the industrial structure effect. Upgrading industrial structures can replace extensive production modes with high energy consumption and high pollution with high added value, high income, and low pollution, thereby promoting GTFP. The industrial structure (*stru*), expressed by the proportion of the secondary industry's added value in the cities' GDP, represents the structure effect.

The third mechanism is the learning effect. One of the most straightforward ways to learn from peers with high environmental performance is to enact similar policy documents (Stone, 2001). We used text analysis methods to measure the learning effect of green development. Specifically, we collected several keywords associated with green growth in the local government's official annual government work report, including low carbon, green development, carbon emissions, and energy consumption. Generally, the more frequently these words are used, the greater the importance attached to green development by local governments. Second, we take the maximum value of the green development word frequency in a province as a benchmark and compare it to each city's green development word frequency. This is because each province is viewed as a distinct political market in which mayors or municipal party secretaries compete, learning from the regulatory behavior of their provincial competitors. The smaller the difference, the greater the learning effect, and the more effective it is to learn from your competitors.

$$learning_{jt} = wordfre_{jt} - wordfre_{pjt} \tag{15}$$

3.3.4. Data source

Cities in this study include municipalities and prefectural-level cities. Due to the lack of statistical data, the sample consists of 283 cities, 4 provincial capitals, and 279 prefecture-level cities between 2004 and 2020. The original socioeconomic data were obtained from the China City Statistical Yearbook, China Energy Statistical Yearbook, the annual statistical bulletins of each city, and the CEIC database. The Emissions Database for Global Atmospheric Research (EDGAR) measures carbon emissions for cities. Data on the frequency of policy-related words in city government work reports were manually collected. Green market development index data were obtained from Wang and Wang (2023) in 2023. Interpolation was used to handle missing data in this study, resulting in balanced panel data. All prices in this study are adjusted for inflation using the year 2000 as the base year. The descriptive statistics for each variable are presented in Table 1.

Table 1
Descriptive statistics of variables in 2004–2020.

Variable	Definition	Full sample			Treatment group[a]			Control group		
		Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Independent variable										
GTFP	Green total factor productivity of cities	4811	−0.00	0.06	1252	−0.00	0.05	3079	−0.01	0.06
Dependent variable										
pergdp	Per capita real GDP(Yuan/people)	4811	8450	8604	1252	10008.02	6999.34	3079	6948.20	7691.95
open	Total annual import and export transactions account for GDP(%)	4811	19.73	34.34	1252	30.06	46.53	3079	12.50	19.47
fixed	Fixed-asset investment (10^9 Yuan)	4811	22.74	24.59	1252	24.89	22.30	3079	17.77	16.94
fiscal	Fiscal decentralization, the ratio of urban fiscal expenditure to total fiscal expenditure (%)	4811	0.23	0.08	1252	0.24	0.08	3079	0.21	0.07
density	Population density(100 people/km^2)	4811	4.33	3.45	1252	5.29	3.02	3079	3.74	3.29
urban	Ratio of urban population to the total population(%)	4811	52.08	16.39	1252	55.62	14.76	3079	48.27	15.50
educ	Total number of teachers in regular institutional of higher education, regular secondary schools and primary school(10^3 people)	4811	40.49	33.13	1252	38.51	24.34	3079	36.59	24.28
Mediating variables										
cflo	Mobility of technology capital (see E.q12)	4811	0.12	0.10	1252	0.17	0.13	3079	0.10	0.07
lflo	Mobility of high-skilled labor (see Eq. (14))	4811	0.22	0.15	1252	0.30	0.16	3079	0.18	0.11
stru	Added value of secondary industry/added value of three major industries (%)	4811	0.47	0.11	1252	0.50	0.10	3079	0.46	0.12
learn	Difference in the word frequency of green development	4811	10.46	9.75	1252	10.02	8.93	3079	10.80	10.04

[a] "Treatment group" refers to the non-pilot cities within a certain distance in the in Eq. (10).

4. Results

4.1. GTFP growth

Fig. 3 displays the average trend of GTFP growth for the 283 cities from 2004 to 2020, along with the spatial distribution of GTFP growth for the three LCCP policies' start years. The darker the colour, the higher the level of green development. GTFP growth values above 0 indicate progress, zero indicates GTFP stagnation, whereas values below 0 indicate a decrease in GTFP. Temporally, GTFP growth is generally negative and fluctuates upward, indicating an overall lack of growth over the 17-year period, whereas the extent of negative growth decreased. This result is consistent with the findings of He et al. (2021). Specifically, from 2004 to 2010, there were sharp fluctuations, with decreases

