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A green path towards sustainable development: The impact of low-carbon city pilot on energy transition

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ABSTRACT

With the increasing emphasis on sustainable development issues such as ensuring energy security, addressing climate change, and protecting the ecological environment, countries around the world have reached a general consensus to accelerate their energy transition (ET). In fact, China implemented a low-carbon city pilot (LCCP) policy in 2010 to explore green development and ET by reducing carbon dioxide (CO_2) emissions and improving environmental quality. Using panel data for 253 cities at the prefecture level, this paper creatively divides the dimensions of ET into energy consumption (EC), energy structure (ES), and energy intensity (EI) from the supply-side and demand-side perspectives and measures the local and spatial spillover effects of LCCP on ET by employing a difference-in-differences (DID) model and a spatial difference-in-differences (SDID) model. The results indicate that LCCP accelerates ET, and the conclusions still hold after a series of robustness tests. Moreover, the results of the mechanism verification suggest that LCCP affects ET indirectly through total factor productivity (TFP), and its impact depends on the construction of public transportation (PT). Heterogeneity analysis of city location, size, and features reveals that LCCP is beneficial to ET in south cities, large cities, non-resource-based cities, and old industrial cities. We also find that LCCP generates positive spatial spillover effects on EC and EI and negative spatial spillover effects on ES in non-pilot cities.

1. Introduction

Resource depletion, environmental pollution, and climate change caused by fossil energy consumption (EC) are seriously threatening human activities and sustainable development (Wang et al., 2018; Lee et al., 2021; Chiu and Lee, 2020; Tiwari et al., 2022). Therefore, countries around the world have reached a consensus to promote a third energy revolution focusing on low-carbon and clean energy transition (ET) (Lee et al., 2022a; Lee and Ho, 2022; Dogan et al., 2020). Given the resource endowment of more coal, less oil, and less gas and the critical period of economic transformation, what strategy should China adopt to spur ET? In fact, the National Development and Reform Commission (NDRC) released a low-carbon city pilot (LCCP) policy in 2010 (Chen et al., 2021; Lee and He, 2022). Can LCCP effectively drive ET? Through what mechanisms does the impact occur? Are there regional heterogeneity and spatial correlation in the policy's impact? This paper answers these questions through theoretical analysis and empirical results.

Scholars have conducted a wealth of research on low-carbon city construction and ET in the past. Given that China is the largest energy consumer and CO_2 emitter in the world, energy conservation and emission reduction have become the primary goals of low-carbon city construction. Scholars have found the task of reducing CO_2 emissions, EC, and energy intensity (EI) in China to be daunting and urgent after initially examining their trends (Chen et al., 2007; Hu et al., 2011; Zhou et al., 2014; Chen et al., 2019). Zhao et al. (2019) subsequently propose the leading role of policy in building low-carbon cities. With the implementation of LCCP policy in China, numerous studies have shown that LCCP is beneficial for industrial transformation, green and low-carbon innovation, CO_2 emission reduction, green growth, and ecological efficiency (Zheng et al., 2021; Huo et al., 2022; Song et al., 2020; Pan et al., 2022). Therefore, LCCP is an effective way for China to achieve sustainable and green development (Yang et al., 2021; Hussain et al., 2022; Ren et al., 2022).

As the main source of CO_2 emissions, coal is an important part of China's energy structure (ES). Therefore, rapid and deep decarbonization of energy systems through energy mix adjustment and energy

Abbreviations: LCCP, low-carbon city pilot; ET, energy transition; EC, energy consumption; ES, energy structure; EI, energy intensity; TFP, total factor productivity; PT, public transportation; DID, difference-in-differences; SDID, spatial difference-in-differences; CO_2, carbon dioxide.

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efficiency improvement has become the key to ET (Gambhir et al., 2019; Sachs et al., 2016; Lee et al., 2022b). At the same time, government intervention, social acceptance, science, technology, and innovation have been successively proposed as important factors for ET (Kraan et al., 2019; Komendantova, 2021; Nochta and Skelcher, 2020; Hess and Sovacool, 2020). For example, Guo et al. (2019) find that the competitiveness of the coal industry, customer habits, and coal infrastructure are negative for ET. Shahbaz et al. (2022) argue that the digital economy contributes to ET. Qi et al. (2022) show that government subsidies and R&D investment are beneficial to ET. Regarding government intervention, however, there are no studies that address the impact of LCCP on ET or describe the specific path of ET in China under the LCCP policy.

In summary, it is critical to explore the path of ET based on a policy perspective, but the available studies do not provide sufficient evidence that LCCP is an effective path towards ET. Using panel data for 253 cities from 2006 to 2019, this paper examines the impact of LCCP on ET and makes three main contributions. First, previous studies on ET are mainly based on one dimension such as CO_2 emissions or energy efficiency or only theoretically propose a specific path for ET. From the supply-side and demand-side viewpoints and combining the connotation of ET with the reality in China, this study systematically summarizes the performance of ET into reducing EC and EI and optimizing ES. Second, to fill the research gap between LCCP and ET, this paper initially explores the effects of LCCP on three pathways of ET, along with mechanism validation and heterogeneity analysis. Third, in addition to considering the local effects of the policy in pilot cities, this paper also studies the spillover effects in non-pilot cities, which is an unprecedented study on the spatial expansion of LCCP. In conclusion, this study not only provides a theoretical basis for China and other developing countries to accelerate ET and explore the path of low-carbon green development, but also contributes to sustainable development.

The rest of this paper is structured as follows. Section 2 discusses the policy background and theorized mechanisms. Section 3 describes the empirical methods, variables, and data. Section 4 presents the empirical results and robustness test. Section 5 verifies the mechanisms and analyzes heterogeneity. Section 6 studies the spatial spillover effects. Section 7 discusses the conclusion and policy implication.

2. Policy background and theorized mechanisms

2.1. Background of LCCP

Since China has entered rapid industrialization and urbanization, environmental pollution and energy stress have become increasingly severe (Lee and Lee, 2022; Zhong et al., 2022). First, total CO_2 emissions and EC are huge in China. According to the Netherlands Environmental Assessment Agency (NEAA), China has become the highest carbon emitter in the world since 2007 (Li et al., 2022). In 2020, China accounted for about 30% of the world's total CO_2 emissions. It has seen its total EC increase from 602 million tons of standard coal to 5.24 billion tons of standard coal from 1980 to 2021. Second, ES and industrial structure are unreasonable. Most of the industrial enterprises in China use coal as direct or indirect fuel, leading to its long-term dominance in EC. For example, 56% of total EC in China was accounted for by coal, but only 25.3% of that was clean energy in 2021. Finally, EI is high and energy efficiency is low. EC per unit of gross domestic product (GDP) in China was 3.4 tons of standard coal per US dollar in 2020, which is significantly higher than the global average and much higher than that of developed countries.

Under the background of global low-carbon development, NDRC implemented three batches of LCCP projects in 2010, 2012, and 2017, including 6 provinces, 80 cities, and 1 region (Zhu and Lee, 2022). In order to achieve industrial restructuring, ES upgrading, and low-carbon technology innovation, the first batch of pilot cities established low-carbon industrial systems, advocated low-carbon green lifestyles, and improved CO_2 emission data and management systems. Subsequently, NDRC expanded the scope of LCCP to build a beautiful China. With the positive results of the first two batches of pilots, the third batch of pilot cities focusing on innovation was initiated. This is a further exploration of low-carbon development in the policy context of the National Plan to Address Climate Change (2014–2020) and the 13th Five-Year Plan to Control Greenhouse Gas Emissions.

2.2. Theoretical analysis of influence mechanism

The current discourse on the concept and connotation of ET focuses on the change of energy types (Solomon and Krishna, 2011; He et al., 2015; Chen et al., 2022) and the restructuring of energy sources (Fouquet, 2016; Cai et al., 2022; Fouquet and Pearson, 2012). The World Energy Council (WEC) defines ET as a fundamental change in the energy mix caused by an increase in the share of renewable energy and the phase-out of fossil energy. Combining the concept of ET with the reality of supply-side and demand-side energy in China, we believe that ET is a process of fundamental transformation of energy form, energy technology, ES, energy efficiency, and other main elements of the energy system (Kocaarslan and Soytas, 2019; Ye et al., 2022). The paths to achieve ET are as follows: first, control total EC, save energy, and reduce emissions; second, use clean energy, develop carbon-free modern service industries, and optimize ES and industrial structure; third, reduce EI and improve energy utilization. The influencing mechanism of LCCP on ET is shown in Fig. 1.

