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RESEARCH ARTICLE

The impact of low-carbon city pilot policy on green total-factor productivity in China's cities

Ke-Liang Wang[1] · Jin Li[1] · Ru-Yu Xu[1] · Su-Qin Pang[1] · Zhuang Miao[2] · Hua-Ping Sun[3]

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Abstract
Whether the low-carbon city construction can coordinate urban economy and environment has attracted increasing attention in recent years. In this study, the impact of low-carbon city pilot (LCCP) policy on urban green total-factor productivity is systematically examined theoretically and empirically. Specifically, the biennial Malmquist-Luenberger (BML) index is adopted to measure urban green productivity. Then, propensity score matching-difference-in-differences (PSM-DID) and spatial DID model are used to quantitatively identify the local and spatial spillover effect of the LCCP policy on urban green productivity during 2004–2018 in China. The results show that (1) The LCCP policy can significantly promote urban green productivity, as confirmed through a series of robustness tests. (2) For transmission mechanism, the LCCP policy can enhance urban green productivity through energy consumption reduction and technological innovation but not through industrial structure optimization. (3) With regard to heterogeneity, cities with better transportation infrastructure, stricter environmental regulation and higher urbanization level, as well as non-resource-based cities have more significantly positive effects of the LCCP policy on urban green productivity. (4) The LCCP policy mainly relies on technological progress rather than technical efficiency improvement to drive urban green productivity. (5) The LCCP policy's effect on urban green productivity has significant positive spatial spillover feature, which can significantly promote green productivity in both pilot cities and their neighboring cities. Our findings can provide valuable insights for low-carbon city construction to promote urban sustainable development in China.

Keywords The low-carbon city pilot policy · Green total-factor productivity · Difference-in-differences · Heterogeneity

Introduction

Global climate change caused by the excessive emissions of greenhouse gases with carbon dioxide as its main source has seriously damaged the natural ecological system, and then threatened the human survival and development (Chen et al. 2019; Li et al. 2018; Shen et al. 2018). It has led to a series of negative effects and natural catastrophes, including the reduction of biological species, the extreme weather changes, sea-level rise, and other various global problems, posing a major threat to the ecological environment (Liu et al. 2019; Wang et al. 2022; Wu et al. 2021). How to take effective measures to mitigate global climate warming has become a major issue of widespread concern all over the world. China, as the largest populous developing country, its fossil energy consumption and carbon emissions have increased sharply due to the rapid industrialization and urbanization in the past few decades since 1978. In 2006, China has surpassed the USA to become the world's largest carbon emitter. In 2019, China's total carbon emissions reached 9.876 billion tons, accounting for approximately 30% of the world's total (Cheng and Jin 2020). This makes China face unprecedented pressure in carbon emission mitigation from international community.

To address global warming, China has formulated a variety of ambitious carbon mitigation plans and achieved

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✉ Ke-Liang Wang
klwang@163.com

1 School of Economics, Ocean University of China, Qingdao 266011, Shandong, China

2 China Western Economic Research Center, Southwestern University of Finance and Economics, Chengdu 611130, Sichuan, China

3 School of Finance and Economics, Jiangsu University, Zhenjiang 212013, Jiangsu, China

remarkable results in recent years (Song et al. 2021; Wang et al. 2018; Wang et al. 2021a, b). At the 2009 Copenhagen climate change conference, China promised to reduce carbon intensity by 40–45% compared to the level in 2005 by 2020. At the 2015 Paris climate change conference, it further committed to achieve the target of reducing carbon intensity by 60–5% during 2005–2030, and pledged to peak its total carbon emission before 2030. Furthermore, in 2020, China issued its first long-term target that it would realize carbon neutrality by 2060. In this context, how to transition to a green and low-carbon economy has become an arduous challenge facing China at present and for a long time in the future (Fu et al. 2021; Shen et al. 2018; Zhou et al. 2015a).

Cities, as the centers of population, industry, transport and infrastructure, are not only the main participants in driving economic development, but also the principal source causing eco-environment problems (Liu et al. 2019; Yang and Li 2013; Yu and Zhang 2021). Statistics show that cities account for about 75% of the world's energy consumption and 80% of greenhouse gases emissions (Khanna et al. 2014). Therefore, cities have become the forefront of efforts to mitigate carbon emission, playing increasingly critical role in addressing global climate change (Liu and Qin 2016; Wang et al. 2019, 2020). In regard to China, with the accelerating urbanization in the last few decades, the proportion of its urban residents in the total population has increased from 20.16% in 1981 to 59.58% in 2018. Such rapid urbanization characterized by large amounts of resource usages and pollution emissions makes China's resources and environmental problems increasingly severe. In 2018, China's 338 cities consumed 85% energy, 39.2% domestic water, 60% electricity and emitted 75% carbon emissions, and 57 of the world's 100 most polluted cities came from China (Qiu et al., 2021).

Facing the challenges brought about by rapid urbanization, the Chinese government announced three batches of LCCP programs in 2010, 2012, and 2017, so as to vigorously promote cities' low-carbon transformation and development. The target of LCCP policy in China is multidimensional, which not only includes reducing carbon emissions, but also contains ensuring urban economic sustained growth and improving resident's life quality (Tian et al. 2021). Numerous studies have confirmed that the promotion of green economic growth, i.e., green total factor productivity, is a critically vital pathway to realize the multiple targets of LCCP policy (Chen et al. 2021; Cheng et al. 2019; Qiu et al. 2021). Consistent with the core concept of low-carbon city, green total-factor productivity aims to maximize economic benefits while minimizing resource usage and pollution emission given the required input factors. Hence, it is considered a scientific tool to comprehensively evaluate the performance of low-carbon city construction (Cheng et al. 2019; Qiu et al. 2021).

The primary objective of this paper is to quantitatively investigate the net effect of LCCP policy on urban green productivity in China. Through this research, we strive to find out accurate answers to the following questions. Can China's LCCP policy significantly promote urban green productivity growth? Or achieve the double dividend of economy and environment? Besides this, what is the transmission channel through which the LCCP policy affects urban green productivity? Is there heterogeneity in this effect of LCCP policy across different pilot cities? Does the LCCP policy's effect on urban green productivity exhibit spatial spillover characteristics? Answering these questions above clearly helps to clarify the causality between environmental supervision policies and urban green development.

The main contributions of this study to the previous literature are mainly shown as follows. Firstly, this study quantitatively evaluates the LCCP policy's effect on China's urban green productivity by using DID and spatial DID method with using the BML index to measure urban green productivity. Secondly, to overcome the potential endogenous problem caused by the non-exogenous nature of the pilot policy, IV estimation is adopted with urban air flow coefficient as an IV for determining whether a city is chosen as a pilot city, thus further ensuring the reliabilities of benchmark conclusions. Thirdly, this study theoretically expounds the mechanism of LCCP policy affecting urban green productivity from three channels: energy consumption reduction, industrial structure optimization, and technological innovation. Finally, different from the related studies, this study not only evaluates the LCCP policy's effect on pilot cities, but also analyzes the policy's effect on pilot cities' neighboring cities by utilizing spatial DID method, generally bringing an innovative perspective to the spatial spillover effect of the LCCP policy on China's urban green productivity.

The remainder of this paper is arranged as follows. The "Literature review" section presents related literature view. Policy background and mechanism analysis are illustrated in the "Policy background and mechanism analysis" Sect. 3. Research design and empirical analysis are provided in the "Research design" and "empirical analysis" sections, respectively. The "Conclusions and policy implications" section concludes this study and presents some policy implications.

Literature review

Over the past decade, increasing attention has been paid to China's low carbon city construction by scholars and policymakers (Croci et al. 2021; Gomi et al. 2011; Zhou et al. 2015a, b). The subjects concerned are different among previous related studies. Among them, some literature concentrated on the connotations and features of the low-carbon city as an emerging concept of urban development.

Su et al. (2012) stated that the main task of low-carbon city construction is to reduce carbon emissions as much as possible while maintaining sustained economic development. Chen and Zhu (2013) argued that the typical feature of low-carbon city is the decoupling between economic development and energy consumption or carbon emissions. Yang and Li (2013) believed that the construction of low-carbon cities aims to advocate low-carbon transformation in both production and consumption. Jiang and Kang (2019) summarized the related researches of low-carbon city and found that although the definitions of low-carbon city pilot city are different, the core concept is to achieve a win–win situation between economic sustainability and environmental protection. Wen et al. (2022) held that the target of constructing low-carbon city is to decouple economic development from fossil energy usages by improving energy utilization efficiency, optimizing energy structure and advocating green transportation. Based on the existing studies, it can be summarized that the ultimate target of low-carbon city construction is to pursue a win–win situation between economy and environment (Liu and Qin 2016; Paloheimo and Salmi 2013). Given that the substantial connotation of green total-factor productivity is to acquire the double dividend of economy and environment, it is well aligned with the target of low-carbon city construction, and thus can be adopted as an effective tool to quantitatively appraise the comprehensive performance of low-carbon city construction.

On basis of the core concept and basic target of low-carbon city construction, the second strand of previous studies focused on evaluating the effectiveness of low-carbon city construction by utilizing different multi-indicator systems. Baeumler et al. (2012) provided an index system for assessing the effect of low-carbon city construction from five aspects, including energy, carbon emission, sustainable transportation, smart city, and green buildings. Lawrence Berkeley National Laboratory established a low-carbon city evaluation index with 33 indexes from eight perspectives, containing water resource, energy, air, waste, transportation, economic health, social health, and land use (Zhou et al. 2015a, b). Similarly, from seven perspectives of energy, carbon and environment, waste, water, economy, society, and life, as well as urban mobility, Tan et al. (2017) established a comprehensive evaluation indicator system for low-carbon city evaluation, and then conducted an empirical analysis by the entropy method with 10 major cities around the world as research object. Wang et al. (2021a, b) put forward a low-carbon city assessment framework based on the five aspects of energy, environment, economy, society, and urban planning, and then utilized TOPSIS method to quantitatively estimate the effectiveness of low-carbon city construction. Such researches above can help to obtain insight into the low-carbon city construction practice in China.

