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RESEARCH ARTICLE

Boosting the green total factor energy efficiency in urban China: Does low-carbon city policy matter?

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Abstract
Low-carbon city (LCC) pilot is a strategic policy to deal with global climate change and energy poverty. Using the city-level data from 2006 to 2019, this paper applies a multiple difference-in-difference (DID) analysis to explore the impact of LCC policy on urban green total factor energy efficiency(GTFEE) and its potential mechanism. The results show that the LCC pilot policy can significantly improve urban GTFEE, and the finding remains robust with various tests. Secondly, we shed light on the mechanism of the LCC policy and explore the possible channels through green innovation and structural upgrading to improve the urban GTFEE. Third, the policy effect is affected by different levels of urban economic development, urban development scale, and urban development types. In cities with higher levels of economic development, super-large resource-based cities, the pilot policy has a more significant improvement effect on GTFEE. On the other hand, in the less developed regions, pilot policies will hinder the improvement of GTFEE.

Keywords Environmental decentralization governance · Low-carbon city pilot · Green total factor energy efficiency · Difference-in-difference design · Mediating effect analysis

Introduction

With the dramatic rise of greenhouse gas emissions, climate change and energy poverty have become significant challenges worldwide (Dubey et al. 2019; Gao et al. 2021a). China is the largest energy consumer worldwide, increasing from 602 million tons of standard coal in 1980 to 4.64 billion tons in 2018, accounting for 23.6% of total global energy consumption (British Petroleum, 2019; Wen et al. 2021a, b). To fulfill global environmental governance commitment, China signed the Paris Agreement at the United Nations in April 2016. Furthermore, at the Climate Ambition Summit held in December 2020, China pledged to cut carbon dioxide emissions per GDP by more than 65% from the 2005 level by 2030 and raise the share of non-fossil energy and primary energy consumption to about 25%. Under the pressure of economic growth and international emission reduction agreements, improving green total factor energy efficiency (GTFEE) has become an important measure to solve China's energy problems and achieve sustainable and high-quality development. Based on the low-carbon city (LCC) pilots in 2010, this study explores the impacts of carbon governance on urban GTFEE from the perspective of local government and tries to answer the following questions: Does the introduction of LCC policy enhance GTFEE? What are the potential mechanisms affecting GTFEE? Is there heterogeneity in the effect of the LCC policy in different regions?

The impact of environmental policy on energy efficiency is widely debated. One view holds that environmental policies will increase costs and reduce energy efficiency, while the other argues that environmental policies can improve energy efficiency through technological innovation and other mechanisms. Specifically, some scholars believe that environmental policies increase firms' production and pollution control costs, thus weakening their competitiveness, while the "race to the bottom" effect increases the difficulty of

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local governance, which harms energy efficiency. For example, Hancevic (2016) analyzes the impact of the 1990 Clean Air Act amendment on productivity and energy efficiency in Mexico and argues that the negative effect of environmental regulation on energy efficiency comes from productivity. Adua et al. (2021) find a paradox between energy policy and efficiency in the United States because their fixed effects estimates show that state policy positively impacts energy consumption.

On the other hand, Porter's hypothesis holds that appropriate environmental regulation partially or wholly offsets the negative impact of cost-effectiveness and enhances energy efficiency by facilitating technological innovation (Porter and Linde, 1995). For example, by studying energy efficiency in OECD and non-OECD countries, Aldieri et al. (2021) conclude that knowledge spillovers and green innovation stimulate energy adaptation, thereby increasing efficiency. Curtis and Lee (2019) analyze micro-data at the factory level from manufacturers' annual survey and find that environmental regulations can directly stimulate investment related to energy efficiency, which improves energy efficiency and reduces pollution emissions. These studies often employ panel data for linear regression, which might be biased when policy is endogenous. In addition, the policy indicators collected from survey such as environmental investment, emission charge revenue, and government reports are susceptible to systematic errors due to the multidimensional pollutants (Li and Wu, 2017).

Another strand of literature related to our paper has extensively studied the design, indicators, and policy effects of LCC policy (Tan et al. 2017). Many countries take LCC policy as an aggressive strategy to deal with climate change, such as Germany and China (Ferreira et al. 2019; Syahza and Asmit, 2019). Some researchers find low emission zones in Germany have improved local air quality significantly, while being beneficial to local freight transport's economic activities, although no significant enhancement in infant health is found (Gehrsitz, 2017; Cruz and Montenon, 2016). Compared with developed countries, LCC construction might encounter more difficulties in developing economies. With the implementation of low-carbon city pilots in China, more and more scholars have carried out studies to evaluate the policy's impacts on environmental and economic systems, such as carbon emission, air pollution, ecological efficiency, industrial structures, and foreign direct investment (Yu and Zhang, 2021; Song et al. 2020, 2019; Liu et al. 2020). However, with various methods, scope, and datasets adopted in previous research, it is hard to reach a consensus. Moreover, limited efforts have been made to explore LCC construction's impact on energy efficiency.

To fill the gap, we aim to discuss the impact of China's low-carbon city construction on urban energy efficiency with a staggered difference-in-difference (DID) analysis in this study. To identify the real effect of LCC policy, we take the three batches of pilots in China as a quasi-natural experiment with a panel dataset of prefecture-level cities in China from 2006 to 2019. The possible contribution of our paper is threefold. First, it is a valuable supplement to the literature on the environmental effect of low-carbon cities by providing a unique case of China. Extant literature focuses on the theories and index construction of low-carbon cities (Tan et al. 2017; Zhao et al. 2019). Some studies have proved the carbon emission reduction effect of LCC pilots, but its impact on energy efficiency remains unclear (Cheng et al. 2019; Song et al. 2020). This paper evaluates low-carbon city construction from the perspective of energy efficiency for the first time. By testing the plausible transmission mechanisms, including green technological innovation and industrial structural upgrading effects, our results provide practical implications for developing low-carbon cities.

Secondly, we develop green total factor energy efficiency (GTFEE) to measure urban energy efficiency with an undesirable slacks-based model (SBM), which contributes to energy efficiency measurement. Compared with single factor indicators such as energy consumption intensity, our measure is more holistic to reflect the efficiency of the energy-economic system (Gao et al. 2021b). In addition, with data from Chinese prefecture-level cities, we apply a DID design and the propensity score matching (PSM) to explore the effect of low-carbon city pilot policy on GTFEE. Our design avoids biased estimation and thereby help policymaker to evaluate the real impact of LCC policy.

Thirdly, we also contribute to the studies on local policy diffusion by discussing the effects of heterogeneity and providing suggestions for different regions to make differentiated goals. Instead of conducting heterogeneity effects, many empirical studies on low-carbon cities conclude with the baseline estimation result (Liu et al. 2020; Du et al. 2021). However, their findings might be overthrown in a specific situation. We hypothesize that results might vary along several dimensions: urban economic development, urban scale, and the dependence on urban resources. Our estimates provide insights into the diffusion of low-carbon city policy in other areas and economies.