Subjects implementing the LCCP policy include governments, enterprises, and residents, and its impact on ET is top-down. Faced with climate change, environmental pollution, and energy problems, a government first sets action goals and industry plans, regulates and supervises the market through policy instruments, and also establishes CO_2 emission data statistics and management systems to directly control the EC and CO_2 emissions of enterprises and regions (Zhou et al., 2022; Gehrsitz, 2017; Shi et al., 2022). At the same time, the government can encourage enterprises to produce low-carbon products and achieve technological innovation through taxation and subsidies to optimize ES and improve energy efficiency (Madaleno et al., 2022; Zhu et al., 2022). With the transformation of enterprises, the industry will also be optimized to form a low-carbon industry and circular economy. Additionally, by establishing a low-carbon transportation system, the government encourages the large-scale promotion of renewable energy sources in buildings and promotes low-carbon concepts among residents in order to guide them to low-carbon consumption and low-carbon living (Zhang et al., 2022c; Zhao et al., 2022). In short, the realization of low-carbon production and low-carbon consumption will accelerate the low-carbon green transition on both the demand and supply sides of energy. Hence, we hypothesize the following.

Hypothesis 1. *LCCP accelerates ET in pilot cities.*

A low-carbon city means promoting comprehensive low-carbon urban development through energy efficiency improvements, energy restructuring, transformation of high-carbon industries to low-carbon industries, and more environmentally friendly resource allocation. Under the guidance of policies, humans, materials, and technological resources will be biased and flock to low-carbon products, low-carbon technologies, and low-carbon industries, which are conducive to the redistribution and optimization of resources and the improvement of resource allocation efficiency (Albrizio et al., 2017; Wen et al., 2022; Wang et al., 2022b; Wen et al., 2023). At the same time, companies have access to more open market information on technology improvements and learning, which help reduce costs, thereby promoting technological innovation and productivity and ultimately improving total factor productivity (TFP) (Chen et al., 2021; Zeqiraj et al., 2020). Furthermore, the construction of public transportation (PT) is not only conducive to the establishment of a low-carbon transportation system, but also conducive to guiding residents to travel in a low-carbon manner. Reducing transportation CO_2 emissions through PT development is an integral part of

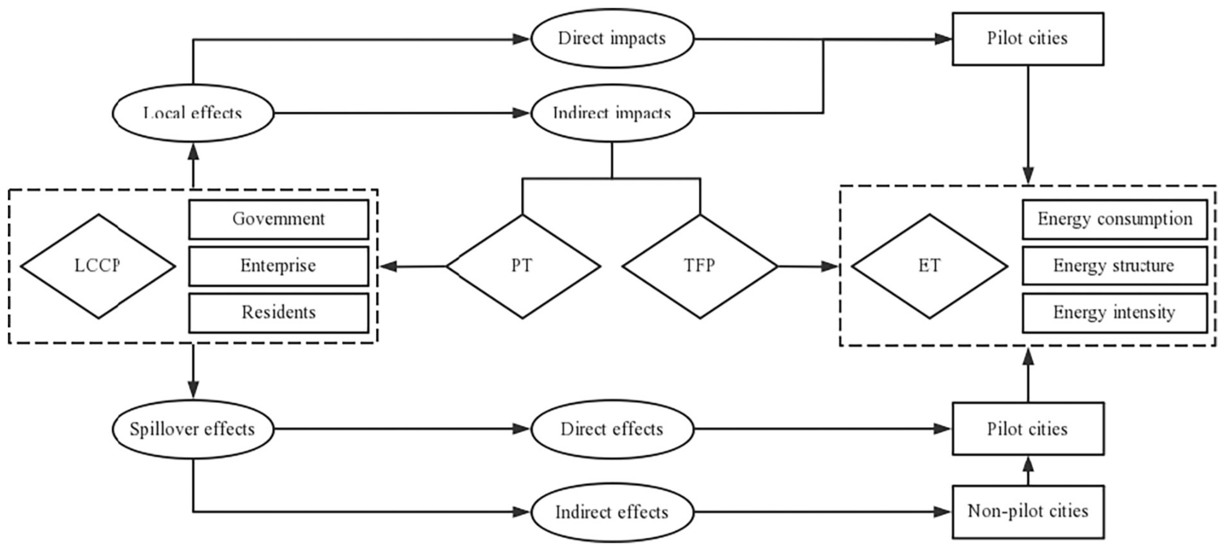

Fig. 1. The influencing mechanism of LCCP on ET.

low-carbon city construction (Wimbadi et al., 2021; Jia et al., 2021). Therefore, we propose the next hypothesis.

Hypothesis 2. *LCCP accelerates ET by improving TFP, and the contribution of LCCP to ET is influenced by PT.*

A demonstration effect may occur when the LCCP policy affects ET in pilot cities. In other words, the surrounding non-pilot cities will imitate the pilot cities in the production of low-carbon products, industrial restructuring, and optimization. Moreover, technology and knowledge from pilot cities may generate positive spillovers (Hu, 2021; Wang and Lee, 2022), which in turn drive technological innovation and improve energy efficiency in neighboring cities. In the meantime, due to the pressure of low-carbon targets and low-carbon data, pilot cities may simply and brutally transfer pollution and may further concentrate surrounding elements such as technology and knowledge to strengthen the siphon effect, which in turn is detrimental to ET of non-pilot cities (Huang and Chen, 2022; Nie et al., 2022). Therefore, we formulate the third hypothesis.

Hypothesis 3. *LCCP impacts ET in non-pilot cities, and the magnitude and direction of the effect depend on the siphon effect and the spillover effect.*

3. Empirical strategy

3.1. Empirical method

3.1.1. DID model

The DID model based on quasi-natural experiments can avoid endogeneity problems and is widely used in policy evaluation. Therefore, based on the study by Beck et al. (2010), we take LCCP as a quasi-natural experiment to study its impact on ET and set the model as follows.

$$ET_{it} = \alpha_0 + \alpha_1 Pilot_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{1}$$

Here, the subscripts i and t denote city and year, respectively; ET represents energy transition; $Pilot$ is the interaction term between the city dummy variable and the time dummy variable, which takes the value of 1 if the city is included in the pilot city after the implementation of LCCP policy and 0 otherwise; X is the control variable; u is the city fixed effect; v is the time fixed effect; and ε is the random error.

3.1.2. Mediating effect model

Based on the above analysis of mechanisms, we hypothesize that LCCP may have an indirect effect on ET through the mediating path of TFP. Therefore, we introduce a mediating effect model to verify this hypothesis. Following Baron and Kenny (1986), the identification mechanism of the intermediary effect is divided into three steps, and the model is as follows.

$$ET_{it} = \alpha_0 + \alpha_1 Pilot_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{2}$$

$$TFP_{it} = \beta_0 + \beta_1 Pilot_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{3}$$

$$ET_{it} = \theta_0 + \theta_1 Pilot_{it} + \theta_2 TFP_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{4}$$

Here, coefficient β_1 captures the effect of LCCP on TFP; coefficient θ_2 separates the effect of TFP on ET; the product of coefficients β_1 and θ_2 is called the mediating effect, which is used to identify the indirect effect of LCCP on ET; coefficient θ_1 is the direct effect of policy on ET after excluding the mediating effect. The mediating effect holds if the coefficients α_1, β_1, and θ_2 are significant, indicating the presence of a mediating effect.

3.1.3. Moderating effect model

Based on the above analysis of mechanisms, the effect of LCCP on ET may depend on PT. Therefore, we introduce PT as a moderating variable to test its effect (Chang, 2022). First, eq. (5) is built by taking *Pilot* and *PT* as explanatory variables and *ET* as the explained variable. Eq. (6) then adds the multiplicative term of *Pilot* and *PT* as an explanatory variable to eq. (5). If coefficient φ_3 is significant, indicating that PT moderates the effect of *Pilot* on *ET*, then the moderating effect holds.

$$ET_{it} = \delta_0 + \delta_1 Pilot_{it} + \delta_2 PT_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{5}$$

$$ET_{it} = \varphi_0 + \varphi_1 Pilot_{it} + \varphi_2 PT_{it} + \varphi_3 Pilot_{it} \times PT_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{6}$$

3.1.4. SDID model

The premise of the DID model set-up is that individuals are independent of each other - namely, individuals in the study sample are not influenced by whether other individuals are treated or not. According to Hypothesis 3, LCCP will affect not only the pilot cities, but also the surrounding non-pilot cities - that is, there is a spatial spillover effect. In this way, the causal effects identified by the DID model will fail, and so it is necessary to extend the model. Therefore, this paper draws on Dubé et al. (2014) and Li and Du (2021) to construct a spatial difference-in-differences (SDID) model based on eq. (1).

$$\begin{aligned} ET_{it} = {} & \rho W \times ET_{it} + \alpha_1 Pilot_{it} + \alpha_2 W \times Pilot_{it} + \gamma_1 X_{it} + \gamma_2 W \times X_{it} \\ & + u_i + v_t + (1 - \lambda W)^{-1} \varepsilon_{it} \end{aligned} \tag{7}$$

Here, W is a geospatial weight matrix generated from latitude-longitude distances; ρ is the spatial autocorrelation coefficient of the dependent variable; α_2 is the policy spillover effect; γ_2 is the spillover effect of the control variable; and λ is the spatial autocorrelation coefficient of the random error. Eq. (7) is the general form of the SDID model, which can be classified into the spatial error DID model (SEM-DID), the spatial lagged DID model (SLM-DID) and the spatial Durbin DID model (SDM-DID) according to whether the correlation coefficient is zero or not. The above three models will be further selected by correlation tests in the spatial spillover effect analysis.