In the past few years, to promote urban low-carbon transformation and green development, the Chinese government has successively approved three batches of LCCP projects in 2010, 2012, and 2017, respectively. Under this background, some essentially critical questions are naturally proposed. Whether the implementation of LCCP policy can bring about the expected results? What's the transmission channels through which the LCCP policy affects urban economic and social development? Such issues have attracted increasing attention from various scholars. Given that the Chinese government gradually implemented the LCCP policy in three stages, it could be deemed as a quasi-natural experiment, and thus provide a good chance to evaluate the pilot policy's effect (Chen et al. 2021). According to the idea, by using the DID method, various studies have investigated the impact of LCCP policy on urban planning (Chen 2015), urban green development (Cheng et al. 2019; Qiu et al. 2021), urban eco-efficiency (Song et al. 2020), urban green innovation (Tian et al. 2021), urban carbon abatement (Falahatkar and Rezaei 2020; Liu et al. 2022), urban carbon emission efficiency (Yu and Zhang 2021), urban carbon intensity (Feng et al. 2021), urban industrial structure adjustment (Zheng et al. 2021), and enterprise total factor productivity (Chen et al. 2021). Among them, the works closely related to our study were carried out by Cheng et al. (2019) and Qiu et al. (2021). Consistent with this study, they empirically tested the impact of LCCP policy on urban green productivity. However, compared with recent studies, our empirical analysis is unique in the following three aspects.

First, both Cheng et al. (2019) and Qiu et al. (2021) adopted Malmquist-Luenberger (ML) productivity index or Luenberger (L) productivity index constructed by slacks-based measure (SBM) and directional distance function (DDF) model to estimate green total-factor productivity. However, both ML and L index cannot address the infeasibility problem when calculating linear programming (Wang et al. 2020). Besides this, they still have the shortcoming that the DDF is needed to be recalculated when adding a new period data set to the original sample data set, which would increase the workload and lower the calculation efficiency (Du et al. 2014; Liu et al. 2016; Wang et al. 2020). Given this, an improved ML index, namely biennial ML (BML) index (Pastor et al. 2011), is introduced to measure urban green productivity in this study. Compared with other indexes, BML index enjoys three distinctive advantages: completely addressing the infeasible problem, technical regress being allowed, and not requiring being recalculated when adding a new time data to the sample (Hou et al. 2019; Liu et al. 2020). Thus, using BML index can enable us to evaluate urban green productivity more accurately and conveniently.

Second, neither Cheng et al. (2019) nor Qiu et al. (2021) addressed the endogeneity problem arising from the non-exogenous feature of LCCP policy. It has been proved that the identification of pilot cities must be random to objectively examine the impact of LCCP policy, i.e. satisfy the exogeneity assumption (Chen et al. 2021). However, in fact, the Chinese central government gave full consideration to various city's inherent attributes when selecting low-carbon pilot cities, including geographical location, economic development, population density, environmental constraints, and openness (Zhang 2020). In this way, the differences between cities resulting from these attributes might have different effects on urban green productivity over time, thus creating endogeneity problems and ultimately leading to biased estimates. Given this, with reference to Chen et al. (2021), our study utilizes the air flow coefficient as the IV for reflecting the LCCP policy to conduct a robustness test, thus well addressing the potential endogeneity problem.

Finally, Chen and Wang (2022) pointed out that the spatial spillover effects of LCCP policy usually exist due to technology spillover and the "promotion championship" between local officials. However, both Cheng et al. (2019) and Qiu et al. (2021) did not consider the spatial spillover effect of the LCCP policy on urban green productivity.The DID model used in previous studies requires that exogenous shocks affect specific individuals while having no impact on other individuals. This assumption is known as the stable unit treatment value assumption (SUTVA) (Rubin 1974). However, environmental governance has an obvious spatial correlation effect, the implementation of environmental regulations in a city could have an impact on other neighboring cities in space. Most existing studies ignore the spatial spillover effects and fail to satisfy the SUTVA, thus can substantially weaken the robustness and credibility of their conclusions (Feng et al. 2021; Song et al. 2020; Zheng et al. 2021). To solve this problem with reference to Yu and Zhang (2021), this study constructs a spatial DID model based on a spatial Durbin model to quantitatively investigate the LCCP policy impact on both pilot cities and their neighboring cities in China, thus providing a fresh study perspective on the impact of LCCP policy on urban green productivity.

In summary, based on abovementioned studies, regarding the LCCP policy as a quasi-natural experiment and based on the panel data of China's 283 prefecture level cities during the period 2004–2018, this study systematically examines the impact of LCCP policy on urban green productivity by employing DID method, with a series of robustness tests for ensuring the reliability of the benchmark conclusions. Afterwards, the heterogeneities, transmission mechanisms, and spatial spillover characteristics of the pilot policy's effect are well investigated. We believe that the findings of our study can provide meaningful references for the Chinese government to set targeted policies aiming at the promotion of low-carbon city construction and the realization of urban high-quality development in China. The logical flow chart is illustrated in Fig. 1.

Policy background and mechanism analysis

Policy background

With large amounts of fossil energy usage caused by the rapid urbanization and industrialization, cities have become increasingly important subjects of responsibility in low-carbon transformation and response to climate change (Liao et al. 2021; Song et al. 2021; Zhou et al. 2015a, b). Aiming at ensuring the target of controlling greenhouse gas emissions by 2030 proposed by the Chinese government, in July 2010, the National Development and Reform Commission (NDRC) first implemented the LCCP policy in 5 provinces and 8 prefecture level cities, to explore the experience of low-carbon city construction. In November 2012, the NDRC selected 28 prefecture level cities as the second batch of low carbon pilot cities, and established target responsibility for controlling carbon emissions. In January 2017, the NDRC approved the third batch of low carbon pilot cities in 45 prefecture level cities, and encouraged these pilot cities to seek low-carbon transformation mode based on their own local conditions, and established a carbon emission target assessment system, as well as clearly required each pilot city to set a carbon emission peak. The LCCP policy is a comprehensive environmental regulation, including both command-and-control environmental regulation, market-based environmental regulation and public participation environmental regulation, thus forming multilevel and multiplayer systematic development (Cheng et al. 2019). In addition, the LCCP policy does not formulate a clear policy content. The governments of pilot cities can formulate corresponding low-carbon policies according to the actual local conditions, with greater flexibility and autonomy. However, the LCCP policy also has some shortcomings. The LCCP policy has the characteristics of weak constraints and weak incentives. The LCCP policy does not stipulate mandatory constraints, which may lead to the pilot cities still choose extensive development mode. Additionally, the LCCP policy does not provide sufficient financial support to pilot cities, which will reduce the enthusiasm of pilot cities to explore green development mode. Therefore, the characteristics of weak constraint and weak incentive of LCCP policy will have a negative impact on the policy effect.

Based on the availability of data, this study chooses China's 68 low-carbon pilot cities in the three batches as the treatment group. In 2010, the GDP and carbon emissions of these pilot

