



How low-carbon innovation drives city's green development? Evidence from China

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Received: 1 September 2022 / Accepted: 28 February 2023 / Published online: 13 March 2023
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Abstract

The development of a city's green infrastructure is increasingly being driven by low-carbon innovation (LCI). However, knowledge of how LCI affects green economic efficiency (GEE) in China is largely unknown. This study investigates the spatial effects of LCI on GEE in 285 Chinese prefecture-level cities. The empirical findings show that LCI exerts significant beneficial effects on its GEE but negative effects on its neighbors. The positive direct effects on GEE are offset by negative indirect effects due to the lack of spatial linkage effect and the existence of the siphon and crowding-out effects among cities. Using a mediating effect model, we have identified three channels of LCI that affect GEE: industrial structure, energy consumption structure, and human capital. A further heterogeneity analysis indicates that the impacts of LCI on GEE differ by region and city development level. Furthermore, LCI in the building, greenhouse gas treatment, transportation, and sewage and pollutant treatment categories could greatly enhance local GEE. The findings herein provide an empirical experience for accurately accessing the spatial effect of LCI on GEE, and offer a critical decision-making reference for implementing a cross-city green linkage development mechanism.

Keywords Low-carbon innovation · Green economic efficiency · Spatial effect · China

1 Introduction

Climate change caused by global warming and excessive greenhouse gas emissions has become a global concern since the twenty-first century (Dietz et al., 2020), and these challenges it brings are driving people to explore solutions to confront the development

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dilemma. Many nations and international organizations are interested in finding a solution to this conundrum because of its potential to satisfy environmental goals. The green economy proposal was put forth by the United Nations Environment Programme (UNEP) in 2011 and was described as one type of development that can increase social justice and human well-being while at the same time lowering environmental hazards and ecological scarcities. Recently, the green development model has been deemed the best pathway to change our earth, and academics and policymakers have been focusing on developing a green economy. Various relevant national platforms, programs, and other measures support countries in putting the green economy perspective into practice for achieving green development (Loiseau et al., 2016), thus studying this topic is important for accessing the sustainability of environmental risk mitigation and economic development.

Traditional economic efficiency ignores the resource input and ecological cost in the production process, which increases the error of economic development evaluation. However, green economic efficiency (GEE) is a revision and extension of traditional economic efficiency. GEE takes economic growth, resource consumption, and environmental pollution into consideration at the same time, and is a “green” economic efficiency value after deducting resource inputs and environmental costs. Therefore, green economic efficiency is an important indicator to measure green development (Lee & Lee, 2022). Earlier growth models assume that economic efficiency is primarily determined by technological progress. Low-carbon innovation (LCI) refers to the reduction in greenhouse gas emissions through a technological paradigm shift and is regarded as one of the most critical tools to promote green development (Yan et al., 2017). It has the dual attributes of green development and innovation-driven, thus is widely used in construction, energy, transportation, and other fields closely related to production and life. It is worth mentioning that LCI is a branch of green innovation, and this paper mainly focuses on LCI regarding the reduction in carbon emissions, rather than all environment-related green technology. It is because the research on LCI is more targeted in the context of mitigating global climate change. Therefore, we present a viewpoint that highlights the importance of low-carbon advancement while pointing out that a city’s GEE is influenced by LCI. Case studies from developed and developing nations have also shown the crucial role that LCI plays in the process of development (Jordaan et al., 2017; Popp, 2012; Yang & Liu, 2020). To discover the fundamental traits of technological innovation that reduce carbon, it is often classified into carbon-free technologies, decarbonization technologies, and CO₂ reduction technologies. The first two mainly affect factor efficiency, while the latter mostly influences the level of pollution. The categories of LCI chosen as the independent variable in the model exert a significant impact on how LCI affects green development, so whether different LCIs are effective for GEE deserves further exploration.

China has made great achievements since the 1970s, yet this progress harmed the environment and the pace of global climate change. Based on BP statistics, China’s CO₂ emissions from energy reach 10.87 billion tons in 2021, the world’s top emitter of carbon emissions, accounting for 32.07% of global CO₂ emissions in the same year. Moreover, according to the environmental performance index published by Yale University and Columbia University, China is placed 160th in 2022, down 40 places from 2018. Statistics show that China is relatively behind the world in terms of its degree of greening and low-carbonization, and China’s green development is threatened by both current and potential environmental risks. The Chinese government has recognized the seriousness of this issue and underlined the value of LCI for green development. China has now emerged as a world bellwether in creating LCIs in large quantities (Helveston & Nahm, 2019), and developed low-carbon-related programs. However, knowledge regarding the impact of LCI on the

GEE in China is still limited. Therefore, this study targets Chinese prefecture-level cities, and primarily focuses on whether LCI has a synergistic effect on the GEE of local and neighboring cities.