3.2. Variable definition

From the above analysis, we believe that the three ways of ET are reducing total EC, adjusting ES, and reducing EI. In this paper, *lnEC*, *ES*, and *EI* (Feng et al., 2022) are the dependent variables, as shown in Table 1. This paper considers the LCCP policy (*Pilot*) as a quasi-natural experiment, which is the independent variable. Based on the factors influencing ET, we select the following control variables (Yu et al., 2022; Tian and Ma, 2008; Wang et al., 2022; Lin and Zhou, 2021): level of economic development (*lnGDP*), level of urbanization (*Urban*), level of finance (*Financial*), level of financial development (*Finance*), and level of informationization (*lnInformation*). According to Hypothesis 2, we choose TFP as the mediating variable and PT as the moderating variable. Using real GDP as output and the number of employees and fixed assets as input factors, we refer to the Stochastic Frontier Analysis (SFA) method proposed by Battese and Coelli (1992) to calculate TFP. In addition, we select the number of buses per 10,000 people as a measure of PT.

3.3. Sample and data

After excluding cities with severely underdeveloped data and cities in all provinces without pilot cities, the study in this paper covers 253 cities in China from 2006 to 2019. According to the Notice on the Piloting of Low-Carbon Provinces and Low-Carbon Cities issued by NDRC, 68 cities in the research sample of this paper are pilot cities.

The original data are obtained from the China City Statistical Yearbook, the China Energy Statistical Yearbook, the annual statistical bulletin of each city, the CSMAR database, and the CNRDS database. Missing data for some years in some sample cities are excluded in the DID model analysis to obtain unbalanced panel data with a sample size of 3462. The latter SDID model analysis is performed by balancing the unbalanced panel data to obtain balanced panel data with a sample size of 2758 before calculation. The descriptive statistics of each variable are shown in Table 2.

Table 1
Definition of the variables.

Variable	Definition
Pilot	Equal to 1 for pilot cities after policy is implemented; 0 otherwise
lnEC	Natural logarithm of total energy consumption
ES	Ratio of secondary industry added value to GDP
EI	Ratio of total energy consumption to GDP
lnGDP	Natural logarithm of per capita GDP
Urban	Ratio of urban population to resident population
Financial	Ratio of local finance general budget expenditure to GDP
Finance	Ratio of financial institutions' loan balances to GDP
lnInformation	Natural logarithm of number of Internet users per million people
TFP	Total factor productivity calculated by SFA
PT	Number of buses per 10,000 people

Table 2
Summary statistics.

Variable	S.D.	Mean	Min	Max
Pilot	0.300	0.100	0.000	1.000
lnEC	1.284	4.399	0.072	8.381
ES	0.101	0.481	0.158	0.911
EI	0.105	0.108	0.004	1.807
lnGDP	0.712	10.423	7.923	12.278
Urban	0.162	0.507	0.099	1.000
Financial	0.098	0.180	0.043	0.916
Finance	0.534	0.901	0.075	4.240
lnInformation	0.886	7.061	3.637	10.020
TFP	0.739	1.461	0.042	2.948
PT	25.897	28.061	0.839	154.062

4. Impact of LCCP on ET without spatial spillover effect

4.1. DID model regression results

According to eq. (1), this section examines the direct impact of the implementation of LCCP policy on ET, and the estimated results are shown in Table 3. Columns (1), (3), and (5) are the results without adding control variables, and columns (2), (4), and (6) are the results after adding control variables.

The regression results show that the coefficient of *Pilot* is significantly negative at the 1% and 5% levels respectively, indicating that LCCP is effective in promoting ET. Specifically, compared to non-pilot cities, *lnEC* of the pilot cities can be reduced by 22.3%, *CS* by 1.3% and *EI* by 3.3%. This suggests that LCCP can effectively reduce EC, improve ES, and reduce EI, thereby accelerating ET, and this result supports Hypothesis 1.

The comparison of the coefficient magnitudes leads to the conclusion that the policy has a greater impact on EC than on ES and EI. It shows that environmental regulation, with stricter emission reduction targets and clear technical standards to limit EC, can work quickly (Zhang et al., 2022a). However, the adjustment of ES and EI are dependent on the development and utilization of clean energy, industrial restructuring, and the use of low-carbon technologies, and so the time cost is larger along with the investment of large amounts of capital, labor, technology, and other resources (Su and Fan, 2022). Therefore, EC is more sensitive to policy and more likely to be reduced due to LCCP in the short term.

4.2. Robustness tests

4.2.1. Parallel trend tests

This paper uses the DID method to estimate the impact of LCCP on ET, but the use of the DID method assumes that the trends of *lnEC*, *ES*, and *EI* in the pilot and non-pilot cities do not differ before the policy. Therefore, this paper first conducts parallel trend tests, and the results are shown in Fig. 2 (a-c). Since the years before and after the policy implementation span a wide range, the tailing process is carried out. *Pre_4-Pre_1* indicates the 4 years to 1 year before the policy implementation; *Current* indicates the year of policy implementation; and *Post_1-Post_4* indicates the 1 year after to 4 years after the policy implementation. We see no significant difference in *lnEC*, *ES*, and *EI* between pilot cities and non-pilot cities in the years before the policy, and the difference gradually rises after the policy, indicating that this change is indeed caused by the LCCP policy.

4.2.2. Placebo tests

To ensure that the regression results of the DID model are not influenced by other unobservable urban characteristics and other factors, a placebo test is required (Wu et al., 2022). Specifically, in this paper, 500 samples are taken from all 253 cities, 68 cities are randomly selected as the dummy experimental group in each sample, and the remaining cities are used as the control group for the regression of the

Table 3
DID model regression results.

Variable	lnEC		ES		EI	
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot	−0.275***	−0.223***	−0.018**	−0.013**	−0.037***	−0.033***
	(−4.61)	(−3.78)	(−2.45)	(−2.27)	(−4.56)	(−3.85)
lnGDP		0.527***		0.184***		−0.080***
		(4.58)		(13.68)		(−3.83)
Urban		0.722**		−0.027		0.042
		(2.53)		(−0.83)		(0.72)
Financial		1.128***		0.082*		0.155*
		(2.78)		(1.85)		(1.79)
Finance		−0.017		−0.025***		0.015
		(−0.19)		(−3.11)		(0.57)
lnInformation		0.095***		0.001		0.015***
		(2.66)		(0.13)		(4.12)
Constant	3.652***	−2.383**	0.480***	−1.264***	0.126***	0.756***
	(150.04)	(−2.18)	(133.74)	(−10.12)	(27.86)	(3.68)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3462	3462	3462	3462	3462	3462
R-squared	0.708	0.726	0.414	0.647	0.174	0.233