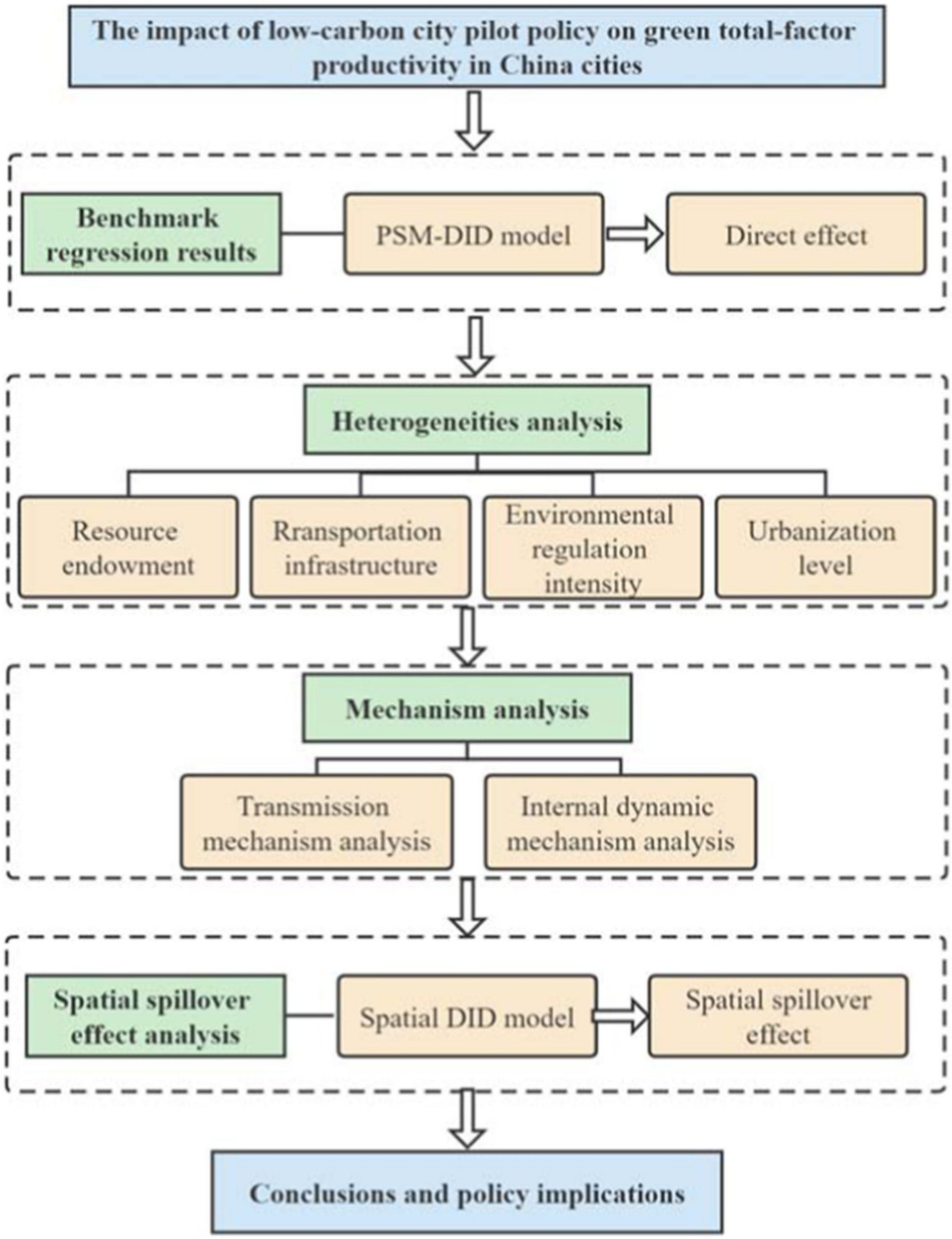


Fig.1 The logical flow chart

cities accounted for 40.21% and 48.77% of the national total, respectively. The distribution of pilot cities is shown in Fig. 2.

Transmission mechanism and research hypotheses

Direct effect

As a comprehensive environmental regulation, the LCCP policy aims to simultaneously develop the economy and protect the environment, which will inevitably improve urban green productivity (Qiu et al., 2021). Firstly, under the pressure of LCCP policy, the governments of the pilot cities will take a series of measures to achieve green development, including formulating stricter environmental policies, encouraging the use of clean energy and strengthening the supervision of polluting enterprises, all of which will improve urban green productivity (Chen and Wang 2022). Secondly, the LCCP policy increases the environmental cost of enterprises. In order to avoid penalties, on the one hand, enterprises will increase investment in pollution control to reduce pollution emissions. On the other hand, enterprises will increase investment in research and development (R&D), and facilitate green technological innovation (Porter and Linde 1995). Technological innovation changes their production mode so as to offset the negative effects of

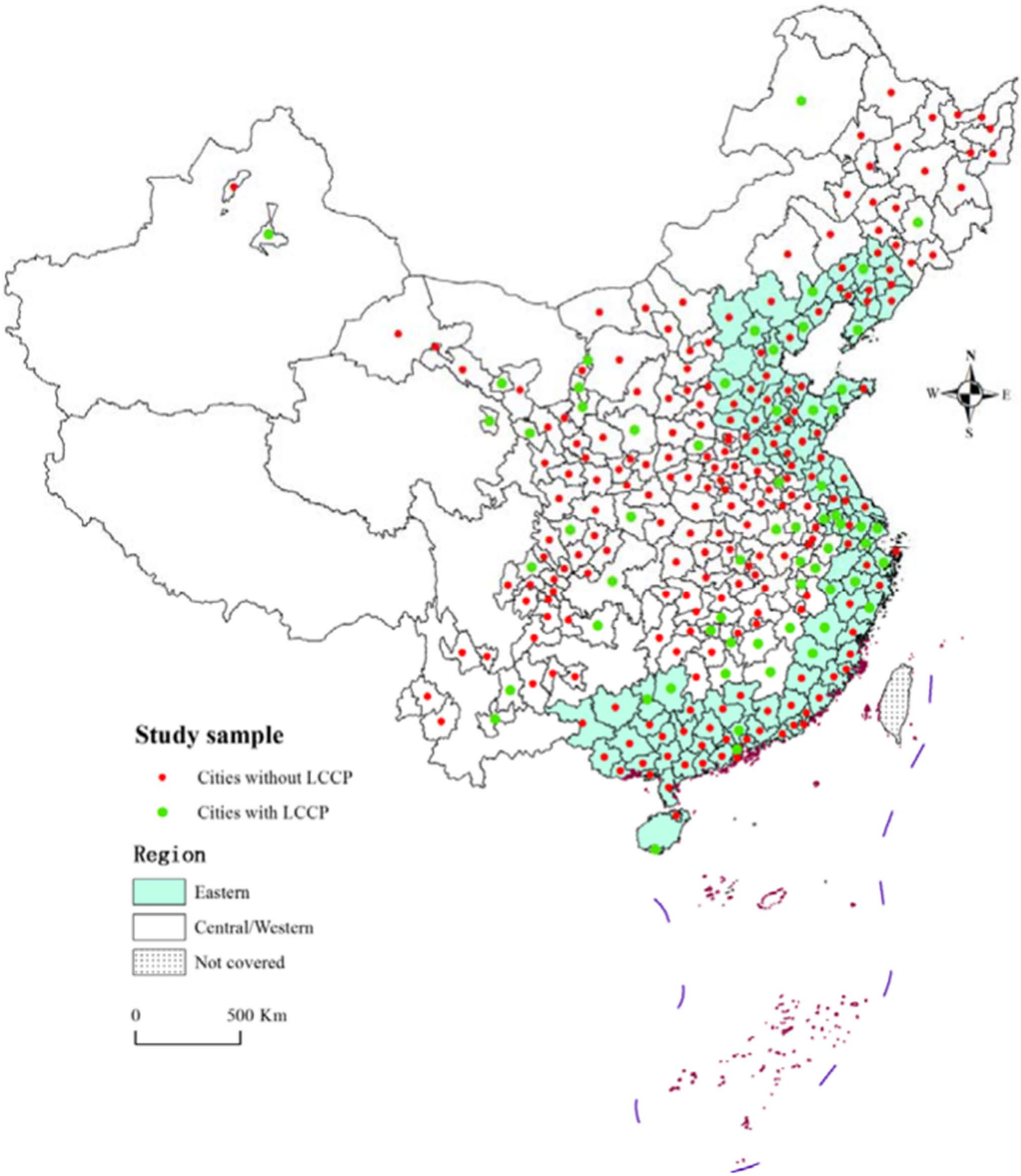


Fig. 2 Geographical distribution of the low-carbon pilot cities in China

environmental protection costs, resulting in a win–win situation of reducing emissions and increasing corporate profits (Song et al. 2020). Finally, the LCCP policy encourages the public to choose a low-carbon lifestyle, which is conducive to reducing pollution emissions (Zhang et al. 2022). To sum up, the LCCP policy can improve urban green productivity by influencing the behavior of government, enterprises and the public.

Based on the analysis above, hypothesis 1 can be presented as follows.

Hypothesis 1: The LCCP policy can improve urban green productivity.

Energy consumption reduction effect

The LCCP policy encourages pilot cities to use clean energy to gradually replace fossil energy, which can significantly reduce greenhouse gas emissions and other pollutants (Shen et al. 2018). This is naturally conducive to the improvement of urban green productivity. To be specific, first, the carbon emission trading system widely implemented in the low-carbon pilot cities can stimulate enterprises to minimize carbon emissions for reducing operation costs, which can decrease urban fossil energy consumption, thus facilitating urban green productivity improvement (Zhu et al. 2020). Second, by establishing a complete carbon emission data accounting system, the governments of low-carbon pilot cities can real-time monitor carbon emissions of such high-consuming and high-polluted industries (Peng and Bai 2018). In the context of increasingly stringent environmental regulation, these industries might be forced to gradually change their traditional high-consuming and high-polluted production modes, with the aim to reduce fossil energy usage and pollution emissions, thus promoting urban green productivity (Lou et al. 2019). Finally, the low-carbon city construction commits to promote green travel by vigorously developing public transport, including constructing infrastructures for walking and riding, and encouraging the public to buy new energy vehicles, etc., which can significantly reduce energy consumption and pollution emissions in transportation sector (Wang et al. 2018). Obviously, it helps to promote urban green productivity. Based on above analysis, Hypothesis 2 is proposed as follows.

Hypothesis 2: The LCCP policy can improve urban green productivity through reducing energy consumption.

Industrial structure optimization effect

The LCCP policy can promote urban green productivity through industrial structure optimization. Firstly, with the pilot policy's implementation, to pursue profit maximization, enterprises tend to reallocate factor resources due to the increased "compliance cost". In this context, production factors will gradually flow from industries with lower production efficiency and higher carbon emissions control cost to industries with higher production efficiency and lower carbon emission control cost, improving the proportion of advantageous industries and realizing resource allocation optimization (Cheng et al. 2019; Kou and Liu 2017). Secondly, the implementation of the pilot policy will be bound to dramatically increase production costs of high-energy-consuming, high-polluted and high-emitted enterprises, forcing them to migrate out pilot cities or choose low-carbon transformation. Thus, the industrial structure of the pilot cities can be optimized. It has been proved by various existing studies that industrial structure optimization is a critically important pathway to enhance urban total-factor productivity (Drucker and Feser 2012; Feng et al. 2019). The main reasons are as follows. On the one hand, the upgrading of industrial structure will make production factors flow from industries with lower productivity to industries with higher productivity, which will promote the optimization of resource allocation and thus drive total-factor productivity (Wang et al. 2022). On the other hand, industrial structure optimization will decrease the proportion of resource and environmental-intensive industries, which can effectively reduce resource usage and pollution emissions, thereby improving urban green productivity. Based on the analysis above, hypothesis 3 can be presented as follows.

Hypothesis 3: The LCCP policy can promote urban green productivity through optimizing industrial structure.