To our knowledge, the contributions of this paper are fourfold compared to recent studies. First, as the largest representative developing country, China's LCI and green development pattern is different from that of developed countries (Du et al., 2019). The relationship between LCI and GEE in China remains a pending question (Yan et al., 2017). This study examines the effect of LCI on green development in the background of China for the first time, to provide some insightful policy references for promoting green transformation in China and even in other developing countries. Second, some scholars used industrial wastewater emission, industrial waste gas emission, and industrial solid waste as the undesirable output of green development (Lee & Lee, 2022; Zhao et al., 2020). The significant negative impact of carbon emissions has not been taken into account, which leads to the overestimation of GEE. We include carbon emissions as undesirable output to calculate GEE, which can better understand the role that LCI plays in promoting China's green development. Third, we establish a causal mediating effect model to reveal the channels of the LCI affecting GEE, including industrial structure, energy consumption structure, and human capital, providing an alternative policy path for coping with the city's green transformation in the long run. Fourth, different from previous studies that only divide technological innovation into invention, utility, and design (Luo et al., 2022), this study categorizes LCI into eight categories and investigates the impact of each category on the improvement in GEE, offering more detailed evidence to reveal the relationship between the LCI and GEE. Furthermore, some research ignores the heterogeneity analysis (Peng et al., 2021), this study estimates the heterogeneous impact of LCI on GEE in cities with different development levels and cities in different regions.

The rest of this study is arranged as follows. Section 2 offers a review of relevant literature. Section 3 introduces the methodology and data. Section 4 illustrates the benchmark regression, channel identification, and heterogeneity analysis. Conclusion and policy implications are drawn in Sect. 5. The study framework is outlined in Fig. 1.

2 Literature review

2.1 Measuring green economic efficiency

Traditional economic efficiency primarily concerned with the ratio of the labor force to capital stock input (Walker et al., 2020), and this development model cannot solve the economic transformation problem. The gradual disappearance of the labor factor dividend renders the development model solely relying on increasing input factors unsustainable (Kumar et al., 2016). Furthermore, failure to consider the economic efficiency of resources and environmental constraints distorts economic performance evaluation, thereby misleading policy implications. However, the proposal of GEE further addresses the energy constraints and undesirable output, which is beneficial to achieving the transformation of factor input into a new innovation-driven "efficiency revolution". As a result, finding a way to measure the GEE has piqued the interest of many scholars.

The classical methods for measuring GEE are primarily divided into two types: parametric and nonparametric methods. Stochastic frontier approach (SFA) is the most commonly used parametric analysis method, but it is risky to impose strong a priori assumptions on