a. Temporal pattern

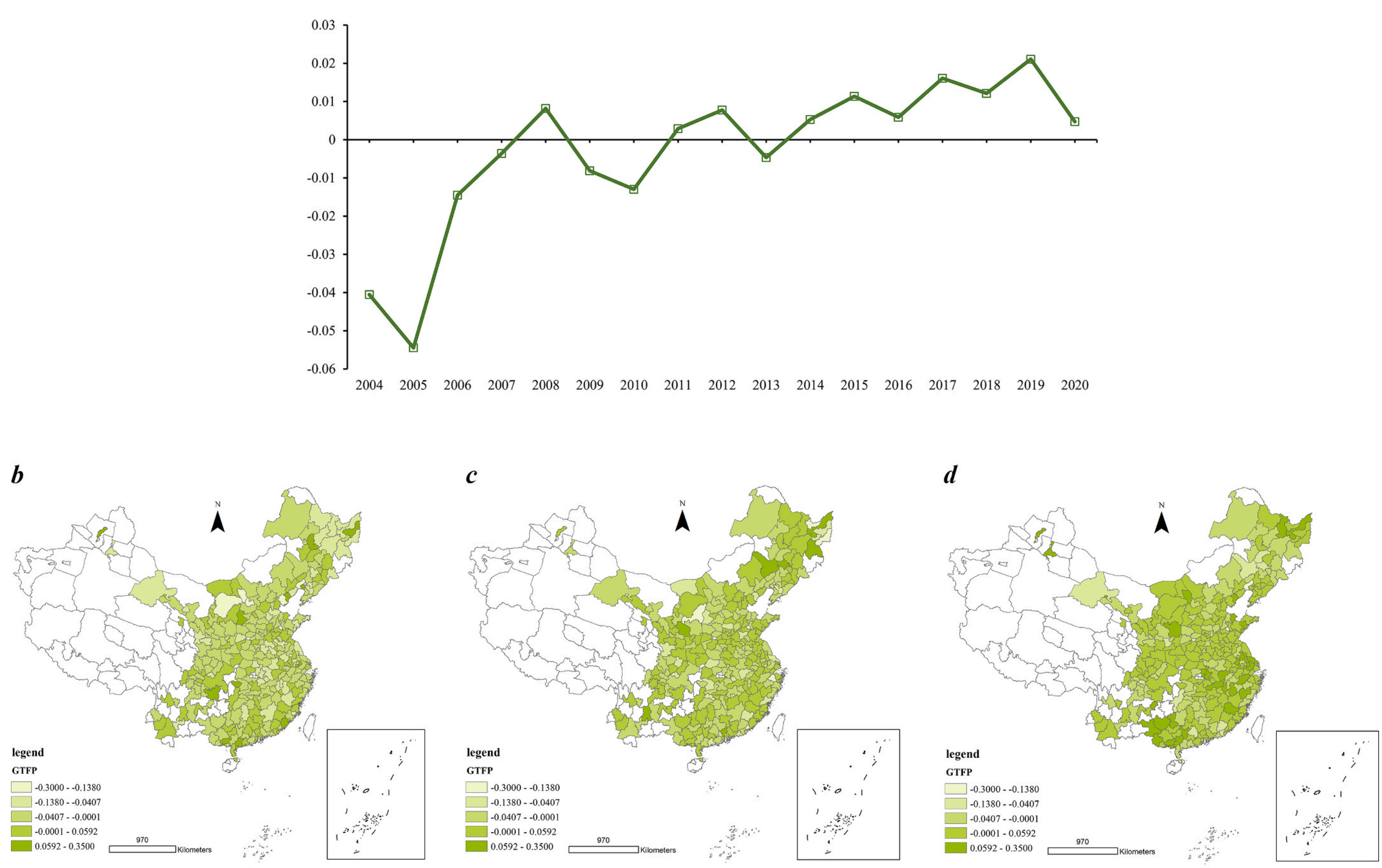

Fig. 3. Spatio-temporal variations of GTFP growth over China from 2004 to 2020.

observed in 2005,2009 and 2010. This occurred due to the long-term extensive development mode and the 2008 global financial crisis when China intensified its investment and increased employment, thus, resulting in inefficient production conditions that did not substantially improve. Notably, the average GTFP growth has increased since 2014, when the LCCP was enacted, particularly in 2017 and 2019.

Furthermore, we conducted a visualization of the pattern of GTFP growth in Chinese cities for three policy years: 2010, 2013, and 2017. Compared to 2010 and 2013, GTFP increased in 2017. The number of cities with GTFP growth above zero rose from 91 in 2010 to 139 in 2013 and 196 in 2017. Notably, the growth trend of GTFP varies from city to city. First, when compared to the eastern region (-0.001), cities in the middle (-0.005), western (-0.002), and northeastern (-0.002) regions experienced lower average GTFP growth over the analysis period. Second, regional differences in GTFP growth has narrowed: in 2010, the average growth gap between the eastern and northeastern regions was 0.025; in 2020, the gap narrowed to 0.012.

4.2. Results for the benchmark model

As mentioned in Section 3.2, we first need to estimate the distance threshold for LCCPs' spillover. Fig. 4 plots the coefficient of δ_s and its 95% confidence interval in Eq. (9). The horizontal axis represents different distance intervals. For example, (50–100] represents the spillover effect of LCCPs on neighboring cities within 50–100 km. As shown in Fig. 4, we found a significantly positive spillover effect of LCCPs within the distance intervals of (0–50] and (50–100], implying that LCCPs can have a positive impact on neighboring cities within 100 km. Therefore, this study uses 100 km as the threshold for studying spillover effects.

Second, we estimated the spillover effect. In Table 2, column (1) reports the results, including only the core *DIDs* variable, and column (2) presents the benchmark regression results. Columns (3)–(5) list the decompositions of the GLPI. The effects of the fixed year and city are controlled for in all columns.

In Columns (1) and (2), the coefficients of DID^s suggest a significant positive correlation between the spillover effect and neighboring non-pilot cities' GTFP growth. On average, neighboring non-pilot cities' green development can benefit from the LCCP policy and gain annual GTFP growth of 1.43%–1.50%, compared to non-pilot cities over a 100-km range, and the results support Hypothesis 1.

Columns (3)–(5) of Table 2 report the results for the three sources of GTFP growth (BPC, PEC and SEC). Columns (4) show that the LCCP policy has a positive impact on the PEC index. In other words, the LCCP contributed to the GTFP growth of nearby (within 100 km) non-pilot cities through the efficiency catch-up effect. However, there was no

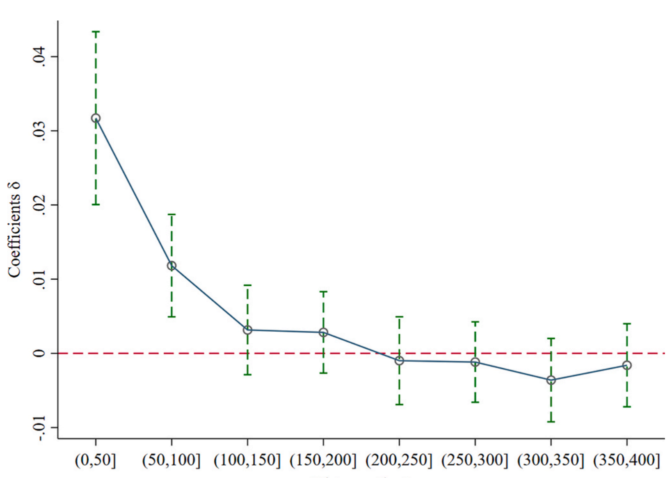

Fig. 4. Spatial scope of policy spillovers from LCCPs.

Table 2
Regression results.