Technological innovation effect

The LCCP policy can promote urban green productivity by technological innovation. We believe that there exist three main channels through which the LCCP policy affects enterprise technological innovation. Firstly, a variety of green financial policies issued during the low-carbon city construction can provide financial support for enterprises through investment subsides, reducing loan interest rates and tax incentives, alleviate enterprises' financing constraints, encourage enterprises to increase R&D investment, and facilitate green technological innovation (Fu et al. 2021). Secondly, the LCCP policy can provide enterprises with more open information related to technological innovation, promote knowledge spillover, as well as strengthen technological learning and cooperation among enterprises, thus promoting enterprises' technological innovation. Finally, as a tool of government environmental regulation, the LCCP policy will naturally bring about compliance costs for enterprises. However, according to the Porter hypothesis, it will also force enterprises to adopt technological innovation for reducing fossil energy usage and pollution emissions, thus triggering "innovation compensation" effect (Porter and Linde 1995; Yang et al. 2019; Bu et al. 2020). It has been evident that technological innovation can not only improve resource utilization efficiency, but also enhance the abilities of source control and end treatment of environmental pollution, thus being beneficial to promoting urban green productivity (Wang et al. 2021a, b). Therefore, hypothesis 4 is provided as follows.

Hypothesis 4: The LCCP policy can promote urban green productivity through technological innovation.

Spatial spillover effect

The LCCP policy has a spatial spillover effect due to the obvious spatial correlation characteristics of environmental governance. Firstly, the LCCP policy can promote local green innovation (Pan et al. 2022). The spillover effect of knowledge and technology can reduce the cost and risk of green innovation in neighboring cities, thereby promoting green innovation in neighboring cities (Fornahl and Brenner, 2009). Green innovation can not only improve the productivity of enterprises, but also reduce pollution emissions in the production process, which is conducive to improving urban green productivity (Peng et al. 2021). Second, an important goal of the LCCP policy is to explore and promote low-carbon development experience, so the LCCP policy will have a demonstration effect. Neighboring cities can promote urban green productivity by learning the successful experience and management models of pilot cities. Finally, the LCCP policy also has a warning effect. The pilot cities have increased the green pressure on neighboring cities, prompting neighboring cities to pay attention to environmental governance to improve urban green productivity (Ren et al. 2022). Based on the above analysis, we propose Hypothesis 5.

Hypothesis 5: The LCCP policy is beneficial to improve the green productivity of neighboring cities through spatial spillover effects.

Research design

Model specification

Regarding the LCCP policy as a quasi-natural experiment, this study uses the continuous DID method to quantitatively evaluated the impact of LCCP policy on urban green productivity. The continuous DID model can be constructed as follows:

$$GTFP_{it} = \alpha + \beta did_{it} + \lambda X_{it} + u_t + \theta_i + treat_{pt} + \varepsilon_{it} \tag{1}$$

where $GTFP_{it}$ represents the green productivity of city i in year t; the did_{it} represents the core explanatory variable in the DID model. If city i is a pilot city in year t, then $did_{it}=1$; otherwise, $did_{it}=0$. X_{it} denotes a series of control variables. u_t represents city fixed effect; θ_i represents time fixed effect; $treat_{pt}$ represents province-time fixed effect, which controls different provinces with different time trend;ε_{it} is random error term. β_1 represents the net effect of the LCCP policy on urban green productivity. If $\widehat{\beta}_1$ is significantly positive, it can be speculated that the LCCP policy can promote urban green productivity effectively.

The prerequisite of policy evaluation using DID method is to satisfy the parallel trend assumption, so as to ensure the randomness of the selection of the treatment group and the control group (Huang and Wang 2020; Wang et al. 2022). However, in fact, when selecting pilot cities, the Chinese government may comprehensively consider the differences in urban economic development level, resource utilization and air pollution, and etc. (Zhang 2020), which does not meet the randomness of sample selection, thereby resulting in "selective error." In this case, the DID method is not applicable. To address this, we first employ the PSM method to match an optimal control group for the treatment group to meet the parallel trend assumption, and then carry out DID regression, i.e., the so-called PSM-DID method.

Variable selection

Green productivity and its decomposition

Given the purpose of this study is to identify the effect the LCCP policy on China's urban green total factor productivity, urban green productivity is therefore chosen as the explained variable in the regression model. Regarding the measured method of urban green productivity, the BML index is adopted. Compared with other indexes, BML index can enable efficiency evaluation more convenient (Pastor et al. 2011; Wang et al. 2020), and it is constructed as follows:

$$BML_t^{t+1} = \frac{1 + \overrightarrow{D_0^B}(x_{n,k}^t, y_{m,k}^t, b_{i,k}^t; g)}{1 + \overrightarrow{D_0^B}(x_{n,k}^{t+1}, y_{m,k}^{t+1}, b_{i,k}^{t+1}; g)} \tag{2}$$

where x_n ($n=1,\ldots, N$) represents the vector of input variable; y_m ($m=1,\ldots,M$) represents the vector of desirable outputs; b_i($i=1,\ldots,I$) represents the vectors of undesirable outputs; k ($k=1,\ldots,K$) is the number of decision-making units (DMUs); $\overrightarrow{D_0^B}(x_{i,k}^t, y_{j,k}^t, b_{h,k}^t; g)$ represents the DDF used for urban green productivity measurement, where the superscript B represents biennial environmental technology, which merges all cities of year t and year $t+1$ to build production frontier (Pastor et al. 2011; Liu et al. 2016; Wang et al. 2020); g denotes direction vector and is chosen as $(-x, y, -b)$, suggesting that the city's production activity that seeks to contract inputs and undesirable outputs and expand desirable outputs. The DDF can be obtained by calculating the following linear programming:

$$\overrightarrow{D_0^B}(x^t, y^t, b^t; g) = max\beta$$
$$s.t.\begin{cases} \sum_{k=1}^{K} z_k^t y_{km}^t + \sum_{k=1}^{K} z_k^{t+1} y_{km}^{t+1} \geq (1+\beta) y_{k'm}^t, m = 1, \ldots, M \\ \sum_{k=1}^{K} z_k^t x_{kn}^t + \sum_{k=1}^{K} z_k^{t+1} x_{kn}^{t+1} \leq (1-\beta) x_{k'n}^t, n = 1, \ldots, N \\ \sum_{k=1}^{K} z_k^t b_{ki}^t + \sum_{k=1}^{K} z_k^{t+1} b_{ki}^{t+1} = (1-\beta) b_{k'i}^t, i = 1, \ldots, I \\ z_k^t \geq 0, k = 1, \ldots K; \end{cases} \tag{3}$$

where β is the value of biennial DDF at period t; k' represents the DMU to be evaluated; if $\beta = 0$, it indicates that k' is at the production frontier. Similarly, the biennial DDF at period $t+1$ also can be calculated.

If the BML index is larger than (smaller, equal to) 1, it respectively suggests that urban green productivity increases (decreases, unchanged). Similar to traditional productivity indexes, the BML index can also be further decomposed into two components: technical efficiency promotion (EFFCH), and technological change (TECH), among which EFFCH stands for a catching-up effect and TECH represents a technological change effect. The decomposition results of BML index are presented as follows:

$$BML = EFFCH \times TECH = \left[\frac{1+\overrightarrow{D_0^t}(x_{n,k}^t, y_{m,k}^t, b_{i,k}^t; g)}{1+\overrightarrow{D_0^{t+1}}(x_{n,k}^{t+1}, y_{m,k}^{t+1}, b_{i,k}^{t+1}; g)}\right] \times \left[\frac{1+\overrightarrow{D_0^B}(x_{n,k}^t, y_{m,k}^t, b_{i,k}^t; g)}{1+\overrightarrow{D_0^t}(x_{n,k}^t, y_{m,k}^t, b_{i,k}^t; g)} \times \frac{1+\overrightarrow{D_0^{t+1}}(x_{n,k}^{t+1}, y_{m,k}^{t+1}, b_{i,k}^{t+1}; g)}{1+\overrightarrow{D_0^B}(x_{n,k}^{t+1}, y_{m,k}^{t+1}, b_{i,k}^{t+1}; g)}\right] \tag{4}$$

where $\overrightarrow{D_0^t}(x_{n,k}^t, y_{m,k}^t, b_{i,k}^t; g)$ represents the DDF at period t under the environmental technology at period t, which can be calculated by the linear programming shown as follows. Similarly, the DDF at period $t+1$ also can be measured.

$$\overrightarrow{D_0^t}(x^t, y^t, b^t; g) = max\beta$$
$$s.t.\begin{cases} \sum_{k=1}^{K} z_k^t y_{km}^t \geq (1+\beta) y_{k'm}^t, m = 1, \ldots, M \\ \sum_{k=1}^{K} z_k^t x_{km}^t \leq (1-\beta) x_{k'n}^t, n = 1, \ldots, N \\ \sum_{k=1}^{K} z_k^t b_{ki}^t = (1-\beta) b_{k'i}^t, i = 1, \ldots, I \\ z_k^t \geq 0, k = 1, \ldots K; \end{cases} \tag{5}$$

For measuring urban green productivity, capital stock, labor force,and energy input are selected as input variables in this study. Specifically, China's urban capital stock is estimated by the Perpetual Inventory Method, the number of urban employees at the end of one year is regarded as urban labor force, and urban power consumption is considered as the proxy variable of urban energy consumption. Urban actual GDP is chosen as desirable output, and urban emissions of SO_2, smoke, and wastewater emission are established as three undesirable outputs.