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

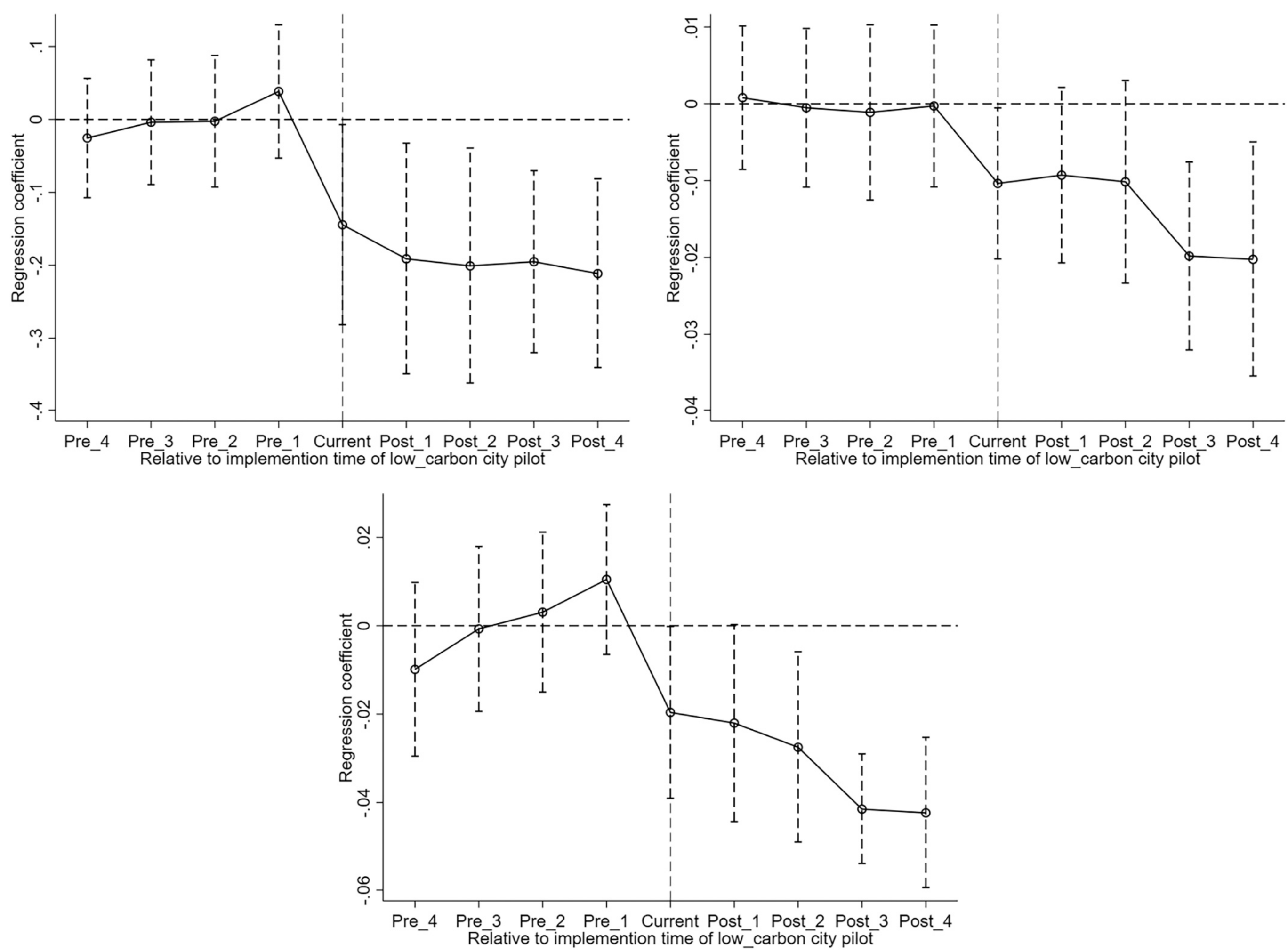

Fig. 2. a. Parallel trend test for lnEC. b Parallel trend test for ES. c Parallel trend test for EI.

DID model. The kernel density distribution of the policy dummy variables is shown in Figs. 3(a-c). It is not difficult to see that the randomized coefficients of *Pilot* deviate significantly from the true values, with the kernel density plot of the observations being centrally distributed around 0. Therefore, the empirical findings are robust.

4.2.3. PSM-DID estimation

While the LCCP policy was announced by NDRC, the selection of

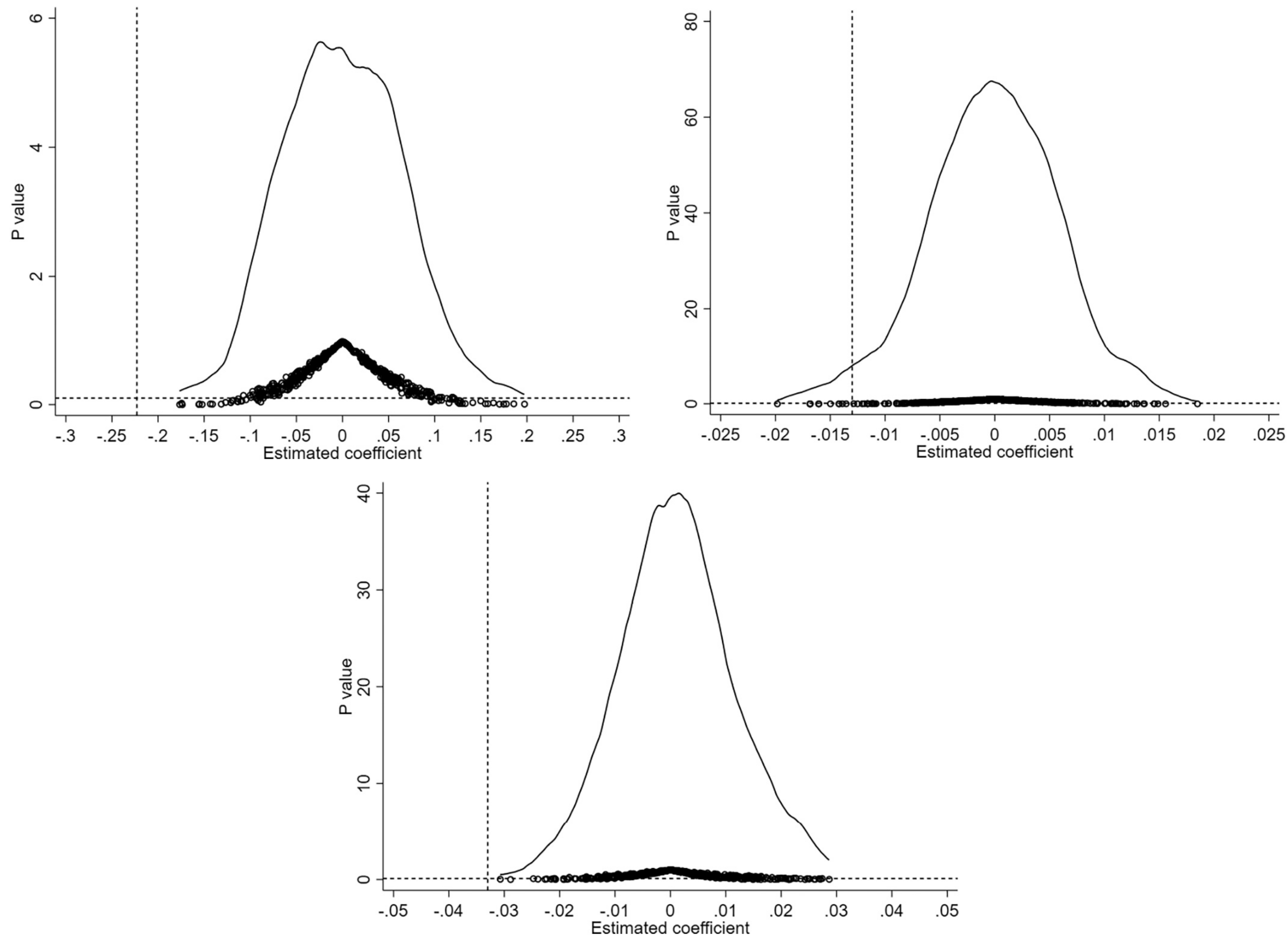

Fig. 3. a Placebo test for lnEC. b Placebo test for ES.c Placebo test for EI.

these cities may be influenced by economic and social factors, such as economic development status, resource endowment, and industrial base. Therefore, to reduce sample selection bias, the regression results of eq. (1) are re-tested using the propensity score matching DID (PSM-DID) method. We employ *lnGDP*, *Urban*, *Finance*, *Financial* and *lnInformation* as covariates for the logit regression to obtain the propensity matching scores of cities, and the control group is obtained by nearest neighbor with put-back matching according to the ratio of 1:2 and 1:5, respectively. After the PSM operation, the *t*-test results for the above variables are all non-significant, indicating that the PSM results are valid. On this

Table 4
PSM-DID estimation.