	(1)	(2)	(3)	(4)	(5)
	GTFP growth	GTFP growth	BPC	PEC	SEC
DID^s	0.0150***	0.0143***	0.0018	0.0085*	-0.0023
	(0.0042)	(0.0042)	(0.0039)	(0.0051)	(0.0027)
lnpergdp		0.0519***	-0.0253***	0.0646***	0.0227
		(0.0172)	(0.0087)	(0.0134)	(0.0163)
open		-0.0002**	-0.0000	-0.0001	-0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
lnfixed		-0.0232***	0.0081***	-0.0269***	-0.0031
		(0.0038)	(0.0031)	(0.0046)	(0.0046)
fiscal		0.0622	0.0170	-0.0279	0.0946*
		(0.0458)	(0.0351)	(0.0535)	(0.0495)
density		0.0056***	-0.0022**	0.0079***	0.0011
		(0.0014)	(0.0011)	(0.0020)	(0.0013)
urban		0.0002	0.0006**	-0.0002	−0.0002
		(0.0003)	(0.0002)	(0.0003)	(0.0002)
lneduc		0.0165**	0.0109	0.0159**	-0.0095
		(0.0068)	(0.0089)	(0.0078)	(0.0113)
_cons	−0.0228***	-0.4520***	0.0071	-0.4929***	-0.0858
	(0.0004)	(0.1581)	(0.1199)	(0.1418)	(0.1728)
N	4331	4331	4331	4331	4331
R^2	0.164	0.185	0.244	0.071	0.050

Note: *, **, and *** are significant at the levels of 10%, 5%, and 1%, respectively.

statistically significant relationship between the treatment group's LCCP and BPC index and SEC index. This indicates that the LCCP policy does not contribute to GTFP growth by shifting frontier and optimizing the production scale of neighboring non-pilot cities.

Cities' socioeconomic characteristics also influence GTFP growth. In column (2), "pergdp" helps cities improve their green productivity, which aligns with theoretical expectations. "open" is statistically significant and negative, and a unit increase in trade can cause a 0.02% decrease in cities' GTFP growth, verifying the pollution haven hypothesis. However, "fixed" is not conducive to cities' GTFP growth; a unit increase in fixed investment can cause a 2.32% decrease in GTFP growth. This is partly because investments in economic development crowd out investments in environmental governance, thereby not contributing to green development (Bovenberg and Smulders, 1996). As for "density," the coefficient is positive at the 1% significance level, proving that scale effects of the population are beneficial to the increase in GTFP. In addition, a larger population may stimulate economic activities, thus increasing the GTFP growth. The education benefits GTFP growth as it reflects the quality of cities' human capital, and higher education tends to be high-tech in the development mode. The coefficients of the remaining control variables are not significant, indicating that these variables are not the core elements affecting the GTFP in this sample. The results shown in the study have used clustered standard errors in all regressions.

4.3. Robust test

4.3.1. Parallel trend

An essential precondition for consistently estimating the DID model is that the GTFP growth in the treatment and control groups would have similar time trends before the spillover shock. In other words, if a parallel trend holds, the coefficients of β_k are insignificant before a spillover shock. Following Beck et al. (2010) and Wang (2013), we estimate the dynamics of spillover effects as follows:

$$GTFP_{jt} = \beta_0 + \sum_{k=-5}^{k=+5} \beta_k Treat_j \times Time_{t_0+k} + \gamma ZX_{j,t} + \mu_j + \lambda_t + \varepsilon_{j,t} \tag{16}$$

where $Time_{t0+k}$ is a series of dummy variables that take the value 1 when the year equals t_0+k; otherwise, it takes the value 0. t_0 represents the spillover year for each city (i.e., 2010 for the first spillover year and 2013 for the second spillover year). In the benchmark models, $Treat_i$ equals 1 if the city is included in the treatment group and 0 otherwise. Z_{it} is the control variable. μ_j is the city fixed effect, λ_t is the year effect, and ε_{it} is the error term. Fig. 5 shows the results at 95% confidence intervals. First, it demonstrates no systematic difference between the pre-trends of treated and untreated cities. This is in line with the expectation that policy spillover coefficients are not significantly different from zero in the five years prior to the pilot. Second, the spillover effect remained positive and significant three years after the pilot year. One possible explanation is that the spillover effect of LCCP is dependent on how responsive non-pilot cities are.

4.3.2. Placebo test

Pan et al. (2022) conducted a robustness test using a counterfactual method. It involved randomly specifying a group of false treatment groups in the 283 sample cities and selecting the spillover year for these cities to obtain a fictitious DID variable. This process was repeated 1000 times, with 69 cities randomly selected each time as the treatment group, resulting in 1000 simulated spillover effects. If the simulated effects are not clustered around zero and its nearby intervals, the results may be influenced by unobserved factors (JG Slusky, 2017). Fig. 6 displays the kernel density of false coefficient β_1 and the distribution of the p-values. It reveals that 95.8% of the confidence intervals for false spillover effects contain zero, indicating weaker significance (90.7% of the p-values are over 0.1). There is a significant difference between the false spillover effects and the real spillover effects of LCCPs (red vertical line). Consequently, the empirical results of this study are unlikely to have been affected by random factors.

4.3.3. PSM-DID

Pilot cities may be selected based on economic factors such as their level of development and industrial base. To address sample selection bias, a propensity score matching DID (PSM-DID) method is employed to re-evaluate the regression results presented in Eq. (10). It aims to reduce sample selection bias (Heckman et al., 1997) by matching treatment cities with control cities possessing similar characteristics based on observable factors. Logit regression calculates the propensity matching scores for cities using covariates such as the lnpergdp, open, fixed, fiscal, density, urban, and lneduc covariates. The control group is formed by employing various methods, including conducting radius within a caliper equal to 0.05, nearest-neighbor (1:1) matching, kernel matching, and local linear regression matching to minimize the mean square error. After matching, the study's balance criteria are met as a standardized percentage bias of less than 10% is observed in the control variables. Furthermore, in Table 3, the coefficients of explanatory variables for the DID^s are consistently positive and significant at the 5% level, even after controlling for exogenous variables, which supports the baseline regression results.