The rest of this study proceeds as follows. The "Background and research hypothesis" section supplies the background of LCC policy and research hypothesis. The "Mmethodology and data" section describes our methods and data. The "Empirical results" section presents empirical results and provides a thorough discussion. The "Mechanism analysis" section examines the transmission mechanism. The "Heterogeneity analysis" section discusses the heterogeneity. The "Conclusion and policy implications" section concludes.

Background and research hypothesis

Institutional background of LCC policy in China

Processing to a crucial period of urbanization, China faces a growing energy demand. While expanding the economy and enhancing people's livelihood, China needs to effectively reduce greenhouse gas emissions to address climate change and improve energy efficiency to address the energy dilemma challenge. Cities accounted for 60% of the country's energy consumption in China in 2009. The Chinese government has put energy-saving and emissions-reducing into the long-term strategic plan to control energy consumption to cope with energy supply and demand imbalance. In the 11th, 12th, and 13th Five-Year Plan, China aimed to decrease energy consumption per unit GDP by 20%, 17%, and 15%, respectively (Yang et al. 2020; Duan et al. 2021).

Meanwhile, China proposed a series of policies and programs to fulfill the goals. In 2010, the National Development and Reform Commission (NDRC) issued the Notice on the Pilot Work of Low-carbon Provinces and Cities (the Notice), then successively initiated three batches of pilots. The first batch of pilots started in 2010, including Guangdong, Liaoning, Hubei, Shaanxi, Yunnan province, Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, and Nanchang Guiyang, Baoding City (82 cities included). The second batch of pilots started in 2013, consisting of Hainan province and other 28 cities (33 cities contained). In 2017, 45 cities (districts and counties) were designated as the third batch of pilot projects. See the list of the pilot low-carbon cities of the first three batches in Table1.

"Low-carbon city" policy puts forward the following requirements. First, pilot provinces and cities should seek suitable low-carbon and green development modes according to economic development, factor endowment, and location conditions within their jurisdiction, thereby accelerating the establishment of low-carbon energy, construction, transportation, and other industrial systems. They should advocate low-carbon travel and green consumption lifestyles as well. Second, all pilot provinces and cities are required to construct assessment systems for controlling greenhouse gas emissions according to their respective carbon emission peak targets and pilot construction targets and implement a total amount control and decomposition implementation mechanism. Third, the pilot provinces and cities should actively explore innovation policy and diffuse the successful experience. With low-carbon development funds, they should construct urban infrastructure such as transportation, energy, water supply and drainage, heating, sewage, and garbage disposal according to the low-carbon concept. Moreover, they should release industrial policies, fiscal and taxation policies, and technology diffusion policies in promoting the construction of low-carbon city.

Research hypothesis

Basic hypothesis

The LCC policy can be incorporated into the theoretical framework of environmental federalism. Local governments in pilot cities will be empowered to set specific carbon emission targets and low-carbon development plans based on local conditions while adopting a top-down regulatory mechanism to ensure the achievement of the targets. First, local governments have cost advantages in environmental regulation. When the benefit is large enough, decentralization will improve environmental governance quality (D'Amato and Valentini, 2011). Second, decentralization will promote energy structure optimization and contribute to green production by enhancing the effective allocation of local resources (Fredriksson and Wollscheid, 2014). Additionally, decentralization also helps local governments play the role of National Policy Laboratory, promoting local policy innovation and realizing bottom-up reforms (Oates, 1999).

As a comprehensive environmental regulation policy under the governance of local governments, LCC pilot areas

Table 1 List of pilot "low-carbon cities" from 2010 to 2017 in China

Time	Region (province, city, district, county)
The first batch (2010)	Guangdong, Liaoning, Hubei, Shaanxi and Yunnan; Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, Baoding
The second batch (2013)	Hainan; Beijing, Shanghai, Shijiazhuang, Qinhuangdao, Jincheng, Hulun Buir, Jilin, Greater Hinggan Mountains region, Suzhou, Huai'an, Zhenjiang, Ningbo, Wenzhou, Chizhou, Nanping, Jingdezhen, Ganzhou, Qingdao, Jiyuan, Wuhan, Guangzhou, Guilin, Guangyuan, Zunyi, Kunming, Yan'an, Jinchang, Urumqi
The third batch (2017)	Nanjing, Changzhou, Jiaxing, Jinhua, Chuzhou, Sanming, Jinan, Yantai, Weifang, Zhongshan, Shenyang, Dalian, Chaoyang, Xunke, Sanya, QiongZhong, Hefei, Huaibei, Huangshan, Liuan, Xuancheng, Gongqingcheng, Gian, Fuzhou, Changyang, Changsha, Zhuzhou, Xiangtan, Chenzhou, Wuhai, Liuzhou, Chengdu, Yuxi, Puer, Lhasa, Ankang, Lanzhou, Dunhuang, Xining, Yinchuan, Wuzhong, Changji, Yining, Hotan, Xinjiang Corps

are subject to multiple target constraint effects and improve the economic level and production efficiency of pilot areas. First, the carbon emission peak targets imposed by the LCC policy increase enterprises' production costs, forcing enterprises to improve energy efficiency. According to the innovation compensation theory, strict environmental regulation policies will prompt enterprises to increase R&D investment in clean technology and change production mode to offset the negative impact of treatment costs (Porter and Linde, 1995). The local government of pilot cities assigns carbon emissions targets to critical enterprises. Under explicit constraints, the cost of high pollution, high energy consumption, and low-efficiency enterprises increases while profits decrease accordingly. These enterprises have three choices: stopping production, relocating, or improving efficiency through innovation. Considering sunk costs, rational enterprises will choose the third way (Qi et al. 2018). Second, LCC policy supports industrial policies and fiscal incentives, including setting up low-carbon development special funds, designing carbon emissions trading mechanisms, constructing tax incentive mechanisms, strengthening the human capital support, providing the relevant infrastructure measures, and optimizing the innovation services. These supportive policies help adjust the costs and benefits of enterprises. When innovation revenue is greater than the cost of pollution, enterprises will increase technological innovation input to improve production efficiency. Third, LCC construction enables pilot areas to form a "demonstration effect," which is conducive to attracting foreign direct investment and helps improve corporate competitiveness and foreign export trade, thereby accelerating urban economic development. By attracting technology-intensive foreign investment through market incentives, voluntary participation, information disclosure, and other mechanisms, LCC policy helps promote local industries transformation and improve energy efficiency.

Hypothesis 1:The construction of the low-carbon cities policy can help improve urban GTFEE.