Control variables

To weaken the endogenous problem due to the missing variables, a series of control variables are added to the DID model, which include: economic growth (PGDP) reflected by urban per capita GDP, urbanization (*Urb*) measured by the proportion of urban construction area in total urban area (Tang et al. 2022), industrial structure (Ins) represented by the proportion of added value of tertiary industry in urban GDP, government intervention (Gov) represented by the ratio of urban fiscal revenue to fiscal expenditure (Wang et al. 2022), infrastructure construction (Inf) denoted by urban per capita Road area, and the degree of openness (FDI) reflected by the proportion of foreign direct investment in urban GDP. To avoid the estimation errors caused by heteroscedasticity, the above control variables are introduced into DID model in logarithmic form.

Data description

Based on data availability, this paper chooses China's 283 prefecture level and above cities as research sample during the period 2004–2018. Ultimately, among the three batches of low carbon pilot cities, 68 cities are established as the treatment group, and the rest as the control group. The descriptive statistics of related variables in DID model are presented in Table 1. All data used were obtained from the China Statistical Yearbook and China City Statistical Yearbook.

Empirical results

Balance test of PSM

In order to overcome the "selective bias" of samples, this paper first uses PSM method based on Kernel matching to select suitable samples for comparison. The Logit model was constructed based on covariates to calculate the propensity score for matching the treated group, and the covariates are consistent with the control variables in Eq. (1). The balance

Table 1 Descriptive statistics of variables

Variable	*Obs*	*Mean*	*Std. dev*	*Min*	*Max*
GTFP	*4245*	*1.038*	*0.520*	*0.066*	*10.603*
EFFCH	*4245*	*1.031*	*0.261*	*0.159*	*4.297*
TECH	*4245*	*1.005*	*0.311*	*0.209*	*3.791*
PGDP	*4245*	*41,153.74*	*103,206.3*	*1847*	*6,421,762*
Urb	*4245*	*8.513*	*9.668*	*0.02*	*97.18*
Ins	*4245*	*37.941*	*9.285*	*8.580*	*85.340*
Gov	*4245*	*0.480*	*0.228*	*0.025*	*1.541*
Inf	*4245*	*11.048*	*8.058*	*0.31*	*108.37*
FDI	*4245*	*2.942*	*5.902*	*0.0003*	*204.375*

Obs. and std. dev. stand for observations and standard deviation, respectively

Table 2 Balance test of variables before and after PSM

Variable	Unmatched	Mean		% bias	p value
	Matched	Treated	Control		
lnPGDP	U	10.61	10.194	54.3	0.000
	M	10.61	10.55	7.9	0.079
lnUrb	U	1.898	1.485	37.4	0.000
	M	1.907	1.846	5.8	0.167
lnIns	U	3.717	3.571	59.6	0.000
	M	3.719	3.698	8.8	0.043
Gov	U	0.625	0.435	85.4	0.000
	M	0.622	0.629	− 3.4	0.498
lnRoa	U	2.371	2.156	35.8	0.000
	M	2.370	2.400	− 4.8	0.286
lnFDI	U	0.701	0.305	46.2	0.000
	M	0.716	0.615	6.9	0.100

Table 3 The results of the baseline regression

Variables	DID		PSM-DID	
	(1)	(2)	(3)	(4)
did	0.081**	0.076**	0.076**	0.071**
	(0.033)	(0.034)	(0.033)	(0.034)
cons	1.242***	2.065***	1.238***	2.10***
	(0.026)	(0.706)	(0.026)	(0.714)
Control variables	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Province-time fixed effects	Yes	Yes	Yes	Yes
Obs	4245	3678	4235	4235
R^2	0.441	0.517	0.442	0.445

The standard errors in parentheses are the robust standard errors clustered to the prefecture-level city; *** $p<0.01$, ** $p<0.05$, * $p<0.1$, and the same below

test results after matching are reported in Table 2. It is shown that the mean value of the covariates of the treated and the control has been very close after PSM, and *t*-test further confirms that there is no systematic difference between them. Then, the matched samples are adopted for DID regression, and the reliability of the estimated results can be guaranteed.

Benchmark regression results

In this section, based on Eq. (1), the average effect of LCCP policy on urban green productivity in China is estimated by utilizing the samples after PSM, and the results are listed in columns (3) and (4) of Table 3. By comparison, the results without PSM treatment are also presented in columns (1) and (2) of Table 3. It is seen that the *did* coefficients are all significantly positive, which indicates that the LCCP policy can significantly improve urban green productivity. As shown in column (3) controlling for time, city and province-time fixed effect, the net effect of LCCP policy on urban green productivity is about 0.076. It suggests that compared with the non-pilot cities, the LCCP policy can improve the green productivity of the pilot cities by 7.6% on average, ceteris paribus.

Subsequently, the control variables are introduced into Eq. (1) for re-regression to get more robust results. As can be seen in column (4) of Table 3, after adding the control variables, the *did* coefficient is still significantly positive, with the value of 0.071. Therefore, the conclusion that the LCCP policy can significantly improve urban green productivity is robust.

Robustness tests

Parallel trend test

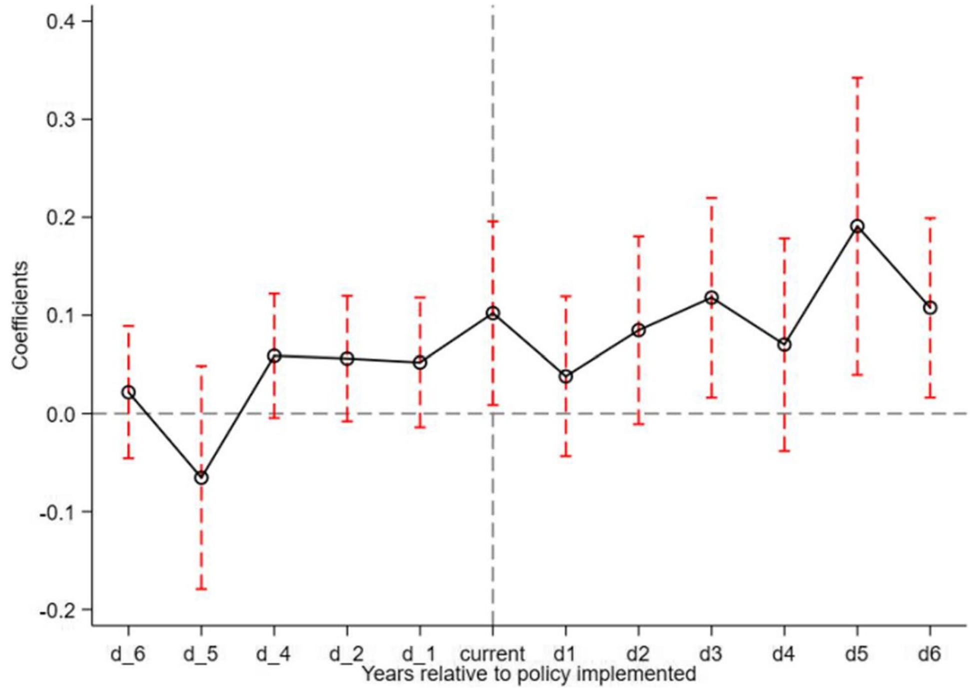
The precise of using DID method to conduct policy effect evaluation is to satisfy the parallel trend consumption, i.e., before the implementation of LCCP policy, the green productivity of pilot cities and non-pilot cities should have the common varying trend. Given this, we employ the event study method to identify whether the samples processed by PSM meet the parallel trend assumption (Lin and Zhu 2019), and the model is set up as follows:

$$GTFP_{it} = \alpha + \sum_{k=-6}^{6} \rho_k did_{it}^k + \lambda X_{it} + u_t + \theta_i + treat_{pt} + \varepsilon_{it} \tag{6}$$

It is assumed that the year in which the LCCP policy is implemented is p ($p=2010, 2012, 2017$), and $k=t-p$ is set. When the value of k is negative, if t is smaller than the year when the LCCP policy is carried out, then we assign $did_{it}^k=1$; otherwise, we assign $did_{it}^k=0$. when the value of k is no smaller than 0, if t is larger than the year when the LCCP policy is conducted, then we assign $did_{it}^k=1$; otherwise, we assign $did_{it}^k=0$. We focus on the estimated coefficients of ρ_k which indicates the differences in urban green productivity between the treated and the control group in the year t after the LCCP policy implementation. If the trend of ρ_k is relatively flat while k is negative, it indicates that the parallel trend assumption is met; otherwise, it suggests that the green productivity varies significantly across the two groups before the implementation of LCCP policy and the parallel trend assumption is not satisfied.

Figure 3 illustrated the estimation results of ρ_k under the 95% confidence intervals for the urban green productivity indexes. It can be seen that ρ_k was not significant before implementing the LCCP policy, which indicates that little

Fig. 3 Parallel trend analysis (see the online version of this figure for the color image)



differences exist between the treated and the control, and thus the parallel trend assumption is satisfied. Additionally, it is found that from the 3rd year after implementing the LCCP policy, ρ_k began to become significant and showed an increasing trend year by year, which indicates that the effect of the LCCP policy requires time to accumulate (Liu et al. 2022).

Introducing other matching methods

In the benchmark regression model, the Kernel matching method was used for PSM-DID regression. To further ensure the reliability, the Radius matching method and the Nearest Neighbor matching method have been introduced to the PSM-DID regression one after another, and the results are reported in columns (2) and (3) of Table 4. The results show that when using these two matching methods, both estimated coefficients of *did* are significantly positive, indicating the robustness of benchmark conclusions.