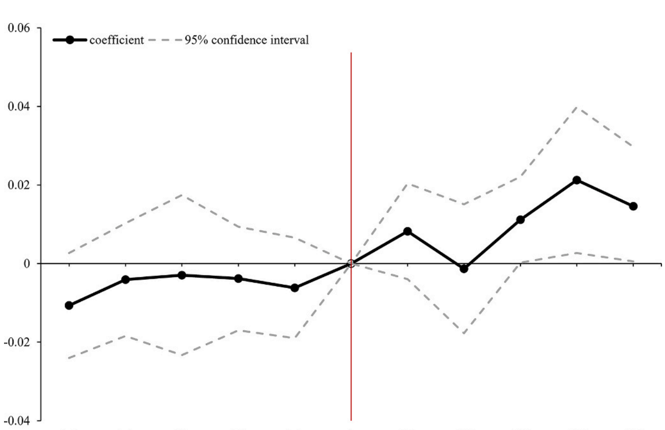

Fig. 5. Parallel trend test of the spillover effect.

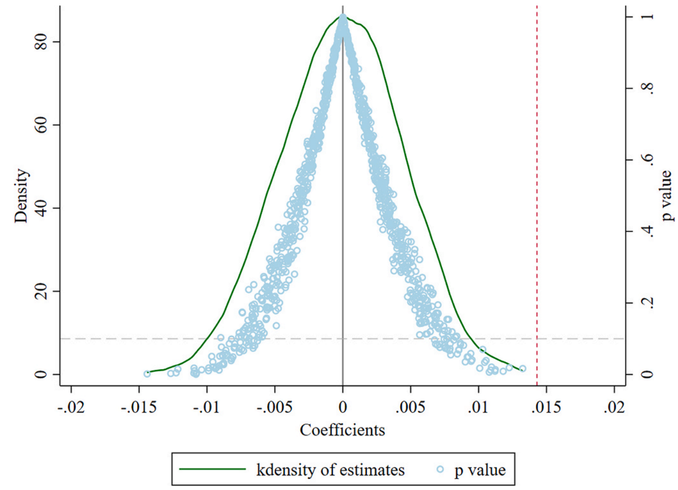

Fig. 6. Placebo test.
Notes: According to Eq. (10), the coefficients and p-values of the average treatment effects were plotted. The average treatment effect and p-value of the simulation are represented on the two axes. The kernel density of this estimate is indicated in green line. Blue dots represent the simulation p-values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Robust test results of PSM-DID.

	(1) radius	(2) nearest-neighbor	(3) kernel	(4) local linear
DID^s	0.0163**	0.0211***	0.0204***	0.0162***
	(0.0062)	(0.0055)	(0.0058)	(0.0059)
Control	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
City effect	Yes	Yes	Yes	Yes
R^2	0.1997	0.2186	0.2057	0.2050
N	1700	2176	1870	2278

Note: (1), (2), (3), and (4) report the results of the radius, nearest-neighbor, kernel, and local linear regression matching methods, respectively. *, **, and *** are significant at the levels of 10%, 5%, and 1%, respectively.

4.3.4. Considering other factors

(1) Interference from other pilot cities

It is important to exclude the effects of other policies during the same period, such as the Smart City Pilot in 2012 and the Ecological Civilization Cities Pilot in 2013 (Cheng et al., 2022). To control for the effects of these two policies at the city level, we have developed additional interaction terms for these two policies. The estimated coefficient for β_1 is still significantly positive, while the coefficients for the Smart City Pilot and the Ecological Civilization Cities Pilot are insignificant, as shown in Columns (1) and (2) of Table 4. This indicates that the two pilots do not affect our results.

(2) Policies' effects at the province level

The baseline model incorporates a province-year fixed effect to further control for any potential factors and eliminates all possible province-level policy shocks during the same period. Column (3) in Table 4 indicates that coefficient of β_1 remains positive and statistically significant.

Table 4
Other robust test results.

	Smart city	ecological city	Province-year fixed effect	Drop pilot city	SDID model
DID^s	0.0145*** (0.0041)	0.0149*** (0.0041)	0.0155*** (0.0043)	0.0159*** (0.0044)	
DID^{smart}	0.0044 (0.0035)				
$DID^{ecological}$		-0.0006 (0.0039)			
α					-0.0058 (0.0036)
ρ_1					0.1161*** (0.0289)
ρ_2					0.0185** (0.0094)
Wald test for SAR					3.87**
Wald test for SEM					3.59*
LR test for SAR					17.14**
LR test for SEM					16.02**
Province-year fixed effect			Yes		
Observation	4331	4331	4275	3655	4811
R^2	0.175	0.175	0.326	0.179	0.008
Control	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** are significant at the levels of 10%, 5%, and 1%, respectively.

(3) Exclude pilot cities

Pilot cities are also included in the benchmark measurement. In other words, the spillover effects of LCCPs in the benchmark results were captured when pilot cities did not participate in the pilot projects. Once a city joined the pilot, the related data were deleted from the sample because they were not in the treatment or control groups. For example, Beijing, China's capital, was not part of the second batch of LCCPs, but it was affected by spillovers from Tianjin, the pilot city of the first batch. As Beijing became a second-batch pilot city for the LCCP after 2013, the related data from Beijing were deleted from our sample. Column (4) of Table 4 excludes pilot cities from the sample to mitigate the impacts on pilot cities. The results still demonstrate that LCCPs significantly influence neighboring GTFP growth.

The results still demonstrate that LCCPs significantly influence neighboring GTFP growth.

(4) Spatial-DID model

In this study, the Spatial-DID model was constructed based on the spatial Durbin model (SDM) as outlined by LeSage and Pace (2008):

$$GTFP_{it} = \alpha_0 + \rho_1 \sum_{j=1}^{n} W_{ij} GTFP_{jt} + \alpha_1 DID_{it} + \rho_2 \sum_{j=1}^{n} W_{ij} DID_{jt} + Z_{it}\alpha_2 + \sum_{j=1}^{n} W_{ij} Z_{jt} \rho_3 + \mu_j + v_t + \varepsilon_{jt} \quad (17)$$

Where W_{ij} is the row-standardized spatial weight matrix, α_1 and ρ_2 captures the direct and spillover effects, respectively. $\sum_{j=1}^{n} W_{ij} GTFP_{jt}$ is the interpreted variables' spatial lagged term, and ρ_1 is the spatial autoregressive coefficient. Eq. (17) also considers the control variables and their spatially lagged term. μ_i and v_t represent spatial and time fixed effects, respectively. ε_{it} is the random error term.