Mechanism hypothesis

Green innovation effect According to the "Porter hypothesis," strict environmental regulation policies will prompt enterprises to increase R&D investment in green technologies and change production modes to improve production efficiency to offset the negative impact of treatment costs (Porter and Linde, 1995). First, one of the crucial goals of LCC policy is to build a green technology innovation mechanism, helping to reduce energy consumption and improve production efficiency (Xu and Cui, 2020; Wen et al. 2021a, b). Second, LCC policy enjoys "double preferential" policies provided by central and local governments, including tax breaks, subsidies, and talent incentives. These measures reduce the costs and risks in technological innovation and further encourage enterprises to carry out R&D activities. Thirdly, low energy consumption and high-value enterprises actively seeking green development in pilot cities will form competition and technology spillover effects in the open market. At the same time, the demonstration effect created by successful regional experience will continuously provide the driving force for innovation and economic development (She et al. 2020).

On the other hand, directed technological change (DTC) theory explains the effect of innovation on GTFEE. Technological innovation has a direction; cheap production factors will be used to save relatively expensive production factors. Therefore, low-carbon technological change will reduce energy input and thus improve energy efficiency (Hicks, 1932). Dowlatabadi and Oravetz (2006) find that energy efficiency increases by 1% by promoting DTC during the upward trend period of energy price. Hassler et al. (2012) believe that energy-saving technological change is crucial to reducing energy consumption intensity. Aldieri et al. (2021) find that clean technique change and its spillover effect will increase energy efficiency.

Hypothesis 2: The construction of the LCC policy can improve urban GTFEE through the green innovation effect.

Industrial upgrading effect The upgrading of industrial structure is one of the critical objectives of LCC policy. LCCs are required to establish a low-carbon industrial system centering on low-carbon, green, environmental protection and recycling, and develop strategic emerging industries according to regional industrial advantages. From the perspective of factor input, the increased production and treatment costs of LCC construction will reallocate production factors of enterprises; that is, the factor input of high-pollution and high-energy consumption industries will decrease, while the input of clean sectors will increase. As for industrial development, they aim to cultivate emerging industries with low energy consumption and a high GTFEE. The LCC policy guides resources to gather in technology-intensive emerging industries by issuing supporting industrial policies and gradually eliminating traditional pollution-intensive industries (Song et al. 2020). LCC policy helps enhance overall industry productivity and develop clean industries such as the service industry, upgrading industrial structure.

Regarding the relationship between industrial structure and energy efficiency, the change of industrial structure, especially the adjustment of the secondary and tertiary industries and the industrial weight structure, is the main factor affecting energy efficiency (Wei and Shen, 2008). The "structural dividend" brought by structural upgrading will optimize the industrial spatial structure and improve resource utilization efficiency to achieve green economic development. At the same time, the economies of scale brought by industrial agglomeration will reduce energy consumption and improve GTFEE.

Hypothesis 3: The construction of the LCC policy can improve urban GTFEE through the industrial upgrading effect.

Methodology and data

Model setting

We apply a multiple DID method to explore the causal relationship between LCC policy and GTFEE, which provides an exogenous estimation framework. Specifically, three batches of LCC pilots were implemented during the sample period; the first batch was introduced in 2010, the second batch began in 2013, and the third batch initiated in 2017. Since LCC pilots were implemented at various times, it allows us to disentangle LCCs' influence from economy-wide trends. Furthermore, the staggered pilots provide a natural control group for the treated group, namely, cities that have yet to enforce this policy. Three batches of pilot cities are defined as the treated group, while non-pilot cities are set as the control group. To implement this estimator, we consider the following model:

$$Y_{it} = \alpha + \beta_1 Policy_{it} + X_{it}^{'}\delta + \lambda_t + \gamma_{0i} + \gamma_{1i} \times t + \varepsilon_{it} \tag{1}$$

where subscript i implies the city and t denotes the year. The dependent variable Y_{it} means green total factor energy efficiency that represents urban energy efficiency. Dummy variable $Policy_{it}$ captures the effect of the LCC pilot policy that tooks place in year t within city i. $Policy_{it}$ equals one in the years after city i becomes eligible, otherwise zero. The coefficient of interest is β_1 that yields the impact of LCC introduction on the outcome of interest. $X_{it}^{'}$ represents a vector of control variables related to cities' characteristics, including population density, level of innovation, energy consumption, sulfur dioxide emissions, and industrial output. City fixed effect γ_{0i} and year fixed effect λ_t are concluded respectively to control the impact of invariant characteristics of cities and time-varying shocks of different years. $\gamma_{1i} \times t$ proxies the time trend term. According to Angrist and Pischke (2008), the time trend term can capture inconsistent trends in various cities, whereas ε_{it} implies the error term.

According to the mediation effect method proposed by Hayes (2009), we consider the following equations:

$$M_{it} = \alpha + \beta_2 Policy_{it} + X_{it}^{'}\psi + \lambda_t + \gamma_{0i} + \gamma_{1i} \times t + \varepsilon_{it} \tag{2}$$

$$Y_{it} = \alpha + \beta_3 Policy_{it} + \theta M_{it} + X_{it}^{'}\delta + \lambda_t + \gamma_{0i} + \gamma_{1i} \times t + \varepsilon_{it} \tag{3}$$

where M_{it} represents mechanism variables, such as green innovation level and industrial structure of advancement. Other variables have the same meaning as above. Models (1) to (3) constitute a recursive formula for testing the mediation effect. At the first step, we assess the influence of LCC on GTFEE by estimating model (1). Then, we estimate model (2) to test the relationship between LCC policy and the intermediary effect. In the final step, we estimate model (3). If $\beta_1, \beta_2 > 0$ and $\beta_3 < \beta_1$, a positive mediating effect exists; if $\beta_2 < 0, \beta_1, \beta_3 > 0 \text{and} \beta_3 > \beta_1$, a negative mediating effect exists.

Data and variables

Dependent variable

Following the method of Gao et al.(2021b), this paper uses the undesirable-SBM model to calculate the dependent variables green total factor energy efficiency (GTFEE) of 277 cities in China from 2006 to 2019. To be specific, it is assumed that there are N decision-making units (DMU), each of which has M inputs, S_1 expected outputs, and S_2 unexpected outputs, respectively, which can be expressed in the form of the $X = (x_{ij}) \in R_{m*n}$、$Y^g = (y_{ij}^g) \in R_{s1*n}$、$Y^b = (y_{ij}^b) \in R_{s2*n}$ the corresponding relaxation vectors of input, expected output, and unexpected output are $S^- \in R_m, S^g \in R_{s1}, S^b \in R_{s2}$, λ is the weight vector. The calculation formula is as follows:

$$\min\ p = \frac{1 - (1/m)\sum_{i=1}^{m} s_i^- / x_{i0}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s1} s_r^g / y_{r0}^g + \sum_{r=1}^{s2} s_r^b / y_{r0}^b\right)} s.t. \begin{cases} x_0 = X\lambda + s^- \\ y_0^g = Y^g\lambda - s^g \\ y_0^b = Y^b\lambda - s^b \\ \lambda \geq 0, s^- \geq 0, s^g \geq 0, s^b \geq 0 \end{cases} \tag{4}$$

The measurement of GTFEE mainly includes input, expected output, and undesirable output. The input variables include capital stock (K), the labor force (L), and energy consumption (EU). The expected output is GDP, and the undesirable output is SO_2, smoke, and effluents (Yan et al. 2019; Li et al. 2021). The calculation values of GTFEE are displayed in Fig. 1 in the form of the topographic map. White represents cities excluded from the sample. The darker the color of other labeled regions, the higher the GTFEE, and the darker green area has the highest green total factor efficiency. Due to space constraints, only the results for the 2006, 2010, 2014, and 2019 years are listed. It can be seen that the number of green areas gradually increased, indicating an upward trend of China's overall GTFEE. Because of the long-term transformation of economic development and the implementation of various environmental protection measures, the emission of pollutants has been effectively controlled. We conclude that remarkable progress has been made in environmental governance.