Excluding provincial capital cities

Due to the special economic and political status and the stronger demonstration of provincial capital cities, it is easier to for them

Table 4 Results of robustness tests

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
did	*0.071***	*0.076***	*0.071***	*0.070***	*0.070***	*0.070***
	(0.034)	*(0.034)*	*(0.034)*	*(0.033)*	*(0.034)*	*(0.034)*
CERTP					*−0.061*	
					(0.142)	
PRTP						*0.235****
						(0.063)
cons	*2.100****	*2.076****	*2.090****	*1.715***	*2.043****	*2.006****
	(0.714)	*(0.708)*	*(0.713)*	*(0.709)*	*(0.664)*	*(0.709)*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province-time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	*4235*	*4243*	*4235*	*4178*	*4235*	*4235*
R^2	*0.445*	*0.443*	*0.445*	*0.444*	*0.445*	*0.445*

be selected as pilot cities by the central government, resulting in the non-randomness of sample section. To this end, we exclude the provincial capital cities from the original sample and conduct the benchmark regression again. The estimated results are shown in column (4) of Table 4. It is seen that the estimation efficient of *did* is still significantly positive, which confirms the robustness of benchmark results.

Eliminating the impacts of other pilot polices

To improve urban green productivity, the Chinese government has promulgated a series of pilot policies in recent years, which may overestimate or underestimate the LCCP policy's effect. Given this, the dummy variables representing other policies are added to the benchmark regression model and re-regress. Among various related pilot polices, the carbon emission rights trading pilot (CERTP) policy and the pollution rights trading pilot (PRTP) policy have been proved to significantly promote urban green transformation and low-carbon development (Liu et al. 2022). The estimated results considering the effects of the two pilot policies are listed in columns (5) and (6) of Table 4. As is shown that compared with the benchmark estimations displayed in column (1), the effects of LCCP policy are still dramatic with the coefficients of *did* decreasing slightly. It suggests that the benchmark results remain robust, even if the effect of the LCCP policy is slightly overestimated without considering the impacts of other pilot polices.

Placebo test

Despite that the impacts of all urban features that do not change over time on urban green productivity can be controlled by some fixed effect used in the benchmark model, such unobservable and time-varying urban characteristics may interfere the DID regression. Hence, we employ the widely applied placebo test to address this problem (Chetty et al., 2009), to ensure the reliability of the estimation results. Based on Eq. (1), the estimated coefficient of β, can be elaborated as follows:

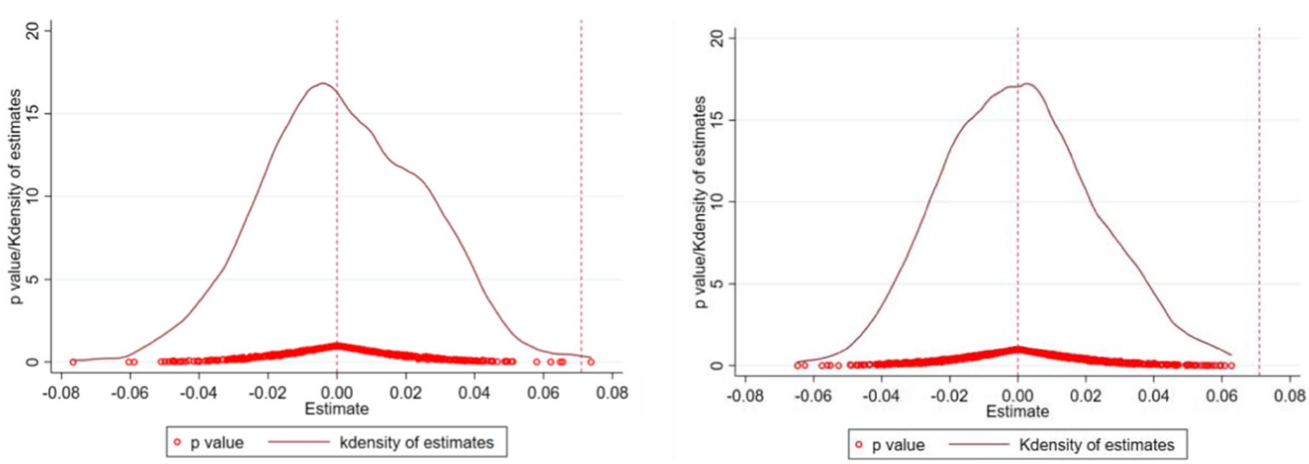
$$\widehat{\beta}=\beta+\gamma * \frac{\mathrm{cov}(Treat_{it},\varepsilon_{it}|W)}{\mathrm{var}(Treat_{it}|W)} \tag{7}$$

where W represents the control variables and fixed-effects; γ stands for the effect of unobservable city features on urban green productivity. If γ is equal to 0, then such unobservable factors do not influence the estimated results and $\widehat{\beta}$ is affirmed to be unbiased, but it cannot be confirmed directly. Given this, the placebo test is adopted to find an error variable to replace $Treat_{it}$, which does not affect the outcome variable. Since the variable is randomly generated, the value of β is 0. If β is not equal to 0, it means that the error variables affect the estimation results, in other words, the unobservable characteristic factors affect the benchmark regression results, and thus the estimated results are unstable. Specifically, in this study, 68 cities as virtual control group are generated to produce the error estimation of $\widehat{\beta}$, and it is repeated 500 and 1000 times, respectively.

Figure 4a and b illustrate the distribution of the 500 and 1000 error estimations of $\widehat{\beta}$, respectively. It can be seen that $\widehat{\beta}$ is roughly normally distributed around 0, indicating the robustness of the benchmark conclusions.

Endogenous treatment: IV method

As analyzed in above section, a variety of potentially confound factors might influence the central government's



(a) 500 times **（b）1000times**

Fig. 4 Distribution of estimates in the randomization test choice of low-carbon pilot cities, thus leading to endogenous problems. To address this, IV method is used to conduct a robustness test in this study (Cai et al., 2016). With reference to Chen et al. (2021), the air flow coefficient is employed as IV to judge whether a city is included to the low-carbon pilot cities. The main reasons lie in that: firstly, the greater the urban air flow coefficient, the faster the diffusion air pollutants, and the smaller the probability of the city being chosen as a low-carbon pilot city, i.e., they are negatively related. This indicates that the correlation hypothesis of IV is met. Secondly, the air flow coefficient is mainly affected by wind speed and atmospheric boundary layer height, both of which are determined by the meteorological and geographical conditions of the city, satisfying the exogenous hypothesis of IV. Specifically, with reference to Broner et al. (2012) and Hering and Poncet (2014), the air flow coefficient can be constructed as follows:

$$VC_{it} = WS_{it} \times BLH_{it} \tag{8}$$

where VC_{it}, WS_{it}, and BLH_{it} stand for the air flow coefficient, wind speed and atmospheric boundary layer height, respectively. The original data of WS_{it} and BLH_{it} are obtained from the longitude and latitude grid meteorological data published by the European Centre for Medium-Range-Weather Forecasts (ECMWF). Then, ArcGIS software is used to further parse them into the data of China's 283 prefecture level cities covering the period 2004–2018.

The estimated results of IV method are reported in Table 5. It is found that the *F* test value of the first stage regression is much larger than 10, indicating that "weak instrumental variable" problem does not exist. Moreover, the estimated coefficient of *did* of the second stage regression is 0.089 and has passed the significant test, verifying the significant effect of LCCP policy on urban green productivity. It further identifies the robustness of benchmark conclusions.

Table 5 Regression results of instrumental variable method

Variables	*The first stage*	*The second stage*
IV	*−0.025****	
	(0.006)	
did		*0.089****
		(0.028)
cons	*0.066*	*1.786****
	(0.181)	*(0.636)*
Control variables	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*
City fixed effects	*Yes*	*Yes*
F -value	*176.28*	
Obs	*4245*	*4245*
R^2	*0.9924*	*0.879*

Heterogeneities analysis

In the above section, it has been demonstrated that the LCCP policy can significantly improve urban green productivity in China. However, it can only reflect the pilot policy effect from the average perspective, but cannot examine the heterogeneities of pilot policy's impact on different cities. Given this, this section further discusses the heterogeneity of the effect of the LCCP policy from four aspects: resource endowment, transportation infrastructure, environmental regulation intensity, and urbanization level.

Heterogeneity in resource endowment

Due to its vast territory, China's natural resource endowment and economic development vary greatly across different cities (Song et al. 2021). To further assess the different effects of LCCP policy on green productivity of cities with different resource endowment, we classify the 283 sample cities into resource-based cities and non-resource-based cities based on the National Sustainable Development Plan for Resource-Based Cities (2013–2020) released by the State Council of China, and construct a difference-difference-difference (DDD) model to perform the regression. Specially, first, we set a dummy variable of resource endowment. If the city is a resource-based city, its value is assigned 1, otherwise it is assigned 0; then, we multiply the dummy variable by *did* to construct a triple interactive term *ddd*, and add it to Eq. (1) for regression, and column (1) of Table 6 shows the estimated results.

It is found that the estimated coefficient of *ddd* is significant negative, which indicates that compared with the resource-based cities, the LCCP policy's effect on urban green productivity is greater in non-resource-based cities. A possible explanation is that the development of resource-based cities relies too much on natural resource and suffers from the "resource curse" dilemma. It could to a certain degree hinder the LCCP policy's effect on improving urban green productivity.

Heterogeneity in transportation infrastructure

Transportation infrastructure is considered a critical driver for regional economic development. Therefore, the LCCP policy's effect on urban green productivity might be affected by the transportation infrastructure level. To investigate the heterogenous effect of LCCP policy on green productivity of cities with different transportation infrastructure level, DDD model is employed. Specifically, we construct a dummy variable based on whether the city has opened high-speed rail. If the city has opened high-speed rail, the dummy variable is assigned 1, otherwise, it is assigned 0. Naturally, cities with

Table 6 Results of the heterogeneity analysis

Variable	*(1)*	*(2)*	*(3)*	*(4)*
ddd	*−0.127**	*0.125***	*0.216****	*0.217****
	(0.077)	*(0.062)*	*(0.061)*	*(0.071)*
did	*0.111****	*−0.016*	*−0.055*	*−0.068*
	(0.034)	*(0.063)*	*(0.056)*	*(0.062)*
cons	*2.090****	*2.063****	*1.938****	*2.071****
	(0.711)	*(0.715)*	*(0.712)*	*(0.711)*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
City fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Province-time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Obs	*4235*	*4235*	*4235*	*4235*
R^2	*0.445*	*0.445*	*0.446*	*0.446*

high-speed rail are recognized as cities with higher transportation infrastructure level. Then, we construct a *ddd* item contains the dummy variable and *did*, and add it to Eq. (1) for regression. Column (2) in Table 6 reports the estimation results.