The results of Wald test and LR test are all significant at the level of 10%, indicating that the SDM is more suitable. The coefficient of the spatial lag term $W \times GTFP$ (ρ_1) in Table 4 is significantly greater than 0, indicating that green development still has a strong spatial correlation even when controlling for other factors. Meanwhile, the coefficient of spatial explanatory variable (ρ_2) is positive at the level of 5% significance level, confirming the spillover effect in our base model. However, the coefficient of direct effect did is not significant which is exceeded our expectations.

(5) Staggered DID model

The LCCPs were implemented in three batches in 2010, 2013, and 2017. Their goals differed, indicating that LCCPs had varying impacts over time. Considering that the two-way fixed effects estimation cannot distinguish heterogeneous effects across different periods, the staggered DID model is adopted to demonstrate the robustness of the benchmark model(Hou et al., 2023; Wang et al., 2023b). This method controls for decomposable time-varying confounders in a panel data setting and reduces the estimation errors caused by heterogeneous treatment effects by including interaction fixed effects. The F-test indicates that the matrix completion estimator method is preferable to the fixed-effects counterfactual and interactive fixed effects counterfactual methods. Fig. 7 shows that the LCCP spillover effect worked for three years after the pilot, confirming the robustness of the benchmark model.

(6) other intervals

To justify the choice of the '50 km' interval, we consider the '100 km' interval and test whether the policy (0, 100], (100, 200], (200, 300], (300, 400] appears robust to spillover effects. Fig. 8 shows the study results, where policy spillovers are significantly positively correlated with GTFP growth in non-pilot cities within 100 km, but not beyond 100 km. The results are consistent with those for the 50-km interval. The statistical analysis also confirms the validity of the 100 km' threshold identified in the first step of the empirical study.

5. Discussion

5.1. Mechanism analysis

To determine how the LCCP policy can impact the GTFP growth of neighboring non-pilot cities, this study constructs the following model to identify the mechanisms outlined in the research hypothesis:

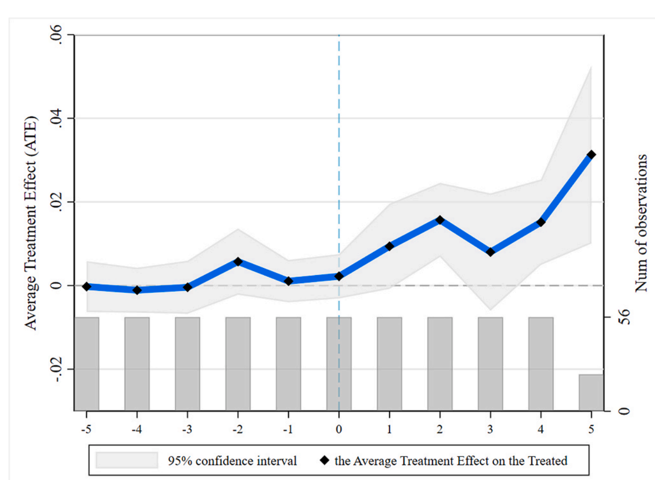

Fig. 7. Estimated results of staggered DID model.

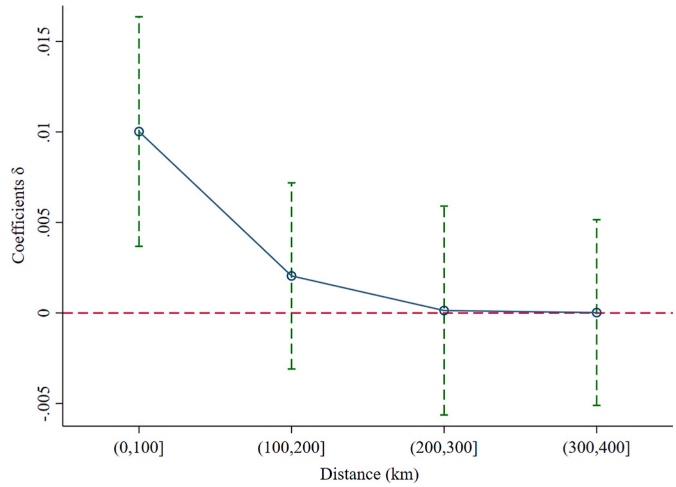

Fig. 8. Robust test of 100- kilometres intervals.

$$M_{jt} = \alpha_2 + \beta_2 DID_{jt} + \gamma Z_{jt} + \mu_j + \nu_t + \varepsilon_{jt} \tag{18}$$

$$GTFP_{jt} = \alpha_3 + \eta M_{jt} + \beta_3 DID^s_{jt} + \gamma_1 Z_{jt} + \mu_j + \nu_t + \varepsilon_{jt} \tag{19}$$

where M_{jt} represents three mediation variables. This study considers the three mechanistic variables mentioned in Section 2.2: innovation, structural, and learning effects. The remaining variables are consistent with those in Eq. (10).

Fig. 9 shows a schematic of this mechanism. Fig. 9a shows that the spillover's impact on the R&D capital flow is 0.0412 at the 1% significance level, indicating that the development of LCCPs is associated with an increased spatial flow of capital factors in neighboring non-pilot cities and thus facilitates their GTFP. This is partly because the collaborative innovation and regional radiation effects optimize the allocation of high-tech capital resources and enhance the GTFP of the element flow region (Fang et al., 2022; Zhao et al., 2022). In addition, based on Eqs. (18) and (19), the capital flow effect on GTFP is marginally $\beta_2*\eta$, which is 0.0013(0.0412*0.0313). This explains 9.02% (0.0013/0.0143) of the spillover's total effect. For example, in 2024, Mang City's mayor led a team to Suzhou City, a LCCP pilot city in Jiangsu Province. In order to attract green investment and high-knowledge talent, the mayor invited low-carbon companies to invest in Mang City and expand its cooperation capabilities. Regarding the R&D labor flow effect, Figure Fig. 9b shows no significant difference between the spillover effect of LCCPs and the labor flow in neighboring cities. In other words, LCCP carbon regulation has not led to a significant reallocation of talented labor. Compared with capital mobility, R&D labor flow is a longer-term process that incorporates more social factors, such as wages, house prices, education levels, and labor market demand. Additionally, R&D talent tends to move more frequently to low-carbon cities than non-pilot cities because of their vibrant economies and employment opportunities (Dou and Cui, 2017). Nevertheless, we can also observe that local labor flow can promote GTFP growth ($\eta = 0.0608$, p-value$\leq$0.05), which can explain 1.40% ((0.0143–0.0141)/0.0143) of GTFP growth.