Variable	PSM (1:2)			PSM (1:5)		
	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.224**	−0.010*	−0.036**	−0.217***	−0.011*	−0.037**
	(−2.17)	(−1.68)	(−2.24)	(−2.68)	(−1.82)	(−2.47)
lnGDP	−0.075	0.153***	−0.186**	0.173	0.140***	−0.173***
	(−0.25)	(6.60)	(−2.58)	(0.79)	(7.61)	(−2.86)
Urban	2.293***	−0.024	0.097	1.180**	0.003	−0.027
	(3.09)	(−0.40)	(0.53)	(2.15)	(0.06)	(−0.15)
Financial	0.800	0.058	−0.148	1.539	−0.018	−0.042
	(0.70)	(0.86)	(−0.77)	(1.35)	(−0.26)	(−0.19)
Finance	−0.072	−0.034**	0.072	−0.081	−0.024*	0.052
	(−0.54)	(−2.21)	(1.18)	(−0.70)	(−1.84)	(0.94)
lnInformation	0.243***	0.005	0.025***	0.193***	−0.000	0.020***
	(3.82)	(0.69)	(3.06)	(3.45)	(−0.06)	(2.60)
Constant	1.836	−0.959***	1.589**	0.384	−0.815***	1.657***
	(0.61)	(−3.94)	(2.34)	(0.17)	(−4.31)	(2.70)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	744	744	744	1113	1113	1113
R-squared	0.672	0.713	0.334	0.663	0.719	0.283

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

basis, we perform further DID, and the results are in Table 4. After controlling for exogenous variables, the coefficients of the core explanatory variable *Pilot* are all negative and significant at the 1%, 5%, and 10% levels, respectively, indicating that the baseline regression results are robust.

4.2.4. Other robustness tests

There is also the implementation of a smart city pilot (SCP) policy during the implementation of LCCP policy. The construction of smart cities may reduce environmental pollution through technological innovation, which in turn affects the estimation results of this paper. In order to accurately identify the impact of LCCP on ET, the interference of the above policy needs to be removed. Therefore, the dummy variable *Pilot1* (if city i is a smart city in year t, *Pilot1* = 1; otherwise, *Pilot1* = 0) is added to eq. (1) as follows.

$$ET_{it} = \omega_0 + \omega_1 Pilot_{it} + \omega_2 Pilot1_{it} + \gamma X_{it} + u_i + v_t + \varepsilon_{it} \tag{8}$$

Table 5 shows the regression results. Findings show that the SCP policy has no significant effect on ET, but the LCCP policy can still have a significant effect after the addition of *Pilot1*. Table 5 shows the results of robustness tests correcting for ET outliers and controlling for other fixed effects. Overall, the coefficient of the variable *Pilot* remains statistically significant.

5. Mechanism verification and heterogeneity analysis

5.1. Mechanism analysis

According to Hypothesis 2, we divide the mechanism tests into two types: one is the mediating effect of TFP, and the other is the moderating effect of PT. Next, we analyze the regression results of the two mechanisms separately.

5.1.1. Mediating effect of TFP

Based on eqs. (2) to (4), we identify the mediating effect of TFP using a stepwise regression coefficient test, presenting the results in Table 6. The results in the first step are the same as the baseline regression. The second step is to verify the effect of policy on TFP, and the results are significantly positive, which indicates that the policy is beneficial to increasing TFP. The third step is the regression result after adding mediating variables. It is known that the coefficients of *Pilot* and *TFP* are both significantly negative, meaning that TFP contributes directly to ET and is also a mediating variable for LCCP to promote ET. In fact, both mandatory environmental regulations and guided tax incentives and fiscal subsidies will lead to technological advances, productivity improvements, and productivity growth (Ansari et al., 2022; Paul and Shankar, 2022), ultimately driving ET to clean and low carbon.

5.1.2. Moderating effect of PT

Table 7 demonstrates the regression results for the moderating effects. The coefficients of *Pilot* in columns (1), (3), and (5) are significantly negative, indicating that the policy still has a facilitating effect on ET after controlling for the moderating and control variables. At the same time, the coefficients of *Pilot* and *PT* cross-products respectively pass the significance levels of 5% and 1% and are negative, indicating the positive moderating effect of PT on the accelerated ET of LCCP. The magnitudes of the moderating effects of PT on reducing lnEC, optimizing ES, and reducing EI are 0.0035, 0.0002, and 0.0005, respectively, further verifying the effectiveness of the moderating effect. PT, as a means of low-carbon transportation means, is a manifestation of energy savings, emission reduction, and green living. The greater willingness of residents to take PT and the increase in the number of urban PT are not only beneficial to the establishment of a low-carbon urban transportation network, but also to the reduction of carbon emissions and energy efficiency (Guo et al., 2022). In conclusion, the results of the mediating and moderating effects support Hypothesis 2.

5.2. Heterogeneity analysis

The overall impact of LCCP on ET is analyzed above, however, this analysis based on the total sample may mask potential regional differences. China is a vast country with large differences among its regions in terms of resource endowments, economic development levels, and institutional arrangements, which may lead to heterogeneous impacts of LCCP on ET. Therefore, we further conduct heterogeneity analysis.

5.2.1. Heterogeneity analysis of city location

This study divides the total sample into east, central, and west regions based on their geographical locations. The regional differences in the impact of LCCP on ET are then examined separately, and the regression results are in Table 8. The effects are in descending order of central, west, and east regions. This may be due to the fact that the

Table 5
Other robustness tests.

Variable	Smart city pilot policy			Controlling province fixed effect			Corrected outlier results		
	lnEC	ES	EI	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.223***	−0.013**	−0.033***	−0.223***	−0.013**	−0.033***	−0.221***	−0.012**	−0.027***
	(−3.78)	(−2.25)	(−3.88)	(−3.77)	(−2.26)	(−3.84)	(−3.82)	(−2.22)	(−3.86)
Pilot1	−0.004	−0.003	−0.002						
	(−0.07)	(−0.67)	(−0.30)						
lnGDP	0.527***	0.184***	−0.080***	0.527***	0.184***	−0.080***	0.473***	0.176***	−0.061***
	(4.58)	(13.68)	(−3.88)	(4.56)	(13.63)	(−3.82)	(4.32)	(13.36)	(−4.34)
Urban	0.721**	−0.028	0.042	0.722**	−0.027	0.042	0.715**	−0.031	0.080**
	(2.53)	(−0.85)	(0.71)	(2.52)	(−0.83)	(0.72)	(2.58)	(−0.94)	(2.06)
Financial	1.126***	0.081*	0.154*	1.128***	0.082*	0.155*	1.002***	0.071	0.161***
	(2.77)	(1.81)	(1.75)	(2.77)	(1.84)	(1.78)	(2.64)	(1.64)	(2.73)
Finance	−0.017	−0.025***	0.015	−0.017	−0.025***	0.015	−0.052	−0.023***	−0.001
	(−0.19)	(−3.08)	(0.57)	(−0.19)	(−3.10)	(0.56)	(−0.64)	(−3.04)	(−0.08)
lnInformation	0.095***	0.001	0.015***	0.095***	0.001	0.015***	0.094***	0.001	0.014***
	(2.66)	(0.17)	(4.21)	(2.65)	(0.13)	(4.11)	(2.82)	(0.34)	(4.37)
Constant	−2.387**	−1.268***	0.754***	−2.295*	−1.415***	0.776***	0.473***	0.176***	−0.061***
	(−2.18)	(−9.85)	(3.74)	(−1.92)	(−10.10)	(3.40)	(4.32)	(13.36)	(−4.34)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	No	No	No	Yes	Yes	Yes	No	No	No
Observations	3462	3462	3462	3462	3462	3462	3462	3462	3462
R-squared	0.726	0.647	0.233	0.924	0.902	0.765	0.731	0.638	0.310

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6
Mediating effect tests.

Variable	Step 1			Step 2	Step 3		
	lnEC	ES	EI	TFP	lnEC	ES	EI
Pilot	−0.223***	−0.013**	−0.033***	0.054***	−0.220***	−0.013**	−0.033***
	(−3.78)	(−2.27)	(−3.85)	(2.64)	(−3.72)	(−2.24)	(−3.82)
TFP					−0.060***	−0.004**	−0.005*
					(−2.77)	(−1.98)	(−1.89)
lnGDP	0.527***	0.184***	−0.080***	−0.077**	0.522***	0.184***	−0.080***
	(4.58)	(13.68)	(−3.83)	(−2.00)	(4.54)	(13.67)	(−3.84)
Urban	0.722**	−0.027	0.042	0.091	0.727**	−0.027	0.043
	(2.53)	(−0.83)	(0.72)	(0.81)	(2.53)	(−0.82)	(0.73)
Financial	1.128***	0.082*	0.155*	−0.346**	1.107***	0.081*	0.153*
	(2.78)	(1.85)	(1.79)	(−2.09)	(2.73)	(1.82)	(1.77)
Finance	−0.017	−0.025***	0.015	0.001	−0.017	−0.025***	0.015
	(−0.19)	(−3.11)	(0.57)	(0.05)	(−0.19)	(−3.11)	(0.57)
lnInformation	0.095***	0.001	0.015***	0.007	0.095***	0.001	0.015***
	(2.66)	(0.13)	(4.12)	(0.47)	(2.68)	(0.14)	(4.13)
Constant	−2.383**	−1.264***	0.756***	1.903***	−2.268**	−1.257***	0.767***
	(−2.18)	(−9.84)	(3.68)	(5.11)	(−2.07)	(−9.79)	(3.70)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3462	3462	3462	3462	3462	3462	3462
R-squared	0.726	0.647	0.233	0.866	0.727	0.647	0.234

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 7
Moderating effect tests.