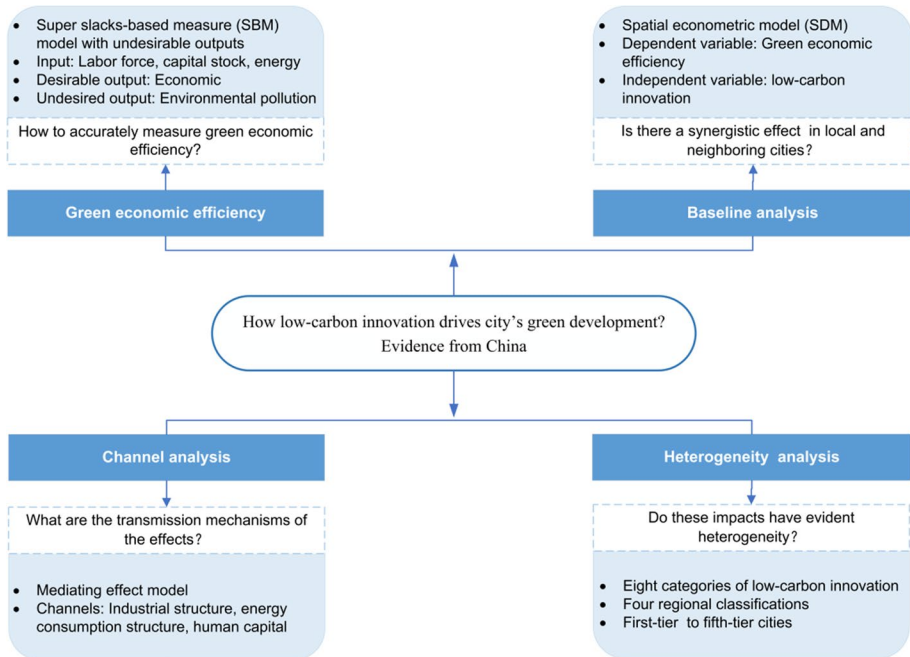


Fig. 1 Framework for the study

the efficiency of decision-making units (DMUs) through the functional form. Besides, SFA only applies to multiple inputs and single output (Cullinane et al., 2006), which can provide a misleading evaluation of GEE. Data envelopment analysis (DEA) is a nonparametric method that can effectively handle irregularities in data and dimensional inconsistency of the variables (Zhou et al., 2017). However, the traditional DEA is limited by the relaxation of input elements, radial, oriented deviation, etc. Therefore, considering the advantages of super-efficiency DEA and slacks-based measure (SBM) methods, Tone (2002) proposed a new model, namely super-SBM, to alleviate variable relaxation and eliminate the radial and oriented deviation. Currently, the super-SBM model has become a widely used method to measure GEE (Lee & Lee, 2022; Zhao et al., 2020).

2.2 The related researches of LCI

As an emerging innovation model, LCI has no unified definition yet, and the concepts summarized in the previous literature can be mainly summarized as the following three. The first concept suggests that LCI is a multi-level item that includes not only innovating on energy-saving, renewables, sustainable consumption, energy conversion, etc., but also innovating on human or social behavior (Shi & Lai, 2013). The second concept suggests that LCI is a development model that creates a green transition by promoting the development of industries and technologies related to carbon reduction under the condition of increasing outputs without increasing productive inputs (Bi et al., 2016; Li et al., 2021). The third and most common concept describes LCI as a fundamental means of decreasing the cost of achieving ultimate environmental policy goals and mitigating climate change

caused by carbon dioxide emissions, as well as balancing the economy and environment (Albino et al., 2014).

Most research topics on LCI have focused on developed countries as their technological innovations started earlier than in the rest of the world. Albino et al. (2014) studied the dynamics trends of LCIs and their relevant technological impact over the last 39 years. Jordaan et al. (2017) systematically evaluated whether energy technology innovations meet international greenhouse gas emissions targets in Canada. Cho and Sohn (2018) analyzed the key factors driving green innovation in the UK, Italy, France, and Germany. Meanwhile, many scholars have started to pay attention to the evolution of LCI in developing countries. Wong et al. (2014) explored the production trends and convergence patterns of LCI in Asian economies. Bi et al. (2016) argued that the performance of LCI varies among manufacturing industries. Helveston and Nahm (2019) analyzed the pivotal role that China plays in the promotion of LCIs regarding manufacturing innovation, commercialization cooperation, risks, and challenges.

2.3 Technological innovation and green development

Many empirical studies have been undertaken in the past to shed light on the function of influencing factors on green development. Economic openness (Zhao et al., 2020), green finance (Lee & Lee, 2022), and technological innovation (Liu & Dong, 2021; Wang et al., 2021b) have been identified as key influencing factors. Among these influencing factors, technological innovation has been identified as the most effective means to promote green development. However, studies on the effect of technological innovation on economic development have come to different conclusions. The neoclassical growth theorists pointed out that continuous technological progress increases capital demand, creating continuous growth (Solow, 1956). Based on this view, the new economic growth theorists suggested that endogenous technological progress is the determinant of economic growth, and technological spillovers are an indispensable condition for sustainable economic growth (Arrow, 1971). Regarding empirical studies, the existing literature has demonstrated that technological innovation can help promote green development (Wang et al., 2021b). Another perspective argued that technological innovation may hinder the improvement in green development. Because technological innovation is either energy-biased or production-biased, it would consume more energy and raise carbon emissions while increasing output, potentially resulting in a “rebound effect” (Shao et al., 2016). It is noteworthy that most studies do not consider the spatial effects of technological innovation on green development, which may lead to inadequate results.