Independent variable

Dummy variable LCC policy, which denotes adopting the low-carbon city construction plan for city i in year t, is the independent variable concerned. The three batches of pilot cities are defined as the treated group, whereas their counterparts that have yet to introduce this plan are served as the control group.

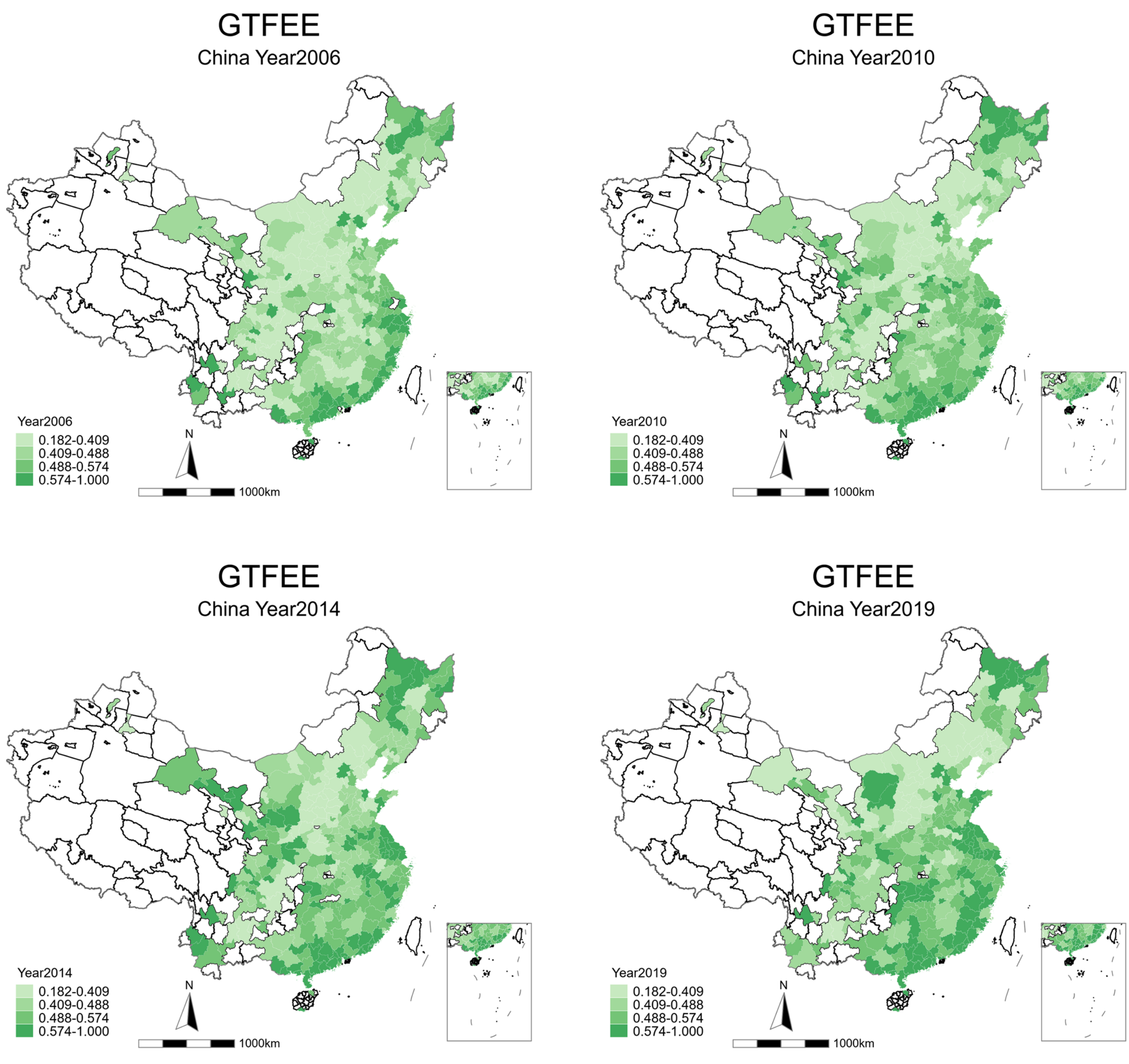

Fig. 1 GTFEE distribution in China

Mechanism variable

Green innovation level (Gpatent) Extant studies mainly apply two measures to obtain firm green technology innovation level, namely, green total factor productivity (Li and Chen, 2019) and the number of green patent applications (authorization) (Qi et al. 2018). In this study, we introduce the latter, accessing the data of green patent applications at the prefecture-level for measuring the urban green innovation level. The advantage of patent data is that it subdivides the field of green innovation, has a strong correlation with R&D, and contains a large amount of information that can be used for research technology diffusion (Wang, 2017). As the endogenous driving force of economic development and transformation, green technological change improves total factor energy efficiency, supported by endogenous growth theory, DTC theory, creative destruction theory, and empirical research (She et al. 2020).

Green innovation level (Gpatent) Industrial structure upgrading (Stu) The connotation of industrial structure advancement is industrial proportion changes and labor productivity improvement, often reflected by the proportion of various industries (Gan et al. 2011). According to Clark's law, the proportion of the third and second industries' gross product is employed to measure industrial structure advancement. The industrial structure is an essential factor influencing energy efficiency. As a transfer between input and output, it determines energy allocation among different industries (Bai et al. 2018). There are considerable differences in energy efficiency between various sectors. Controlling the development of energy-consuming and high-polluting industries, accelerating the elimination of backward production capacity, and optimizing the industrial structure will help improve energy efficiency (Xiong et al. 2019).

Control variable

The other control variables that impact the GTFEE are also considered, including population density, technical level, energy consumption, sulfur dioxide emissions, and industrial output (Gao et al. 2021a, b). To be specific, population density (Pop) is measured by the total population divided by the area of administrative divisions; sulfur dioxide emission (SO_2) measures pollutant emission levels in the city; industrial output (Indgdp) is expressed by the ratio of industrial output value above the designated level in regional GD; technical level (Tech) is represented by the amount of invention patent applications in the city; and energy consumption (Ec) is expressed by the proportion of the regional GDP to the total year-end population in the city.