As can be seen that the estimated coefficient *ddd* is significantly positive, suggesting that compared with cites with worse transportation infrastructure, the LCCP policy plays a stronger effect in improving the green productivity of cities with better transportation infrastructure. The main reasons are as follows. Firstly, better transportation infrastructure is beneficial to the rapid flow of production factors, which facilitates reducing transaction costs and improving resource allocation efficiency. Secondly, the enhancement of transportation infrastructure can significantly advance the technological progress in the field of energy and environment by facilitating knowledge spillover. Hence, transportation infrastructure can lay a solid foundation for playing the role of the LCCP policy on urban green productivity.

Heterogeneity in environmental regulation intensity

It has been proved that environmental regulation can significantly affect the impact of the LCCP policy. Given this, DDD model is used to assess the heterogenous effect of LCCP policy on green productivity of cities with different environmental regulation intensity. Specifically, first, we use the comprehensive utilization rate of industrial solid waste to establish the dummy variable of environmental regulation intensity. If the utilization rate is higher than the average of the sample cities, the dummy variable is assigned 1, otherwise it is assigned 0. Then, we combine the dummy variable and *did* to build a *ddd* item and add it to Eq. (1) for regression. Column (3) of Table 6 listed the estimated results.

As is found that the estimation coefficient of *ddd* is significantly positive, indicating that the LCCP policy plays a greater role in promoting green productivity of cities with stricter environmental regulation. This may be because the "innovation compensation effect" brought about by higher environmental regulation can effectively enhance enterprises' technological innovation capabilities (Porter and Linde 1995), which facilitates the improvement of urban green productivity.

Heterogeneity in urbanization level

It has been verified that urbanization level plays a vital role in improving urban green productivity. Hence, the LCCP policy's effect on urban green productivity might vary across cities with different urbanization level. Thus, the proportion of urban construction area in the total urban area is adopted to measure the level of urbanization, and constructs a dummy variable. In detail, if city urbanization level is higher than the sample average value, the dummy variable is assigned 1; otherwise, it is assigned 0. Then, a *ddd* item is established by multiplying the dummy variable and *did*, and is added to Eq. (1) for regression. The estimation results are illustrated in column (4) of Table 6.

The results show that the estimation coefficient of *ddd* is significantly positive, indicating that the LCCP policy plays a greater effect on green productivity of cities with higher urbanization level. A possible explanation lies in that there exists a U-shaped linkage between urbanization level and environmental pollution. Specifically, in the early stage of urbanization, with a large number of people gathering from rural areas to cities, the proportion of high-consumed and high-polluted secondary industry increases significantly, and thereby the urban eco-environment tends to deteriorate. When urbanization reaches a higher level, industrial structure upgrading, technological innovation, and resource allocation optimization brought by urbanization can substantially promote the coordination of economy and environment. Therefore, the higher the urbanization level, the more significant the promotion effect of LCCP policy on urban green productivity.

Mechanism analysis

Transmission mechanism analysis

The above section has empirically demonstrated that the LCCP policy can significantly improve urban green productivity in China. However, how does the LCCP policy affect urban green productivity in China? As analyzed in the "Transmission mechanism and research hypotheses" section, theoretically, the LCCP policy can affect urban green productivity through energy consumption reduction effect, industrial structure optimization effect, and technological innovation effect. To test whether hypotheses 1 to 3 are true, we employ the two-stage mediating effect model (Baron and Kenny 1986) to examine the transmission channels of the LCCP policy affecting urban green productivity in this study.

In the first stage, the effects of LCCP policy on the three mediating variables are identified. Specifically, on basis of Eq. (1), a comprehensive model for verifying the driving effect of LCCP policy on the mediating variables is constructed in Eq. (9). If β is not significant, it indicates that the mediating effect does not exist, the process will be terminated; otherwise, it implies that the LCCP policy exerts a significant effect on the mediating variable, then the second stage can be conducted.

$$energy_{it}(ins_{it}, innova_{it}) = \alpha + \beta did_{it} + \lambda X_{it} + u_t + \theta_i + treat_{pt} + \varepsilon_{it} \tag{9}$$

where *energy*, *ins*, and *innova* respectively refers to the three mediating variables. *energy* measured by urban per capita electricity consumption represents urban energy usage. *ins* measured by the proportion of tertiary industry output value in urban GDP represents urban industrial structure. *Innova* represents the level of urban technological innovation, which is measured by the China City Innovation Index proposed by Kou and Liu (2017). Other variables are consistent with Eq. (1). Related data are all sourced from *China City Statistical Yearbooks* from 2005 to 2019.

In the second stage, the driving effect of the three mediating variables of the LCCP policy on urban green productivity is examined. Based on Eq. (9), a comprehensive model for verifying the effect of the three mediating variables on urban green productivity is established in Eq. (10). If γ is not significant, it indicates that there is no mediating effect; otherwise, a mediating effect is verified.

$$GTFP_{it} = \alpha + \beta did_{it} + \gamma energy_{it}(ins_{it}, innova_{it}) + \lambda X_{it} + u_t + \theta_i + treat_{pt} + \varepsilon_{it} \tag{10}$$

The estimation results of transmission mechanism analysis the LCCP policy's effect on urban green productivity are shown in Table 7. Column (1) examines the LCCP policy's effect on *energy*. As is shown that the LCCP policy can significantly reduce urban energy consumption. Column (2) tests the effect of *energy* on urban green productivity. The results show that reducing energy consumption can significantly promote green productivity. This indicates that reducing energy consumption is a critical pathway for the LCCP policy to promote urban green productivity in China.

Column (3) presents the LCCP policy's effect on *ins*. The results shows that the estimation coefficient of *did* is not significant, indicating that the mediating effect of *ins* does not exist and the test process is stopped. It suggests that there is lack of empirical evidence to support that upgrading industrial structure is a channel through which the LCCP policy improves urban green productivity in China.

Column (5) offers the LCCP policy's effect on *innova*. The results show that the LCCP policy can inspire urban technological innovation. Column (6) tests the effect of *innova* on urban green productivity, and the results indicate that technological innovation can significantly enhance urban green productivity. It suggests that technological innovation is another vital path for the LCCP policy to promote urban green productivity in China.

Table 7 Results of the analysis of the transmission mechanism

Variable	*(1) energy*	*(2) BML*	*(3) ins*	*(4) BML*	*(5) innova*	*(6) BML*
did	*−0.164****	*0.035*	*0.184*	*0.070***	*19.32**	*0.059*
	(0.345)	*(0.028)*	*(0.547)*	*(0.034)*	*(11.34)*	*(0.043)*
energy		*−0.217****				
		(0.025)				
ins				*0.004*		
				(0.005)		
innova						*0.079****
						(0.021)
cons	*9.236****	*4.096****	*52.56****	*1.823****	*−930.5****	*2.698****
	(1.073)	*(0.724)*	*(7.416)*	*(0.430)*	*(71.08)*	*(0.946)*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
City fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province-time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	*4235*	*4235*	*4235*	*4235*	*3670*	*3670*
R^2	*0.660*	*0.462*	*0.754*	*0.445*	*0.592*	*0.417*

Internal dynamic mechanism analysis

The above analysis results have confirmed that the LCCP policy can significantly improve urban green productivity in China. However, does the LCCP policy promote urban green productivity by technological progress (TECH) or technological efficiency improvement (EFFCH)? In this section, this study uses the two decomposition components of urban green productivity, i.e. TECH and EFFCH, to replace the explained variable in Eq. (1) to investigate the internal dynamic mechanism of the LCCP policy affecting urban green productivity. The estimated results are listed in Table 8.

Columns (1) and (2) report the estimation results with *EFFCH* as the explained variable. It shows that the estimation coefficient of *did* is positive but not pass the significance test, regardless of whether the control variables are added or not. It implies that the LCCP policy's effect in urban EFFCH promotion is not obvious. Columns (3) and (4) show the regression results with TECH as the explained variable. It can be found that the estimation coefficients of did are significantly positive, regardless of whether the control variables are added or not. It indicates that the LCCP policy can significantly promote urban TECH. Base on the above analysis, it can be demonstrated that the LCCP policy mainly depends on technological progress to promote urban green productivity in China, rather than improving technological efficiency.

Spatial spillover effect analysis

The above analysis has systematically analyzed the LCCP policy' effect on urban green productivity in China. However, whether the impact has spatial spillover effect needs to be further explored. In this section, the spatial DID model is introduced to address the issue.

Table 8 The result of the driving force analysis

Variable	(1)	(2)	(3)	(4)
did	0.026	0.027	0.044**	0.039**
	(0.018)	(0.019)	(0.017)	(0.018)
Cons	1.182***	1.284***	1.057***	1.603***
	(0.016)	(0.384)	(0.014)	(0.271)
Control variables	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Province-time fixed effects	Yes	Yes	Yes	Yes
Obs	4235	4235	4235	4235
R^2	0.241	0.244	0.753	0.754

Before the regression of spatial DID model, we adopt Moran's *I* and Geary's *C* indexes to examine the spatial correlation characteristic of urban green productivity in China, and the results are provided in Table 9. It is found that most values of the two indexes are significantly positive during the sample period, which indicates that significant spatial agglomeration features of urban green productivity in China does exist. In addition, Fig. 5 shows the local Moran scatter plots of urban green productivity in 2004, 2009, 2014, and 2018. As is shown that the scatters are mainly concentrated in the 1st and the 3rd quadrants. This indicates that China's urban green productivity shows obvious positive spatial correlation characteristics of "high-high" and "low-low" spatial agglomeration.