In fact, in the transfer of innovation factors, the market factors play a leading role, while governments act as catalysts, appropriately guiding the innovation flow through low-carbon policies. On one hand, innovation theory suggests that markets demand higher returns on capital, which forces cities to invest in riskier projects in order to obtain capital from the capital market. In the low-carbon city pilot program, some financial instruments have been deployed such as green financial subsidies and green credit to provide external financial support for green development. Some pilot cities combine with the regional economic development strategy, making the policy more effective by reallocating resources, and expanding the scope of policy influence. Therefore, non-pilot cities with financial constraints in innovation can access external financial support, easing the financial pressure and thus promoting innovation(Zhu and Lee, 2022). Carbon market trading is one such example. On the other hand, in construction of low-carbon cities, the market requires more high-skilled and high-knowledge staff (Hao et al., 2021). Meanwhile, with the liberalization of national household registration systems and the development of regional integration and

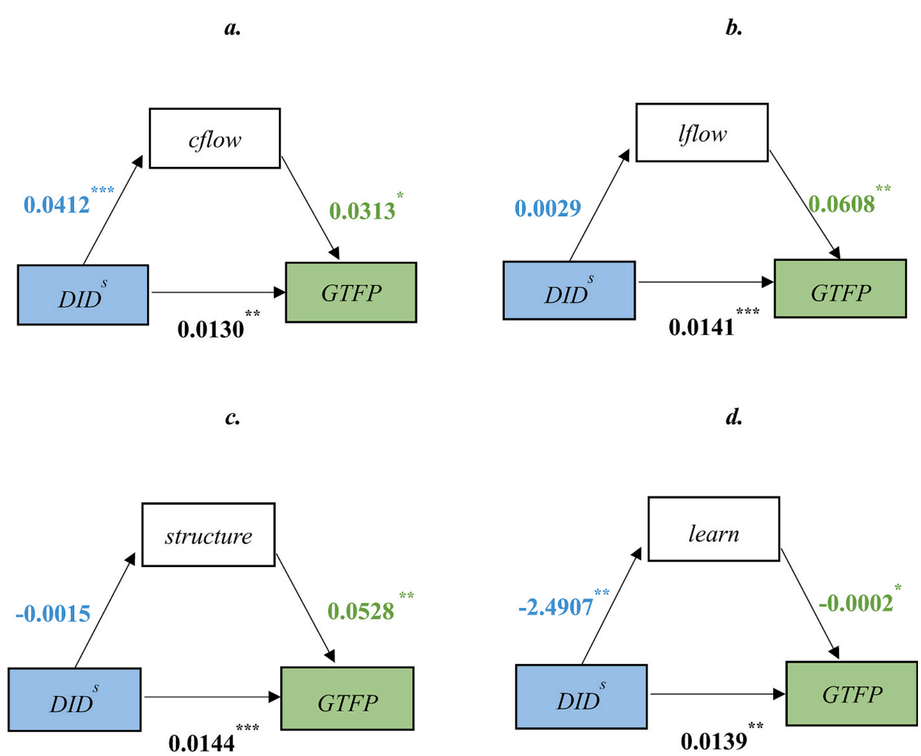

Fig. 9. Mechanism analysis a) R&D capital flow; b) R&D labor flow; c) structural effect; d) learning effect.

digitalization, R&D staff are becoming increasingly able to move across administrative barriers and achieve cross-regional mobility, which has a positive impact on non-pilot regions as well.

No significant structure effects were observed in the GTFP growth of the surrounding non-pilot cities. A possible explanation might be that LCCPs cannot adjust the mature and consolidated industrial structure systems of non-pilot cities. Moreover, LCCPs emphasized a shift from extensive development to low-carbon, intensive development, and the decarbonization of the secondary sector did not result in a decline in output.

Finally, a spillover effect can also arise from the learning effect and peer imitation behavior. Fig. 9d presents the results of the learning effect. Firstly, the spillover effect of LCCPs on learning is -2.4907(p-value≤0.05), indicating that LCCPs can reduce the gap in policy-making between neighboring non-pilot cities and pioneers within the same province. In other words, a spillover effect can occur through learning from and imitating peers with stringent environmental governance in their province. Secondly, *learning* and GTFP growth are negatively correlated (η = -0.0002, p-value≤0.1), implying that the more they can learn from each other's experiences, the smaller the gap in policy-making becomes, improving GTFP growth. Some researchers confirmed that learning mechanisms strengthen the interaction between local governments in urban environmental regulation and can improve environmental performance, which is consistent with our findings (Li et al., 2022; Xu et al., 2022). Generally, the learning effect amounts to 3.48% of the total spillover effect.

For example, in 2023, officials from Dongguan City, a non-pilot city, visited Shenzhen's Green and Low Carbon Industry Expo. By studying low-carbon product and technology applications, carbon-neutral integrated policy solutions, and international green technologies and innovations, more innovative demonstrations will be learnt by non-pilot cities and applied to municipal offices and policy-making.