Data source and descriptive statistics

Our selected sample covers a dataset of prefecture-level cities in China from 2006 to 2019. Energy efficiency measurement is the primary source of data used in this study, so the calculation of GTFEE of data is accessed through China City Statistical Yearbook. The energy consumption data are obtained from the China Energy Statistical Yearbook. Marketization Index is derived from the Marketization Index Report of China by Province (version 2018) (Fan and Wang, 2019), whereas green patent data is accessed via the State Intellectual Property Office's website. Additionally, other mechanism and control variables data are derived from China City Statistical Yearbook. Table 2 displays the summary statistics of our sample's composition and the variables in the baseline results.

Empirical results

The impact of low-carbon city policy on GTFEE

In order to verify the difference in GTFEE between pilot cities and non-pilot cities, the DID method is used to test the effect of policy implementation. Moreover, considering that local governments' policy choice may be non-random, to deal with the endogenous bias caused by the reverse causality effect, this study adopts Propensity Score Matching (PSM) to screen the two groups of samples and re-estimates DID. Based on the fact that the implementation of LCC pilots is multi-phase, this study selects sample cities in the way of matching year by year, referring to Li and Wu (2018). Table 3 reports the baseline results processed by multiple DID and PSM-DID estimates,

Table 2 Descriptive statistics

Variables	Symbol	Observation	Mean	SD	Min	Max
Green total factor energy efficiency	GTFEE	3878	3878	-0.087	0.351	−1.425
Population density	Pop	3878	5.725	0.89	1.681	7.889
Energy consumption	Ec	3878	6.824	0.898	3.809	9.427
Technical level	Tech	3878	3.864	1.968	0	10.738
Sulphur dioxide emissions	SO_2	3878	10.5	1.103	0.693	13.435
Industrial output	Indgdp	3878	0.45	0.651	−2.796	3.307

respectively, with city fixed effects and year fixed effects controlled in all regressions.

Referring to the DID estimation results in columns (1) and (2) of Table 3, whether controls are included or not, pilot policies have a significant positive impact on urban GTFEE. Compared with cities that did not participate in the LCC pilot, the GTFEE of the three batches of cities implementing this policy is approximately 3.6 percentage higher. Thus, LCC policy can help improve urban energy efficiency, consistent with our expectations. When it comes to columns (3) and (4) of Table 3, the dummy variable's estimated coefficient is still significantly positive at the 5% level after eliminating sample selection bias using the PSM method. Moreover, the coefficient's absolute value is relatively large (denoting a 4.1% increase), indicating that our empirical results are still robust. The estimation results seem intuitive. It is worth noting that in Table 4, the standardized deviation of each covariable decreases significantly after matching, with P values greater than 0.1, indicating that there is no systematic difference between the control variables of the treated group and the control group after matching. Moreover, each covariable has a strong explanatory power.

Table 3 The baseline results of the impacts of LCC policy on GTFEE

	DID		PSM-DID	
	(1)	(2)	(3)	(4)
Policy	0.038**	0.036**	0.048***	0.041**
	(2.19)	(2.18)	(2.76)	(2.42)
Constant	0.048	0.886***	0.053	0.744**
	(1.34)	(2.69)	(1.39)	(2.04)
Controls	No	Yes	No	Yes
Time trend	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
N	3878	3878	3297	3297
R^2	0.864	0.874	0.869	0.879

LCC pilots, which empower local governments to formulate low-carbon policies and measures tailored to local conditions, could help set appropriate carbon emission targets (Dai et al., 2019). More importantly, since local governments have greater rights and responsibilities, they could efficiently implement low-carbon work and get favorable outcomes under the extant governance system (Chien and Hong, 2018). In the midst of positive policy incentives, the pilot city has introduced new energy products to reduce fossil energy consumption, adopted low-carbon technologies to reduce carbon emissions, developed low-carbon industries to change energy structure, encouraged greener travel and consumption patterns of the residents, etc., thus improving its energy efficiency. Our finding is consistent with extant literature and confirms the positive role of LCC pilot policy, e.g., the LCC pilot policy helps reduce air pollution, improve ecological efficiency, and increase foreign direct investment inflows (Cheng et al. 2019; Song et al. 2020; Liu et al. 2020). Therefore, Hypothesis 1 has been verified.

Notes: Standard errors account for city-level clustering, and the corresponding t value is present in parentheses. Yes means the variable is controlled, whereas No implies the variable is not controlled. Thus, *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Parallel-trend test and dynamic effects analysis

The validity of the DID estimator for the discussion of energy efficiency rests with the assumption that if there were no introduction of LCC policy, the GTFEE in pilot cities and non-pilot cities would experience a parallel trend. Moreover, the baseline results divide the samples by implementation time and statically analyze the institutional effect by comparing the average treatment effect before and after introducing this policy. The time-varying policy effect needs to be further examined. Therefore, this study draws on the practice

Table 4 Balance test after matching

Variable	Sample	Mean		%Reduct |bias|	t value	p value
		Treated	Control			
Pop	Unmatched	5.80	5.72	60.1	2.66	0.008
	Matched	5.77	5.73		0.96	0.340
Ec	Unmatched	6.91	6.99	88.4	3.50	0.000
	Matched	6.86	6.85		0.35	0.726
Tech	Unmatched	4.00	3.82	53.7	2.60	0.009
	Matched	3.91	3.99		– 1.05	0.292
SO_2	Unmatched	10.57	10.49	87.1	2.15	0.032
	Matched	10.54	10.53		0.24	0.808
Indgdp	Unmatched	0.49	0.49	45.7	1.32	0.188
	Matched	0.48	0.47		0.65	0.518

of Beck et al. (2010) to conduct dynamic DID estimation to determine whether the trend is parallel before LCC pilots and assess the dynamic effects of this policy on energy efficiency in the case of multi-time point quasi-natural experiment. The equation is set as follows:

$$Y_{it} = \alpha + \sum_{k=-m}^{k=n} \beta_k \times Policy_{i,t_0+k} + X_{it}^{\prime}\delta + \lambda_t + \gamma_{0i} + \gamma_{1i} \times t + \varepsilon_{it} \tag{5}$$

where $Policy_{i,t_0+k}$ is a series of dummy variables that equals one when the LCC pilot is k years away from implementation time in city i. We define t_0 the benchmark year when city t introduce the policy, then $Policy_{i,t_0+k}$ takes a value of 1 when $t - t_0 = k$, otherwise 0. We focus on the estimates of β_k that indicates the difference in energy efficiency between the treatment group and the control group k years away from the benchmark year.

The dynamic DID estimate result is displayed in Fig. 2. We can conclude that in $k < 0$ intervals that represent the pre-implementation periods, the estimated coefficient β_k is not significant; thus, no significant alteration is observed between the treated and control groups. The result satisfies the parallel-trend assumption. When $k = 0$, β_k appears to be increasingly significant, indicating that LCC construction significantly improved the energy efficiency of the treated group. In terms of dynamic effects, the GTFEE improves significantly after implementing the pilot policy, and the policy effect is still significant in the following years. One possible reason may be that there is more room for energy efficiency improvement after the pilot project starts. Local governments actively promote enterprises to save energy and reduce emissions in low-carbon city construction, improve energy utilization efficiency, and promote sustainable development transformation.