Variable	lnEC		ES		EI	
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot	−0.2233***	−0.1462**	−0.0126**	−0.0075	−0.0331***	−0.0222***
	(−3.81)	(−2.23)	(−2.20)	(−1.08)	(−3.85)	(−2.86)
PT	0.0001	0.0006	−0.0002	−0.0001	0.0001	0.0001
	(0.07)	(0.35)	(−1.34)	(−1.10)	(0.23)	(0.46)
Pilot*PT		−0.0035**		−0.0002*		−0.0005*
		(−2.24)		(−1.72)		(−1.76)
lnGDP	0.5264***	0.5302***	0.1845***	0.1847***	−0.0803***	−0.0797***
	(4.54)	(4.59)	(13.81)	(13.80)	(−3.81)	(−3.83)
Urban	0.7219**	0.6319**	−0.0279	−0.0338	0.0423	0.0295
	(2.52)	(2.21)	(−0.84)	(−1.03)	(0.72)	(0.50)
Financial	1.1303***	1.0820***	0.0781*	0.0750*	0.1563*	0.1495*
	(2.76)	(2.69)	(1.76)	(1.69)	(1.79)	(1.71)
Finance	−0.0179	0.0039	−0.0243***	−0.0229***	0.0149	0.0180
	(−0.20)	(0.04)	(−3.00)	(−2.84)	(0.55)	(0.66)
lnInformation	0.0953***	0.0831**	0.0002	−0.0006	0.0153***	0.0135***
	(2.66)	(2.31)	(0.05)	(−0.16)	(4.02)	(3.50)
Constant	−2.3821**	−2.3260**	−1.2650***	−1.2614***	0.7565***	0.7645***
	(−2.18)	(−2.14)	(−9.88)	(−9.84)	(3.68)	(3.75)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3462	3462	3462	3462	3462	3462
R-squared	0.726	0.728	0.647	0.648	0.233	0.237

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

economic level and population density in the east region tend to be higher, and the EC and CO_2 emissions are also larger, forming stronger resource dependence and lock-in effect (Ahmad and Wu, 2022). In contrast, the lock-in effect of CO_2 emissions in the central and west regions is weaker and more responsive to LCCP, and so the impact of LCCP on EC in the central and west regions is stronger. Additionally, the policy has a significant effect on EI only in the pilot cities in the east and central regions. The central and east regions, where educational resources and highly skilled human capital are concentrated, are more prone to technological innovation than the west regions (Liu et al., 2022), which makes the policy more sensitive to the impact of energy efficiency that depends on technological progress.

The south is growing significantly faster than the north, widening the north-south divide. Therefore, we wonder if there is also a North-South gap in the impact of LCCP on ET. As observed in Table 8, it seems that the overall impact of LCCP on *lnEC*, *ES*, and *EI* in the south pilot cities is greater than that in the north, and there is no significant impact on *ES* in the north. This is due to the fact that the north cities, with a high share of secondary industries, are highly dependent on ET for economic growth (Siqin et al., 2022). When EI reaches a certain level, the economic cost of energy restructuring by increasing renewable EC and reducing fossil EC is greater. Therefore, the path dependence on traditional energy sources leads to obstacles to the transformation of ES and industrial structure in the north cities.

5.2.2. *Heterogeneity analysis of city size*

The previous analysis shows that LCCP can effectively promote ET in pilot cities. Are there differences for cities of different sizes? From the perspective of city size, larger cities have an economic agglomeration effect and correspondingly higher efficiency in resource allocation and utilization, which are conducive to improving energy utilization through technological innovation. However, cities with too large a scale

Table 8
Heterogeneity test for city location.

Panel A: city location in the east, central, and west

Variable	East			Central			West		
	lnEC	ES	EI	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.160**	−0.011	−0.032***	−0.280**	−0.009	−0.039***	−0.257**	−0.017	−0.026
	(−2.11)	(−1.52)	(−4.46)	(−2.23)	(−1.06)	(−3.06)	(−2.19)	(−1.25)	(−0.89)
lnGDP	0.679***	0.130***	−0.048**	0.497**	0.213***	−0.065**	0.696***	0.205***	−0.119
	(4.07)	(6.50)	(−2.52)	(2.23)	(8.75)	(−2.04)	(3.04)	(6.86)	(−1.34)
Urban	1.277***	−0.072**	0.194***	0.843	−0.099**	0.084	0.341	0.047	−0.106
	(3.25)	(−2.36)	(2.87)	(1.63)	(−2.24)	(1.26)	(0.65)	(0.62)	(−0.86)
Financial	2.553***	−0.061	0.294**	2.003*	0.223***	0.430*	0.735	0.023	0.061
	(3.01)	(−0.79)	(2.14)	(1.72)	(2.82)	(1.80)	(1.66)	(0.41)	(0.43)
Finance	−0.063	−0.024**	0.004	0.227	0.011	−0.006	−0.022	−0.044***	0.033
	(−0.58)	(−2.44)	(0.35)	(1.45)	(0.69)	(−0.31)	(−0.13)	(−4.07)	(0.57)
lnInformation	0.082*	0.004	0.015***	0.153**	0.005	0.015**	0.047	0.002	0.004
	(1.73)	(0.91)	(2.69)	(2.53)	(0.90)	(2.26)	(0.63)	(0.38)	(0.33)
Constant	−3.788**	−0.744***	0.372**	−2.988	−1.576***	0.555*	−3.751*	−1.427***	1.230
	(−2.41)	(−3.64)	(2.22)	(−1.42)	(−7.21)	(1.94)	(−1.73)	(−5.28)	(1.38)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1370	1370	1370	1097	1097	1097	995	995	995
R-squared	0.759	0.733	0.316	0.758	0.714	0.362	0.687	0.622	0.175

Panel B: city location in the north and south

Variable	North			South		
	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.197**	−0.007	−0.025**	−0.256***	−0.019**	−0.039***
	(−2.44)	(−0.74)	(−2.02)	(−3.08)	(−2.57)	(−4.01)
lnGDP	0.560***	0.177***	−0.095***	0.715***	0.210***	−0.014
	(3.58)	(10.14)	(−3.25)	(3.62)	(7.85)	(−0.61)
Urban	0.361	−0.025	−0.035	1.073**	−0.037	0.150**
	(1.03)	(−0.63)	(−0.47)	(2.26)	(−0.63)	(2.10)
Financial	0.828	0.051	0.048	1.251***	0.097	0.214**
	(1.06)	(0.88)	(0.28)	(2.74)	(1.49)	(2.14)
Finance	−0.110	−0.031***	0.008	0.083	−0.017	0.018
	(−0.92)	(−2.92)	(0.19)	(0.60)	(−1.48)	(0.75)
lnInformation	0.135*	0.001	0.020***	0.053	−0.001	0.009**
	(1.92)	(0.11)	(2.97)	(1.47)	(−0.16)	(2.47)
Constant	−2.731*	−1.183***	0.936***	−4.132**	−1.520***	0.101
	(−1.88)	(−6.99)	(3.26)	(−2.23)	(−6.31)	(0.40)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1580	1580	1580	1882	1882	1882
R-squared	0.710	0.717	0.273	0.750	0.565	0.220

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 9
Heterogeneity test for city size.