5.2. Heterogeneous analysis

LCCPs may have varying impacts on different cities (Chen and Wang, 2022), and certain city characteristics may determine their roles in surrounding cities. This section primarily analyzes the heterogeneity in region, city scale, and resource endowment dimensions, see Eq. (20).

$$GTFP_{jt} = \alpha_1 + \beta_1 DID^s_{jt} \times Character_{jt} + \gamma Z_{jt} + \mu_j + \nu_t + \varepsilon_{jt} \tag{20}$$

First, there are 27 pilot cities in the eastern, 18 in the central, 20 in the western, and 4 in the northeastern regions, respectively. In other words, the spatial distribution of pilot cities was uneven. Studies have demonstrated that the location of pilot programs directly affects the success of reforms (Heilmann, 2008; Wang and Yang, 2021). This paper divides cities into four groups to explore regional spillover impacts. Fig. 10a illustrates the results of the heterogeneous tests across different regions. The results reveal that LCCPs only influence GTFP change in neighboring non-pilot cities in the eastern and middle regions, with a more pronounced effect in the eastern area (2.06%) than in the middle region (1.01%). However, the policy coefficients are insignificant, implying no spillover impact on the western and northeastern non-pilot cities. The difference between east-middle, east-west, east-northeast and middle- northeast was significant statistically. The above results due to the following reasons: cities in the eastern and central regions have stronger economic foundations and development visions in promoting low carbon development and optimizing energy structure. They are more adept at recognizing and absorbing advanced practices. However, cities in western and northeastern regions, tend to focus on economic growth, and authorities are less likely to promote low-carbon development. Moreover, the result provides new guidelines for policy implementation in the western and northeastern regions, which should pay attention to the pilot site selection and increase policy promotion efforts.

Second, following Yao et al. (2020), we categorized city scales based on population size: those with less than 1 million residents as small cities, those with more than 5 million as large cities, and the rest as medium-sized cities. Fig. 10b displays the regression results. It appears that LCCP promotes GTFP growth in neighboring cities, in both large and medium-sized cities, while it works reversely in small-sized cities. There are significant differences between small-medium group and between small-large group. The reason may be that large-sized cities typically serve as the region's central hubs, and have better ICT infrastructure, more intensive linkages of economic activities, a higher level of resource allocation efficiency, making policy-making more responsive. Moreover, the larger cities tend to have more competitive markets, making it easier to regulate enterprises and enforce stricter policies. As a result of controlling total CO2 emission control, large cities may shift high-carbon industries to smaller cities, making it challenging for smaller cities to optimize the industrial structures. However, in small-sized cities, urban development is relatively backward. There may

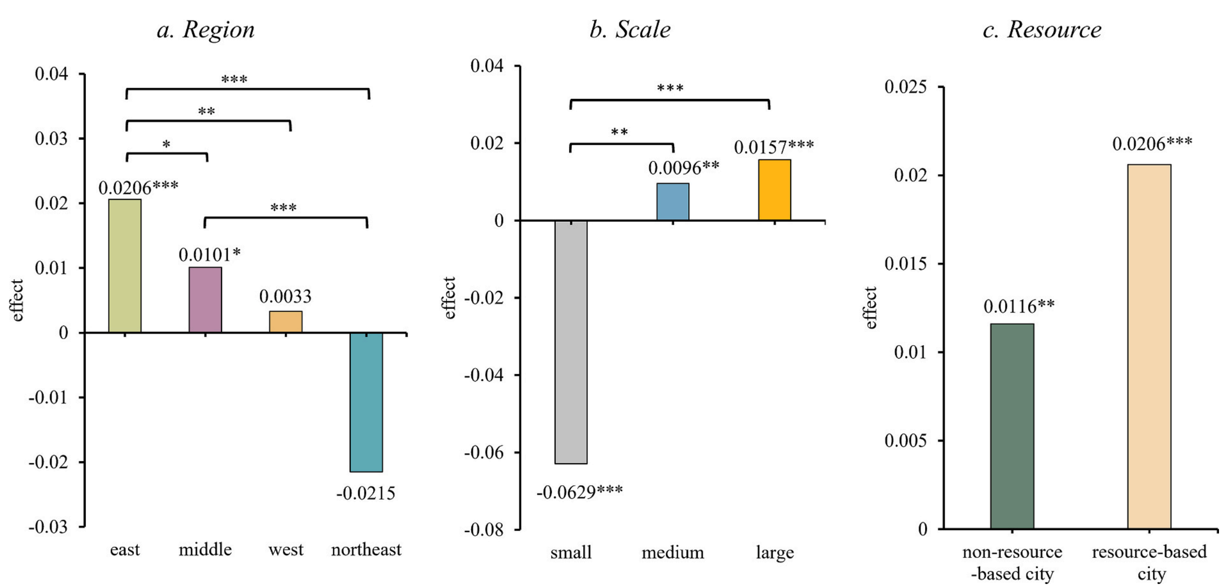

Fig. 10. Heterogeneity analysis results of spillover effect.
Note: The height of the histogram shows the mean of spillover effect coefficients. The black thick line indicates the between-group variance. The asterisks indicate the significance degree of the coefficients (***P < 0.010, **P < 0.050, *P < 0.100).

be problems such as insufficient capital investment, low administrative efficiency, and imperfect infrastructure. As a result, the spillover effect is negative. Accordingly, when implementing the low-carbon city pilot policy, we should emphasize demonstrations in small-sized cities.

Given that the policy effects of LCCP may be influenced by resource endowment, we investigated the response of GTFP growth to policy spillovers from LCCPs in cities with varying levels of resource dependence. According to the National Sustainable Development Plan for Resource-Based Cities (2013–2020), 115 prefecture-level cities are considered resource-based cities. Fig. 10c presents the regression results based on the urban resource endowment. At the 1% significance level, both resource-based cities and non-resource-based cities have benefited from the spillover effects of the LCCP policy. And there was no evidence of significant differences between two groups.

6. Conclusion and policy implications

This study evaluates the spillover effects of LCCPs on the green development of neighboring non-pilot cities. Using a panel dataset of 283 Chinese cities from 2004 to 2020, this study examines the spillover effect and potential mechanisms of the LCCP in non-pilot cities that border pilot cities. Robust tests are conducted to ensure the validity of the benchmark results.

Our main conclusions are as follows. Firstly, implementing LCCPs can have a positive impact on GTFP growth; specifically, cities within 100 km of low-carbon pilot cities experienced a growth of 0.0143 in their GTFP. Secondly, LCCPs affect neighboring non-pilot cities' GTFP growth through two economic mechanisms: the innovation effect and policy-learning effect. Thirdly, heterogeneous influences are significant on GTFP growth; the spillover effect is more pronounced in eastern, middle, and large-sized cities.