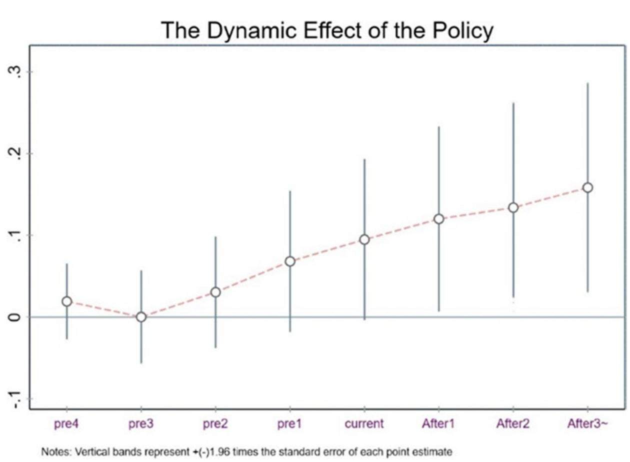

Fig. 2 Parallel trend test and the dynamic effect analysis of LCC policy

Placebo test

Taking the influence of other unobservable factors into account, this study conducts a placebo test by randomly selecting policy time dummy variables (Lu et al. 2017). Precisely, we classify the data according to the province at first and randomly choose a time of the *year* variable within each province group as its pseudo policy time. And then, we re-evaluate the previous estimates. The corresponding cross-product term is $Policy_{it}^{false}$. Since the pseudo-policy time is randomly selected, the coefficient β_1^{false} of $Policy_{it}^{false}$ should theoretically be 0. We repeat the exercise 1000 times in this study in case that our estimation is accidental, and 1000 coefficient estimates results are obtained.

Figure 3 plots the kernel density and the corresponding p value distribution of the estimates after 1000 exercises. The curve denotes the kernel density distribution, the hollow circle represents corresponding p values, and the vertical dotted line on the right is the above-estimated value of the coefficient, β_1, for the dummy variable, $Policy_{it}$. It is clear that the coefficient distribution corresponding to the pseudo-policy time concentrates around 0 and obeys the normal distribution, whereas the distribution of P values indicates that the estimates of these coefficients all significantly reject the null hypothesis of β_1^{false}.Meanwhile, the above-estimated coefficient represented by the vertical dotted line on the right is an outlier in the coefficient distribution of the placebo test, which is in line with our expectation. It illustrates that our above findings are not driven by intrinsic features or unobvious shocks within a city or a time.

Robustness checks

A series of robustness checks are performed in the section to eliminate our findings' suspicion in the estimation as mentioned above. Corresponding results are demonstrated in Table 5.

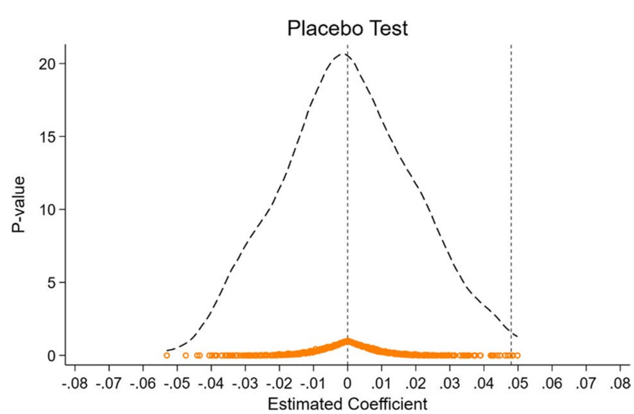

Fig. 3 Placebo test for policy time randomness

Table 5 Robustness checks: DID and PSM-DID estimations

	DID			PSM-DID		
	Excluding interference from energy policy	Excluding non-pilot provinces	EBM	Excluding interference from energy policy	Excluding non-pilot provinces	EBM
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	0.039**	0.037**	0.019**	0.045***	0.039**	0.018**
	(2.34)	(2.22)	(2.36)	(2.61)	(2.28)	(2.12)
NEVPC	0.003			0.004		
	(0.10)			(0.15)		
PCETS	−0.135***			−0.136***		
	(−5.68)			(−5.11)		
Constant	0.863***	0.886**	−1.104***	0.718**	0.788*	−1.180***
	(2.62)	(2.47)	(−4.41)	(1.98)	(1.96)	(−4.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	3108	3234	3878	2596	2786	3297
R^2	0.869	0.877	0.700	0.876	0.883	0.721

Standard errors account for city-level clustering, and the corresponding t value is present in parentheses. Yes means the variable is controlled, whereas No implies the variable is not controlled. Thus, *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Excluding interference of other policies

In the process of LCC construction, the release of other energy policies could also impact urban energy efficiency, making our regression results overestimated or underestimated. For instance, the New Energy Vehicle Pilots Cities (NEVPC) was implemented in 2010 and 2013, and the Pilot Carbon Emission Trading Scheme (PCETS) was introduced in 2013. To exclude the interference of the energy as mentioned policies on the estimation, we add the DID term of the above policies to model (1). As shown in columns (1) and (4) of Table 5, after controlling the interference of other energy policies, there is still a significant positive effect on GTFEE; namely, the new estimates are consistent with the baseline results, suggesting that the findings of this study are robust.

Excluding non-pilot provinces

To make the characteristics of the treatment and control groups more similar, this study changes the control group's range to conduct a robustness check. Expressly, provinces in the control group with no pilot cities between 2006 and 2019 are excluded, so the sample scope of this section is limited to all pilot provinces. Columns (2) and (5) of Table 5 displayed the results. We could find that the policy estimator is still significantly positive, illustrating that baseline results are not affected by the control group selected.

Changing energy efficiency measurement

The estimation results of energy efficiency may vary greatly with different estimation methods. Tone and Tsutsui (2010) propose a mixed distance function EBM model that integrates radial and non-radial features, more accurate and comprehensive advantages in efficiency evaluation. Therefore, the EBM model is adopted to calculate green total factor energy efficiency as the explained variable to carry out a robustness test. To be specific, we assume a linear combination coefficient of λ DMU, each of which has m inputs, q expected outputs, and p unexpected outputs; θ is the radial efficiency value calculated by CCR model; ω^{-}, ω^{g}, and ω^{b} are the relative weights of inputs, expected outputs, and unexpected outputs, respectively; and $\sum \omega = 1$. Its calculation formula is as follows:

$$\min \frac{\theta - \varepsilon_x\left(1/\sum_{i=1}^{m}\omega_i^{-}\right)\sum_{i=1}^{m}\omega_i^{-}s_i^{-}/x_{ik}}{\varphi + \varepsilon_y\left(1/\sum_{r=1}^{q}\omega_r^{g}\right)\sum_{r=1}^{q}\omega_r^{g}s_r^{g}/y_{rk} + \varepsilon_z\left(1/\sum_{t=1}^{p}\omega_t^{b}\right)\sum_{t=1}^{p}\omega_t^{b}s_t^{b}/z_{tk}} s.t.\begin{cases} X\lambda + s_i^{-} = \theta x_k \\ Y^{g}\lambda - s_r^{g} = \varphi y_k \\ Z^{b}\lambda - s_t^{b} = \varphi z_k \\ \lambda \geq 0, s_i^{-} \geq 0, s_r^{g} \geq 0, s_t^{b} \geq 0, \theta \leq 1, \varphi \geq 1 \end{cases} \quad (6)$$

The regression results are shown in columns (3) and (6) of Table 5. It is clear that the regression of total factor energy efficiency measured by the EBM model demonstrates that LCC pilots still positively affect energy efficiency, which enhances the robustness of the conclusion of this paper.