Variable	Small			Big		
	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.321**	0.053*	−0.202	−0.210***	−0.014**	−0.030***
	(−2.32)	(2.19)	(−1.82)	(−3.45)	(−2.43)	(−3.94)
lnGDP	0.396	0.201***	−0.376*	0.509***	0.183***	−0.067***
	(1.27)	(4.91)	(−1.96)	(4.11)	(12.79)	(−3.89)
Urban	−1.097	−0.041	−0.512	0.836***	−0.026	0.093**
	(−0.92)	(−0.31)	(−1.23)	(2.94)	(−0.78)	(2.11)
Financial	−1.716	−0.698***	−0.576	1.281***	0.093**	0.217***
	(−1.79)	(−3.38)	(−1.01)	(3.15)	(2.08)	(2.82)
Finance	0.476***	−0.074***	0.297**	−0.072	−0.019**	−0.014
	(4.02)	(−6.21)	(2.27)	(−0.79)	(−2.42)	(−1.04)
lnInformation	−0.018	0.013	−0.023	0.100***	0.001	0.015***
	(−0.21)	(0.54)	(−0.43)	(2.74)	(0.17)	(4.07)
Constant	0.220	−1.346***	4.498*	−2.250*	−1.267***	0.614***
	(0.07)	(−3.55)	(2.12)	(−1.92)	(−9.24)	(3.69)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113	113	113	3349	3349	3349
R-squared	0.857	0.842	0.623	0.729	0.641	0.273

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

are prone to lock-in effects due to their high dependence on EC, which is not conducive to ET. Based on the above analysis, it is necessary to verify the effect of ET in pilot cities of different sizes. According to the Notice on Adjusting the Criteria for the Classification of City Size issued by the State Council in 2014, this paper considers cities with a resident population of under 1 million as small cities and those over 1 million as large cities.

The results in Table 9 report that policy can significantly accelerate ET in large cities, however, EC in small cities is more sensitive to policy compared to large cities. It is important to note that the implementation of LCCP policy is not conducive to the transformation of ES in small cities. A large city is one with a large resident population, or usually the central city of a region. The concentration of population is typically accompanied by the concentration of other factors resulting in industrial and economic agglomeration, with correspondingly high efficiency in resource allocation and utilization (Xu et al., 2022a), which contribute to ET. However, after the introduction of LCCP, large cities may transfer high-carbon industries to smaller cities due to the difficulty of carbon control caused by large total CO_2 emissions, making it more difficult for small cities to optimize their energy and industrial structures.

5.2.3. *Heterogeneity analysis of city features*

Differences in economic development bases and conditions such as industrial structure may affect the influence of policy implementation as mentioned in the previous regional heterogeneity analysis. According to the National Sustainable Development Plan for Resource-based Cities (2013–2022) and the National Plan for the Adjustment and Transformation of Old Industrial Bases (2013–2022), all cities are distinguished based on whether they are resource-based cities and whether they are old industrial cities for the heterogeneity analysis of city features.

The results in Table 10 demonstrate that the policy has a more pronounced effect on promoting ET in non-resource-based cities. Resource-based cities naturally are abundant in resources, which make their development path-dependent on traditional energy sources. In other words, the economic development of resource cities is highly dependent on traditional energy sources in terms of technology, industrial structure, cognition, and systemic inertia, which make technological innovation and ET face obstacles (Zhang et al., 2022b). Therefore, non-resource-based cities are more sensitive to LCCP.

We can also see that the implementation of LCCP policy is conducive to ET of the old industrial cities. In terms of reducing EC and EI, the policy has a greater impact on non-old industrial cities than on old industrial cities. However, in terms of ES, the policy only has a significant impact on the structural optimization of industrial cities. Since the early development of old industrial cities was relatively crude and overly dependent on secondary industries, the government invested a lot of money and technology in industrial structure optimization and

Table 10
Heterogeneity test for city features.

Panel A: city features of resource and non-resource						
Variable	Resource			Non-resource		
	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.120	0.016	−0.011	−0.268***	−0.023***	−0.044***
	(−1.09)	(1.11)	(−0.93)	(−3.97)	(−4.00)	(−3.85)
lnGDP	1.006***	0.162***	−0.019	0.091	0.210***	−0.145***
	(5.09)	(7.54)	(−0.93)	(0.67)	(12.89)	(−3.37)
Urban	0.109	−0.058	0.004	1.235***	−0.007	0.087
	(0.23)	(−1.25)	(0.06)	(3.65)	(−0.19)	(1.10)
Financial	0.567	0.031	0.106	1.645***	0.137**	0.216
	(1.22)	(0.57)	(1.14)	(2.68)	(2.06)	(1.63)
Finance	0.259	−0.007	0.041	−0.124	−0.030***	0.001
	(1.12)	(−0.43)	(1.42)	(−1.39)	(−3.28)	(0.03)
lnInformation	0.060	−0.004	0.010	0.112**	−0.001	0.019***
	(0.94)	(−0.54)	(1.42)	(2.47)	(−0.14)	(4.03)
Constant	−6.755***	−0.980***	0.222	1.642	−1.549***	1.343***
	(−3.61)	(−5.02)	(1.06)	(1.27)	(−9.68)	(3.27)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1358	1358	1358	2104	2104	2104
R-squared	0.700	0.655	0.290	0.763	0.665	0.246
Panel B: city features of industrial and non-industrial						
Variable	Industrial			Non-industrial		
	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.252**	−0.026***	−0.029*	−0.272***	−0.008	−0.034***
	(−2.16)	(−2.66)	(−1.88)	(−4.25)	(−1.30)	(−4.39)
lnGDP	0.631***	0.153***	−0.049	0.303**	0.203***	−0.089***
	(3.32)	(6.80)	(−1.50)	(2.10)	(12.61)	(−3.68)
Urban	0.086	0.031	−0.104	1.114***	−0.066	0.128**
	(0.19)	(0.69)	(−0.90)	(3.19)	(−1.54)	(2.13)
Financial	1.071	−0.001	−0.097	0.971**	0.102*	0.199**
	(1.46)	(−0.02)	(−0.39)	(2.16)	(1.85)	(2.37)
Finance	0.250	−0.024	0.129	−0.146	−0.029***	−0.026*
	(1.52)	(−1.19)	(1.51)	(−1.56)	(−3.33)	(−1.89)
lnInformation	−0.044	−0.010	0.005	0.138***	0.003	0.017***
	(−0.56)	(−1.27)	(0.44)	(3.38)	(0.85)	(4.22)
Constant	−2.195	−0.889***	0.581	−0.664	−1.465***	0.794***
	(−1.17)	(−4.26)	(1.64)	(−0.49)	(−9.39)	(3.61)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1111	1111	1111	2351	2351	2351
R-squared	0.654	0.711	0.267	0.774	0.618	0.294

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

transformation and upgrading (Zhao et al., 2019). However, due to historical reasons and development inertia, the old industrial cities are more dependent on energy. Coupled with the high technical requirements and high investment costs of large-scale ET, their process of ET is slow.

6. Impact of LCCP on ET with spatial spillover effect

The empirical results above all identify the causal relationship between LCCP and ET using the DID model, but do not consider the spatial effects of LCCP affecting ET. Next, this study takes spatial factors into consideration and uses a spatial econometric model for further analysis.

6.1. Spatial autocorrelation test

It is necessary to verify the spatial correlation of urban ET before estimating the SDID model. The global Moran index can examine the spatial correlation and spatial spillover effects of ET, and so the study measures the global Moran indices of *lnEC*, *ES*, and *EI*, as shown in Table 11. It can be seen that the Moran indices are all positive, and most of them are significant at the 1% level, illustrating a significantly positive spatial correlation of ET among cities. In addition, the Moran indices of *lnEC* and *EI* show a fluctuating upward trend from 2006 to 2019, which indicates that overall the spatial correlation of EC and EI among regions is increasing, and the influence of EC and EI of pilot cities on EC and EI of neighboring regions is rising. On the contrary, the spatial correlation and spillover effects of ES are weakening.

6.2. SDID model test and regression results

Table 12 reports the results of the SDID model selection. Specifically, the LM-test passes the 1% significance level, indicating that a spatial regression model should be selected. The results of the LR-test and the Wald-test demonstrate that using the SDM-DID model is superior to the SEM-DID model and the SLM-DID model. In addition, this paper performs spatial econometric analysis controlling for two-way fixed effects after passing the Hausman test.