Moreover, with the apparent spatial characteristics of technological innovation and green development, a city's green development is not only affected by its technological innovation but also by the neighboring cities. Tobler (1970) proposes closer relationships between more recent things. The new economic geography delves deeply into the spatial effects and mechanisms of externality generation (Krugman, 1991). Recently, scholars have begun to focus on spatial effects and spatial correlations of technological innovation on green development by applying spatial econometric models to study the relevant topics. For example, Torres-Preciado et al. (2014) suggested that technological innovation contributes to economic growth in Mexico, and this beneficial effect comes from the cross-border diffusion effects of technologies. Wang et al. (2021a) found that green technology innovation improves its green total factor productivity but negatively affects that of its neighbors. Liu and Dong (2021) showed that technological innovation significantly enhances GEE

through natural resources and urbanization. Several studies have also examined the relationship between LCI and energy efficiency (Li et al., 2021), climate change (Wang et al., 2018), and haze pollution (Jin et al., 2022). However, the spatial effect of LCI on GEE is still unknown.

In summary, the above research has provided some insight for this study, but the following questions still need to be explored in depth. First, empirical evidence on the spatial effects of LCI on GEE is still scant in the context of China. Second, most studies have focused on innovation in general, rather than on heterogeneous technological innovation, thus reducing the specificity of their results. Third, relative researches lack the heterogeneity analysis of LCI in different regions and cities on GEE. Lastly, based on previous research, an extensive investigation of the channels of LCI on GEE in China is necessary.

3 Methodology and data

3.1 Super-SBM model with undesirable outputs

Capital, labor, and energy input will not only result in economic growth but will also generate environmental pollution, that is, undesirable output. The traditional DEA model excludes slack-based measurement and cannot accurately calculate the efficiency value that considers the undesirable output. Tone first proposed the SBM model based on undesirable output (Tone, 2002), which can effectively deal with the congestion or relaxation of input factors, and is widely used in economic development efficiency (Lee & Lee, 2022; Zhao et al., 2020). When there are multiple DMUs with an efficiency value of 1, the traditional SBM model is unable to distinguish and compare them. However, the results of the super-efficient SBM (Super-SBM) model show values of efficiency greater than 1, so the Super-SBM model could distinguish the efficiency value of all DMUs. Therefore, based on the research of Tone (2003), we adopt the Super-SBM model with undesirable outputs to calculate the GEE of 285 cities in China, which is as follows:

$$\rho^* = \min \frac{\frac{1}{M} \sum_{i=1}^M \frac{\bar{x}_i}{x_{i0}}}{\frac{1}{S_1+S_2} \left(\sum_{r=1}^{S_1} \frac{\bar{y}_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2} \frac{\bar{y}_r^b}{y_{r0}^b} \right)}, \text{ s. t. } \begin{cases} \bar{x} = \sum_{j=1, \neq k}^N \theta_j x_j \\ \bar{y}^g \leq \sum_{j=1, \neq k}^N \theta_j y_j^g \\ \bar{y}^b \geq \sum_{j=1, \neq k}^N \theta_j y_j^b \\ \bar{x} \geq x_0, \bar{y}^g \leq y_0^g, \bar{y}^b \geq y_0^b, \bar{y}^g \geq 0, \bar{y}^b \geq 0, \theta \geq 0 \end{cases} \quad (1)$$

where ρ^* denotes the super-efficiency value of the DMU, and its value can exceed 1. A bigger value of ρ^* indicates a higher level of green development. M, S_1 , and S_2 are input, desirable outputs, and undesirable outputs, respectively. x, y^b, y^g are input matrix, desirable output matrix, and undesirable output matrix, respectively. θ means the weight vector.

3.2 Spatial correlation test

Spatial correlation is the most basic property of the space, because its result affects not only the regression coefficients, but the inferences of the statistical analysis (Elhorst, 2014). According to the available literature (Zhang et al., 2022b), we adopt two commonly used Moran’s indexes

to measure the overall spatial dependence and the impacts at specific locations. I_{global} could only identify whether the city units exist spatial correlation from the global perspective, but ignore the regional heterogeneity characteristic of city elements. Fortunately, the local spatial correlation test makes up for this disadvantage. The equations of the global Moran's index and local Moran's index are written as:

$$I_{\text{global}} = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \tag{2}$$

$$I_{\text{local}} = \frac{n(x_i - \bar{x}) \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \tag{3}$$

where I_{global} stands for the value of global Moran's index, I_{local} is the value of local Moran's index. When the range value of I_{global} is (0,1], it means that the tested variable is positively spatially correlated; when I_{global} takes values in the range is [-1,0), it indicates that the tested variable is negatively spatially correlated. n denotes the number of spatial units, x_i and x_j are the values of tested variables of cities i and j , \bar{x} is the average value of the tested variables, and w_{ij} represents the spatial weight matrix.