Mechanisms analysis

A significant positive effect of LCC policy on urban GTFEE is shown in the "Empirical results" section. Then, what is the transmission mechanism behind it? This study proposes two theoretical hypotheses: LCC pilot policies can improve GTFEE in two ways: green innovation and industrial upgrading effect. Therefore, Eqs. (2) and (3) are used in this section to further empirically test these hypotheses, and Table 6 reports the results (Table 7).

The coefficient of *Policy* in column (1) of Table 6 is significantly positive at the 1% level, indicating that LCC policy enhances urban green innovation level. From Table 6 column (2), after joining the green innovation level variable, the coefficient of *Policy* is still significantly positive, and its absolute value relatively falls compared to the benchmark regression's result in Table 3 column (2), which proves a mediation effect of green innovation. LCC policy has produced a "Porter effect" in pilot cities, optimizing energy structure and improving GTFEE by inducing low-carbon technologies. Hypothesis 2 is verified. The LCC policy can improve urban energy efficiency through green innovation, which is also supported by the results of PSM-DID estimation.

In terms of industrial structural upgrading, the coefficient of policy in column (3) of Table 6 is positive and significant at the level of 10%, indicating that LCC helps promote industrial intensification. After adding the industrial upgrading level variable in column (4) of Table 6, the coefficient of *Policy* is significantly positive, and the absolute value of the coefficient is smaller than that in column (2) of Table 3, indicating that the mediation effect driven by structural upgrading exists, that is, low-carbon pilot projects can improve urban energy efficiency by improving industrial upgrading. Pilot areas set emission targets to restrain enterprises from achieving the goal of eliminating high-pollution and high-energy industries. Therefore, policy constraints help foster emerging industries and promote the development of green service industries, thereby driving the optimization and upgrading of industrial structure and improving resource utilization efficiency. Hypothesis 3 is verified, and the regression results of PSM-DID increase the robustness of the conclusion.

Table 6 Mechanism analysis of the effect of LCC on GTFEE

	DID				PSM-DID			
	Gpatent	Gtfee	Stu	Gtfee	Gpatent	Gtfee	Stu	Gtfee
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy	0.202***	0.019**	0.014*	0.029**	0.196***	0.028**	0.013*	0.032**
	(3.43)	(2.16)	(1.70)	(2.04)	(3.12)	(2.29)	(1.77)	(2.24)
Gpatent		0.010**				0.011**		
		(2.11)				(2.06)		
Stu				0.164***				0.141***
				(4.36)				(4.69)
Constant	2.808**	0.858***	1.395***	1.115***	2.241*	0.720*	1.576***	0.967***
	(2.33)	(2.59)	(4.26)	(3.50)	(1.87)	(1.96)	(4.08)	(2.79)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3878	3878	3878	3878	3297	3297	3297	3297
R^2	0.945	0.874	0.951	0.876	0.948	0.880	0.944	0.881

Standard errors account for city-level clustering, and the corresponding *t* value is present in parentheses. Yes means the variable is controlled, whereas No implies the variable is not controlled. Thus, *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 7 Heterogeneity test: urban economic development level

	DID			PSM-DID		
	Low	Median	High	Low	Median	High
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	−0.044**	0.013	0.044**	−0.034*	0.008	0.047**
	(−2.33)	(0.81)	(2.39)	(−1.78)	(0.51)	(2.51)
Constant	0.884***	0.883***	0.893***	0.732**	0.732**	0.760**
	(2.69)	(2.69)	(2.70)	(2.01)	(2.02)	(2.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	1323	1262	1293	1083	1098	1116
R^2	0.907	0.943	0.927	0.929	0.951	0.925

Standard errors account for city-level clustering, and the corresponding t value is present in parentheses. Yes means the variable is controlled, whereas No implies the variable is not controlled. Thus, *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Heterogeneity analysis

The above results show that LCC policy significantly improves GTFEE in pilot cities. Its mechanism analysis illustrates that technological innovation and industrial structure upgrading are two crucial influencing channels. However, there are considerable differences among cities regarding economic development level, resource endowment, and environmental conditions in China. Considering the potential heterogeneity in the sample, we divide the cities into different groups based on three standards—urban economic development level, urban scale, and urban resource dependence—to explore the heterogeneous effects of LCC policy on urban GTFEE.

City economic development level

The degree of industrialization, marketization, and autonomy could vary dramatically from city to city with different economic development levels, which determines whether pilots could play an effective role. Therefore, based on the tertiles of urban per capita GDP, we categorize the samples and re-estimate them. The results in Table 7 show that a significant positive relationship is found in cities with a high level of economic development. In contrast, no pronounced effect is found in cities with a medium economic level. It is worth noting that LCC pilots significantly negatively impact energy efficiency in less developed cities. In general, economic agglomeration could positively influence energy efficiency from three aspects. First of all, the scale effect reduces the average cost of industries by decreasing the unit output consumption of production factors such as energy. Furthermore, the essence of energy efficiency improvement comes from technological change and technology spillover, and economic agglomeration is the main driving force of technology spillover among firms (Fujita et al.,1999). Additionally, imperfect competition reduces costs by inducing price and quality competition among manufacturers. When energy prices upsurge, such competition could bring energy-saving effects (Shi and Shen, 2013).

City scale

Cities with different populations may also influence the effect of LCC policy. The population agglomeration effect could increase urban resource utilization efficiency. Nevertheless, oversized cities may have a crowding impact, more likely to aggravate urban diseases and pollution (Shi et al. 2018). Based on the size of the urban population, we classify samples to investigate whether the effect of LCC pilot policy varies between cities of different development scales.[1] The results are reported in Table 8. Table 8 illustrates that a positive influence can still be detected in megacities, while small- and medium-sized cities

[1] The criteria for classifying urban population size refer to the Notice on Adjusting the Criteria for Classifying Urban population issued by The Chinese State Council in 2014. Cities with a permanent urban population of less than 500,000 are defined as small cities; cities with a permanent urban population of more than 500,000 and less than 1 million are medium-sized cities; cities with a permanent urban population of more than 1 million and less than 5 million are large cities; megacities are those with a permanent urban population of more than 5 million and less than 10 million.