Table 13 shows the regression results of the SDID model based on the geospatial weight matrix and also on the spatial weight matrix of the economic distance (average of GDP per capita from 2003 to 2019) in order to enhance the robustness of the results. The autocorrelation coefficient ρ of the dependent variable is positive at the 1% significance level after controlling for control variables and two-way fixed effects. This suggests that the spatial linkage in the estimation results of the SDID model is derived from ET. At the same time, the coefficient of the spatially weighted term *W*Pilot* of the core explanatory variables is significant at the 1% level, indicating that LCCP has a spatial spillover effect on ET. However, the positive and negative signs of the coefficients differ, indicating varied directions of the spillover effects. Specifically, LCCP has a positive spillover effect on EC and EI and a negative spillover effect on ES - that is, on the one hand, LCCP will increase EC and EI of the region around the pilot city, while optimizing ES of the surrounding region. This is due to the fact after the implementation of the LCCP policy that the pilot cities start to control the total CO_2 emissions, spurring some high-emission enterprises to move to the surrounding areas and increasing the pressure of energy savings and emission reduction in the surrounding areas (Gao et al., 2022). On the other hand, from the LCCP policy implementation of the demonstration effect and warning effect, neighboring cities go through imitation learning for industrial transformation and continuous optimization of industrial structure. Low-carbon products and low-carbon technologies then begin to spread, and knowledge spillover and technology spillover help to restructure the energy and industrial structure of the surrounding regions (Xu et al., 2022b).

The regression coefficient of *W*Pilot* does not directly reflect the extent of its effect and still needs to be decomposed into direct, indirect, and total effects by means of partial differentiation. The direct effect contains not only the impact of the policy implementation on the pilot city, but also the impact of the pilot city on the surrounding non-pilot cities in turn on the pilot city - that is, the feedback effect. The indirect effect refers to the impact of the policy on the surrounding non-pilot cities. The estimated coefficients of the direct effects are negative and significant at the 1% and 5% levels, respectively, indicating that implementation of the LCCP policy can promote local ET, further supporting Hypothesis 3. The indirect and total effects are then observed. The coefficients of *lnEC* and *EI* are significantly positive, and the coefficient of *ES* is significantly negative. The same conclusion as above is thus obtained.

7. Conclusion and policy implications

Using panel data of 253 prefecture-level cities from 2006 to 2019 and the DID and SDID models, this paper presents the local effects and spatial spillover effects of LCCP on ET. The following three research conclusions are drawn. First, the LCCP policy positively affects ET locally by reducing EC, optimizing ES, and reducing EI. The impacts are EC, EI, and ES in descending order. Second, TFP has a mediating effect on the policy accelerating ET, and PT has a moderating effect. Moreover, there is heterogeneity in the policy impact on ET in terms of city location, city size, and city features. Specifically, the policy is conducive to facilitating ET in south cities, large cities, non-resource-based cities, and old industrial cities. Finally, LCCP has a spillover effect on ET, and the direction and size of the spillover effect vary. Specifically, the spillover effect on EC is greater than that on EI and ES. There is a positive spillover effect on ES of non-pilot cities and a negative spillover effect on EC and EI. Based on the above findings, three policy implications are proposed

Table 11
Moran index of ET.

Variable	lnEC			ES			EI		
Year	Moran's *I*	z	*p*-value	Moran's *I*	z	p-value	Moran's *I*	z	p-value
2006	0.045	6.578	0.000	0.072	10.269	0.000	0.027	4.475	0.000
2007	0.045	6.697	0.000	0.066	9.480	0.000	0.021	3.585	0.000
2008	0.041	6.124	0.000	0.055	7.911	0.000	0.025	4.150	0.000
2009	0.040	6.014	0.000	0.048	6.995	0.000	0.013	2.463	0.007
2010	0.043	6.410	0.000	0.027	4.196	0.000	0.017	3.121	0.001
2011	0.043	6.418	0.000	0.025	3.983	0.000	0.031	5.013	0.000
2012	0.046	6.720	0.000	0.022	3.624	0.000	0.040	6.247	0.000
2013	0.050	7.293	0.000	0.013	2.348	0.009	0.039	5.982	0.000
2014	0.049	7.126	0.000	0.008	1.747	0.040	0.043	6.524	0.000
2015	0.053	7.719	0.000	0.014	2.494	0.006	0.046	7.045	0.000
2016	0.055	8.018	0.000	0.030	4.700	0.000	0.067	9.809	0.000
2017	0.066	9.369	0.000	0.030	4.652	0.000	0.083	12.254	0.000
2018	0.061	8.707	0.000	0.033	5.104	0.000	0.080	11.684	0.000
2019	0.058	8.358	0.000	0.050	7.344	0.000	0.092	13.461	0.000

Table 12
SDID model tests.

	SEM-DID			SLM-DID		
	lnEC	ES	EI	lnEC	ES	EI
LM-test	3759.173***	3445.326***	3110.939***	454.328***	141.893***	1464.478***
LR-test	74.47***	136.17***	1.11	124.21***	253.63***	210.44***
Wald-test	21.51***	48.95***	24.37***	44.97***	110.68***	19.25***

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 13
SDID model regression results.

Variable	Geographic distance			Economic distance		
	lnEC	ES	EI	lnEC	ES	EI
Pilot	−0.326***	−0.008**	−0.049***	−0.246***	−0.008*	−0.040***
	(−7.53)	(−1.99)	(−9.96)	(−5.46)	(−1.87)	(−7.79)
W*Pilot	2.596***	−0.074***	0.203***	0.971***	−0.089***	0.092***
	(7.14)	(−3.71)	(6.38)	(8.94)	(−8.66)	(7.78)
ρ	0.570***	0.747***	0.633***	0.546***	0.426***	0.428***
	(9.85)	(24.60)	(10.48)	(23.41)	(20.19)	(17.01)
Direct Effect	−0.298***	−0.009**	−0.046***	−0.177***	−0.013***	−0.035***
	(−6.98)	(−2.35)	(−9.51)	(−3.89)	(−3.03)	(−6.88)
Indirect Effect	5.617***	−0.312***	0.469***	1.800***	−0.154***	0.129***
	(14.16)	(−4.89)	(8.32)	(8.47)	(−9.71)	(6.76)
Total Effect	5.319***	−0.321***	0.423***	1.622***	−0.167***	0.094***
	(13.29)	(−5.01)	(7.41)	(7.16)	(−9.93)	(4.62)
Control	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2758	2758	2758	2758	2758	2758
R-squared	0.308	0.376	0.019	0.455	0.338	0.011

Notes: Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

as follows.

First, the mediating role of TFP and the moderating role of PT are used to promote and expand LCCP. This research proves that LCCP significantly contributes to ET in pilot cities, and so the continued promotion of LCCP is crucial for achieving energy savings and emission reduction, accelerating ET, and promoting sustainable development. Since low-carbon technology and renewable energy technology innovation are key to enhancing TFP, on the one hand, investment in R&D of low-carbon technologies and renewable energy technologies should continue to be increased during the construction of low-carbon cities, and on the other hand intra-regional technology exchange platforms and cooperation mechanisms should be established to expand the technology spillover effect in order to drive the progress of low-carbon technology and renewable energy technology in the whole region. Reasonable transportation network planning, environmentally friendly construction materials, and financial subsidies for green living are particularly important for bringing out the positive externalities of PT.

Second, the implementation of LCCP policy is considered from local to global based on city heterogeneity. Since the effect of LCCP for ET varies with city location, city size, and city features, the implementation strategy and progress of the LCCP policy also differ accordingly. Specifically, north cities, small cities, resource-based cities, and non-old industrial cities should learn from south cities, large cities, non-resource-based cities, and old industrial cities, respectively. At the same time, against the background of increasingly close regional economic ties, high-level dialogues between regions should be promoted to gradually form a low-carbon city network and a low-carbon city cluster from low-carbon cities in order to contribute to the realization of China's CO2 reduction commitments.

Third, based on the spatial spillover effects of LCCP on non-pilot cities, there is a need to reduce EC, lower EI, and optimize ES to promote ET. For industries with high energy consumption and high pollution emissions, local governments should provide technical subsidies and financial support to reduce the negative externalities of environmental regulation on enterprise production. At the same time, environmental regulation and governance in non-pilot cities should be strengthened to prevent the transfer of pollution sources from pilot cities. Based on technological innovation, new energy sources such as solar energy, wind energy, biomass, geothermal energy, and hydrogen energy should then be applied and promoted to increase the proportion of non-fossil energy consumption in order to reduce carbon emissions and lower EI. Finally, according to regional resource endowment and industrial features, low-carbon industries and energy-saving industries can be cultivated in line with their own advantages, and ET can be promoted by optimizing the industrial structure.

Data availability statement

Data are available from the authors upon request.

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CRediT authorship contribution statement

Chien-Chiang Lee: Supervision, Visualization, Writing – review & editing. **Yi Feng:** Data curation, Software, Visualization, Writing – original draft. **Diyun Peng:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no conflict of interest. This article does not contain any experiments with human participants or animals performed by any of the authors.

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Appendix A. Supplementary data

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