With regard to the selection of spatial econometric model, in this study, through Hausman test, LM test and Wald test, the fixed-effect SDM model is ultimately selected for spatial DID regression, and it is constructed in Eq. (11). The estimation results are shown in columns (5) and (6) of Table 10. Besides, for comparison, the results of SAR and SEM models are also listed in columns (1)–(4) of Table 10.

$$GTFP_{it} = \alpha + \beta_1 did_{it} + \beta_2 X_{it} + \beta_3 W \times did_{it} + \rho W \times GTFP_{it} + \gamma_t + \theta_i + \varepsilon_{itj} \tag{11}$$

where $W \times GTFP_{it}$ and $W \times did$ stand for the spatial lag term of the explained variable and the core explanatory variable, respectively; ρ denotes spatial autoregressive coefficient; γ_t represents time fixed effect; θ_i represents city fixed effect; ε_{itj} is random error term; W is an economic spatial weight matrix. If the coefficient of $W \times did$ is significant, it shows that the LCCP policy plays a significant role in promoting

Table 9 The Moran's Index of urban green productivity during 2004–2018

Year	Moran' I	Z-value	Geary's C	Z-value
2004	0.018*	1.870	0.978	– 0.997
2005	0.025**	2.511	0.958**	– 2.060
2006	0.072***	7.074	0.930*	– 1.830
2007	0.026***	2.630	0.951**	– 2.122
2008	0.042***	3.979	0.943***	– 3.861
2009	0.030***	2.938	0.977	– 0.943
2010	0.041***	3.910	0.956**	– 2.515
2011	0.025***	2.774	0.921*	– 1.940
2012	0.012	1.339	0.948**	– 2.413
2013	– 0.014	– 0.900	0.979	– 1.174
2014	0.070***	7.096	0.903**	– 2.263
2015	0.014	1.559	0.975	– 1.528
2016	0.024**	2.413	0.963**	– 2.312
2017	0.038***	3.616	0.948***	– 3.881
2018	0.011	1.339	0.971	– 1.113

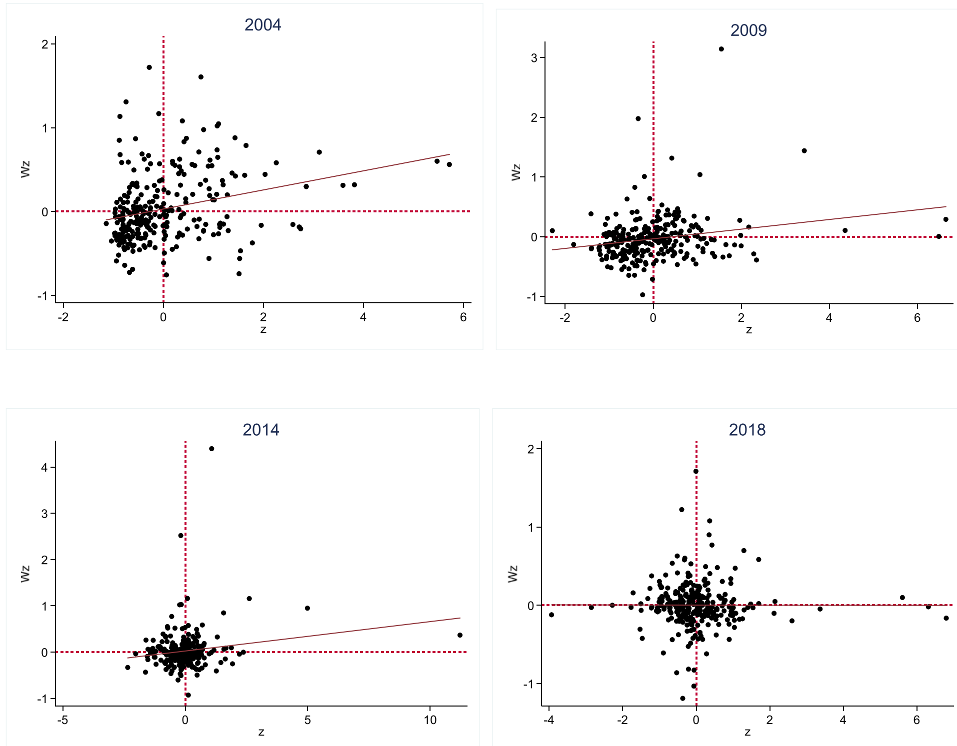


Fig. 5 Scatter plots of the local Moran's *I* of urban green productivity in China

Table 10 The results of the analysis of the spatial spillover effect

Model	*SEM*		*SAR*		*SDM*	
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
did	*0.053**	*0.055**	*0.062***	*0.061**	*0.054**	*0.054**
	(0.032)	*(0.032)*	*(0.032)*	*(0.031)*	*(0.032)*	*(0.032)*
$W \times did$					*0.166***	*0.140**
					(0.083)	*(0.084)*
ρ	*0.366****	*0.363****	*0.367****	*0.685****	*0.365****	*0.363****
	(0.027)	*(0.027)*	*(0.027)*	*(0.016)*	*(0.027)*	*(0.027)*
Control variables	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Direct effect			*0.064**	*0.067**	*0.064**	*0.063**
			(0.033)	*(0.035)*	*(0.033)*	*(0.033)*
Indirect effect			*0.035**	*0.129**	*0.280***	*0.239**
			(0.018)	*(0.067)*	*(0.121)*	*(0.124)*
Total effect			*0.100**	*0.196**	*0.344****	*0.303***
			(0.051)	*0.101*	*(0.129)*	*(0.132)*
Obs	*4245*	*4245*	*4245*	*4245*	*4245*	*4245*
R^2	*0.004*	*0.087*	*0.009*	*0.116*	*0.022*	*0.102*

the green productivity of neighboring cities, i.e., a spatial spillover effect does exist.

The results show that the estimated coefficient of ρ is significantly positive, indicating that a significant positive correlation does exists in green productivity between the pilot cities and their neighboring cities. Besides, the estimated coefficient of $W \times did$ is significantly positive. This suggests that the LCCP policy exerts a dramatic positive spatial spillover effect on urban green productivity. Furthermore, the partial differential method is used to decompose the total policy effect into direct effect and indirect affect, among which the direct effect stands for the LCCP policy's effect on the green productivity of the pilot city itself, and the indirect effect represents the LCCP's effect on the green productivity of its neighboring cities, i.e., spatial spillover effect. It is found that the impact of LCCP policy on urban green productivity has significant positive direct effect and positive spatial spillover effect, and the positive spatial spillover effect plays a leading role.

Conclusions and policy implications

Conclusions

In this study, the panel data of 283 China's prefecture level cities from 2003 to 2018 are adopted to systematically investigate the impact of the LCCP policy on urban green productivity employing the methods including PSM-DID, 2SLS regression, DDD, and spatial DID. The main findings are as follows: (1) The LCCP policy can significantly improve urban green productivity, its resulting win–win situation between economy and environment is proved to be achieved; (2) the LCCP policy can improve urban green productivity through the paths of energy consumption reduction and technological innovation, but has no effect on industrial structure optimization; (3) the green productivity promoting effect of the LCCP policy is more significant in non-resource-based cities and these cities with better transportation infrastructure, stricter environmental regulation and higher urbanization level. (4) The LCCP policy mainly improves urban green productivity through technological progress, and there is room to further enhance its effect on technical efficiency to improve urban green productivity. (5) Significant positive spatial spillover effect can be verified in the impact of LCCP policy on urban green productivity, indicating that both the pilot cities and their neighboring cities can be benefit from the implementation of LCCP policy.

Policy implications

On basis of the findings above, some policy recommendations are offered as follows:

(1) Given that the Benchmark regression identified that the LCCP policy can significantly improve urban green productivity and achieve a win–win situation between economy and environment, it is suggested that the Chinese government expand the pilot scope of low-carbon cities, further promote low-carbon city construction, so as to give full play to the policy dividend.

(2) Transmission mechanism analysis confirmed that the green productivity promotion effect of the LCCP policy mainly comes from energy consumption reduction and technological innovation, while the effect of optimizing industrial structure remains limited. Thus, the local government should actively develop low-carbon industries and build energy-saving and environmental protection industries as well as low-carbon service industries, so as to enable industrial structure optimization to be an important pathway to promote urban high-quality development.

(3) Internal mechanism analysis suggested that the LCCP policy drives urban green productivity mainly through technological progress rather than technical efficiency promotion. As such, to further play the role of improving technical efficiency, during the implementation of LCCP policy, strengthening the institutional guarantee of low-carbon city construction, including formulating and perfecting relevant laws and regulations, improving the level of marketization, and breaking regional barriers, needs to be highlighted.

(4) Heterogeneity analysis results showed that the green productivity promotion effect of the LCCP policy varies greatly across different pilot cities. Given this, during the implementation of LCCP policy, the government should formulate tailored policies based on the actual features of different pilot cities, including economic development, resource endowment, infrastructure construction, environmental regulation and urbanization level, so as to maximize the benefits of low-carbon city construction.

(5) The Chinese central government should scientifically layout and plan low-carbon cities across the country and promote the formation of a low-carbon city network. Meanwhile, the local government should strengthen technical cooperation and exchange to facilitate the diffusion of advanced low-carbon and clean technologies, so as to fully exploit the positive spatial spillover effect of LCCP policy in improving urban green productivity.

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