We propose the following recommendations in light of the above findings. Firstly, the spillover effect or spatial correlation should be considered for overall policy evaluation and decision-making. In this study, the impact of the LCCP policy is not underestimated if the spillover effect is considered, thus enhancing the efficient allocation of political resources. Despite the importance of studying the direct effects in pilot cities, studies in non-pilot cities can provide practical insights into policy revisions. As the pilot program aims to explore replicable and practical development approaches, non-pilot cities do not have a competitive advantage in terms of their economic base, market mechanisms, or financial support, making reform diffusion more challenging. Spillovers enable us to anticipate broad policy effects. Therefore, in addition to incorporating the economic conditions and layouts of the pilot cities as described in LCCPs, the externalities of policy effects, such as spillover range, direction, and impact should also be considered in scientific research and policymaking. Secondly, a more equitable and differentiated strategy should be adopted for selecting the pilot cities. According to this study, the spillover effects vary significantly among cities in terms of region, and scale. This study provides a new perspective for site selection. It is important to consider interregional equity when selecting sites. For example, the numbers of pilot cities in the four regions were 27, 18, 20, and 4, representing 30.68%, 22.5%, 21.05%, and 11.76% of the total number of cities in the eastern, middle, western, and northeastern regions, respectively. The pilot cities were less densely distributed in the western and northeastern regions, which may account for the lack of apparent spillover effects. Therefore, more political resources should be directed towards these regions. This problem is also prevalent in small cities. Thirdly, this study finds compelling evidence that the policy pilot significantly improves the GTFP of neighboring non-pilot cities through the innovation (technology capital flow and talented labor flow) and learning effects. Interregional innovation factor flows (R&D capital and labor factors) have significant spatial innovation effects. Therefore, breaking down regional barriers from pilot cities to non-pilot cities is suggested to promote the flow of innovation factors. For example, a more flexible hiring mechanism (part-time work across regions) could be adopted to strengthen high-tech talent sharing. Enhancing green financial systems, such as interregional green lending and bonds, is also encouraged. Fourthly, with the hypothesis of spillover effect in this study, we are able to provide countries with similar political systems to China with new ideas for policy pilot. Furthermore, the spatial correlation between cities or regions allows other countries to take into account more complex relationships in emission reduction, particularly the scope and direction of this spatial correlation also determines whether an emission reduction on a broader scale is successful or not.

Although this study contributes to examine the spillover effect of China's LCCP both theoretically and practically, the limitations of the study and potential avenues for future research should be acknowledged. Firstly, by 2020, as the successful pilots are gradually replicated nationwide along with other related policies, such as the COVID-19 pandemic, the scope and magnitude of average policy spillovers require further research. Secondly, future research should analyze the transmission of the mechanism of the spillover effect more thoroughly than the mechanism described in this paper. Thirdly, the detailed assessment of the city's low carbon practices using a case study approach is needed.

CRediT authorship contribution statement

Bei Zhu: Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Tomoaki Nakaishi:** Writing – review & editing, Writing – original draft, Funding acquisition, Data curation, Conceptualization. **Shigemi Kagawa:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

A. List of Low-carbon City Pilot Programs

The first batch of low-carbon pilot regions: Guangdong Province, Liaoning Province, Hubei Province, Shaanxi Province, Yunnan Province and Tianjin Municipality, Chongqing Municipality, Shenzhen City, Xiamen City, Hangzhou City, Nanchang City, Guiyang City and Baoding City.

The second batch of low-carbon pilot areas: Hainan Province, Beijing Municipality, Shanghai Municipality, and Shijiazhuang City, Qinhuangdao City, Jincheng City, Hulunbeier City, Jilin City, Daxinganling region, Suzhou City, Huaian City, Zhenjiang City, Ningbo City, Wenzhou City, Chizhou City, Nanping City, Jingdezhen City, Ganzhou City, Qingdao City, Jiyuan County-level City, Wuhan City, Guangzhou City, Guilin City, Guangyuan City, Zunyi City, Kunming City, Yan'an City, Jinchang City, Urumqi City.

The third batch of low-carbon pilot areas: Wuhai City, Shenyang City, Dalian City, Chaoyang City, Sunken County, Nanjing City, Changzhou City, Jiaxing City, Jinhua City, Quzhou City, Hefei City, Huaibei City, Huangshan City, Lu'an City, Xuancheng City, Sanming City, Gongqingcheng County-level City, Ji'an City, Fuzhou City, Jinan City, Yantai City, Weifang City, Changyang Tujia Autonomous County, Changsha City, Zhuzhou City, Xiangtan City, Chenzhou City, Zhongshan City, Liuzhou City, Sanya City, Qiongzhong Li and Miao Autonomous County, Chengdu City, Yuxi City, Pu'er City, Lhasa City, Ankang City, Lanzhou City, Dunhuang County-level City, Xining City, Yinchuan City, Wuzhong City, Changji County-level City, Yining County-level City, Hotan County-level City, and Aral City of the First Division.

B. Figure

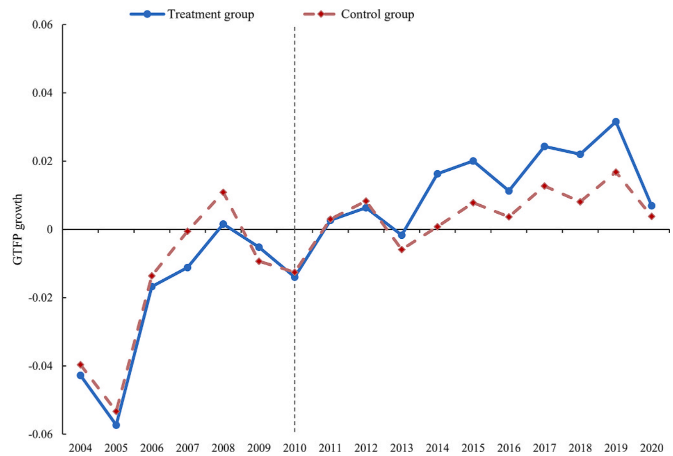

Fig. B1. Temporal pattern of GTFP growth (Treatment group vs. Control group)

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