Table 8 Heterogeneity test: urban development scale

	DID			PSM-DID		
	Small and medium-sized cities	Large cities	Megacities	Small and medium-sized cities	Large cities	Megacities
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	−0.032	0.031*	0.043*	0.073	0.020	0.056**
	(−0.23)	(1.65)	(1.67)	(0.50)	(1.06)	(2.14)
Constant	0.887***	0.885***	0.889***	0.735**	0.737**	0.741**
	(2.70)	(2.70)	(2.69)	(2.03)	(2.03)	(2.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	352	2341	1185	271	2010	1016
R^2	0.849	0.886	0.871	0.835	0.897	0.866

Standard errors account for city-level clustering, and the corresponding t value is present in parentheses. Yes means the variable is controlled, whereas No implies the variable is not controlled. Thus, *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 9 Heterogeneity test: city development type

	DID					
	Resource	Non-resource	Growth	Maturity	Recession	Regeneration
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	0.059**	0.033	−0.031	0.013	0.190**	0.078
	(2.05)	(1.64)	(−0.37)	(0.36)	(2.46)	(1.21)
Constant	−1.142	1.596***	7.895*	−5.757**	−0.889	0.839
	(−1.31)	(4.57)	(1.79)	(−2.08)	(−0.79)	(0.90)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	1540	2338	168	854	322	196
R^2	0.856	0.890	0.937	0.813	0.845	0.906

Standard errors account for city-level clustering, and the corresponding t value is present in parentheses. Yes means the variable is controlled, whereas No implies the variable is not controlled. Thus, *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

are not responsive to LCC policy. Moreover, although a positive effect is found in large cities, it is not stable. These findings confirm that the population agglomeration effect in larger cities contributes to energy efficiency.

City resource dependence

Apart from the above factors, the endowment of natural resources could also induce diversified effects of LCC pilots. For this concern, taking the National Plan for Sustainable Development of Resource-based Cities (2013–2020) promulgated by the State Council as the basis, this study categorizes samples into resource-based cities and non-resource-based cities. The former can be categorized into four types in detail: growth, maturity, recession, and regeneration. Table 9 provides the differentiated influences of LCC pilots in various resource-based cities.

Columns (1) to (6) of Table 9 illustrate a statistically significant relationship at resources-based cities between energy efficiency and the introduction of the LCC pilot.

Among them, we find a positive effect at resource-based recession-type towns, which is statistically significant at the 5% level, but no significant positive influences on urban energy efficiency are detected at other types of resource-based cities and non-resource-based cities.

One possible explanation is that resource-based cities prefer cultivating resource-based industries, so labor and capital input is skewed towards these industries. Consequently, the GTFEE of pilot cities is enhanced through energy-oriented technological change and renewable energy development. Moreover, the recession-type cities are intractable areas to change toward green development on account of the exhaustion of energy and other resources and the lag of economic growth. The construction of LCC in these areas will help promote the transformation and upgrading of the industrial structure by eliminating pollution-intensive firms while introducing firms with clean production technology, thus improving GTFEE.

Conclusions and policy implications

Under the pressure of the Paris Agreement, the LCC pilots aim to drive low-carbon development and advocate low-carbon life in China. Although some studies prove that this policy has contributed to carbon emission reduction, its impact on urban energy efficiency has not been holistically evaluated. This issue is of great significance for improving LCC policies and coping with global climate change.

With a dataset of China's cities from 2006 to 2019, we focus on discussing the effect of LCC pilots on urban GTFEE with a DID design. The result suggests that the implementation of LCC policy has a statistically favorable influence on urban GTFEE, increasing energy efficiency by 3.6% and 4.1% with DID estimates and PSM-DID estimates, respectively. The findings remain consistent under a series of robustness tests. The plausible mechanisms appear to be green innovation and industrial structure upgrading with our mediation effect analysis. We further discuss the impact of urban heterogeneity from three aspects: urban economic development, the scale of urban development, and the dependence on urban resources. The results show that the higher the level of urban economic growth and urban scales, the more significant the policy effect. The efficiency enhancement effect is also more pronounced in resource-based cities.

This study provides strong evidence for supporting LCC construction and policy enlightenment for China and other emerging countries to achieve sustainable development. First, since the LCC policy can improve urban energy efficiency, the government should continue exploring LCC construction and expanding the scope of pilot projects. Meanwhile, to address energy poverty challenge, it is useful to play the model role of pilot cities. The diffusion of successful policies could benefit the construction of a low-carbon society and the formation of citizens' green lifestyles.

Second, to carry forward the effect of LCC policies on energy efficiency through proper guidance, the government should pay attention to relevant supporting measures. Since LCC policy can drive energy efficiency through green innovation, the government should propose incentives such as subsidy and preferential tax to encourage urban R&D investment, vigorously introducing clean production and emission treatment techniques. Meanwhile, it is efficient to accelerate low-carbon development in undeveloped areas with the technology spillover effect. Structure upgrading is another channel for enhancing energy efficiency. The government should also speed up industrial structure adjusting and energy structure optimization by eliminating pollution-intensive firms. Incentives should be adopted to guide capital flow into high-tech industries to support their development and accelerate the decarbonization of polluting sectors such as the transportation sector.

Third, differentiated policy arrangements should be made according to different urban characteristics to improve the top-level design. In underdeveloped cities, the government should focus on introducing talents and constructing the education system to promote innovation research development. As for small-scale towns, the government should rationally allocate resources while prioritizing cultivating emerging technology industries. For resource-based cities, the government should improve supporting policies to promote the complementarity of LCC and resource-based cities. Additionally, it is vital to focus on reforming the development mode of depleted cities.

We conclude by putting forward three directions for future research. First, we only consider the medium-run impact of the low-carbon pilot policy. If the shock is temporary, we expect that the policy might be unable to sustain improvements in energy efficiency. Meanwhile, if there are spillover effects or learning effects between cities, the incentives from the policy can be offset in the long term. Moreover, suppose future firm-level emissions and output data are available. In that case, we can evaluate low-carbon pilot policy by estimating sectoral and company-specific carbon abatement costs and energy efficiency benefits. Finally, our study is limited to China, and the findings might differ from other countries due to various environmental and economic conditions. Future research is warranted to explore other countries' low-carbon city policies. These analyses are beyond the scope of our paper, but future research on these issues is necessary to facilitate low-carbon city construction better and achieve the net-emission goal.

Author contribution Da Gao and Yi Li conceived and designed the research question. Yi Li constructed the models and analyzed the optimal solutions. Da Gao and Yi Li wrote the paper. Da Gao, and Ge Li reviewed and edited the manuscript. All authors read and approved the manuscript.

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Data availability The datasets generated and analyzed during the current study are property of the National Bureau of Statistics; they are available from the corresponding author who will inform the National Bureau of Statistics that the data will be released on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

Conflict of interest The authors declare no competing interests.

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