3.3 Spatial econometric model

The traditional ordinary least squares (OLS) method cannot avoid the problems caused by spatial correlation between units. In other words, if there is a spatial correlation between cities, ignoring the spatial effect will inevitably create bias in the estimation results (Anselin, 2010). Previous studies have found that technological innovation has a spatial spillover effect (Peng et al., 2021). With these considerations, the spatial econometric model can better reflect the spatial effects of LCI on GEE. There are three common spatial econometrics models: Spatial Lag Model (SLM), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). In the SLM, the effect of the independent variable on the dependent variable of adjacent cities can be analyzed. SEM ignores the spatial lags of independent variables. Once the random error term is complicated by multiple factors, the model no longer obeys the normal distribution. SDM includes the spatial interaction terms between the dependent variable and independent variable, which allows for the estimation of the spatial effect of the local independent variable on the dependent variable, as well as that of the neighboring area (LeSage & Pace, 2009). The three models are expressed in Eqs. (4)-(6):

$$\text{SLM } Y_{it} = \rho \sum_{i=1}^N w_{ij} Y_{it} + \beta X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

$$\text{SEM } Y_{it} = \beta X_{it} + \mu_i + \gamma_t + \phi_{it}, \phi_{it} = \lambda \sum_{j=1}^N w_{ij} \phi_{it} + \varepsilon_{it} \tag{5}$$

$$\text{SDM } Y_{it} = \rho \sum_{i=1}^N w_{ij} Y_{it} + \beta X_{it} + \theta \sum_{j=1}^N w_{ij} X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{6}$$

where Y_{it} is the GEE in city i at year t , X_{it} is the LCI in city i at year t . ρ is the spatial regression coefficient, μ_i and γ_t are the space effect and time effect, respectively, ε_{it} is a random error item that follows the normal distribution, ϕ_{it} stands for the spatial autocorrelation error term, λ refers to the spatial autocorrelation coefficient of the error term. w_{ij} denotes the spatial weight matrix.

Due to the spatial lag term in the above model, the regression coefficients cannot directly report the true effect of LCI on GEE, only observing the regression coefficients may lead to model estimation bias (LeSage & Pace, 2009). Therefore, we adopt the partial differential method to subdivide the spatial effects into three effects, namely, direct, indirect, and total average effects. The matrices for three effects are written as:

$$\overline{M}(r)_{\text{total}} = N^{-1}I_N^{-1}S_r(W)I_N \tag{7}$$

$$\overline{M}(r)_{\text{direct}} = N^{-1}tr(S_r(W)) \tag{8}$$

$$\overline{M}(r)_{\text{indirect}} = N^{-1}I_N^{-1}S_r(W)I_N - N^{-1}tr(S_r(W)) \tag{9}$$

where $\overline{M}(r)_{\text{total}}, \overline{M}(r)_{\text{direct}}, \overline{M}(r)_{\text{indirect}}$ represent total, direct and indirect average effects. $S_r(W) = (I_n - \rho W)^{-1}(I_n \beta_r + W \theta_r)$.

Because different matrices can capture different spillover channels, specifying spatial weight matrices is especially important for spatial analysis. To estimate the spatial effects of LCI on GEE, we construct the spatial adjacency weight matrix (W_1). Furthermore, the spatial geographical distance weight matrix (W_2) is constructed to make sure the robustness. The elements of W_1 and W_2 are shown in Eqs. (10)-(11):

$$w_{ij} = \begin{cases} 1, & i \text{ and } j \text{ have a common boundary} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \tag{11}$$

where d_{ij} is the geographical distance between cities i and j , which is from Baidu map.

3.4 Variables and description

3.4.1 Variables selection

Green economic efficiency is identified as the dependent variable in this study. As in most studies (Lee & Lee, 2022; Wang & Salman, 2022), capital, labor, and energy are taken as inputs, GDP is taken as the desirable output, and environmental pollution is taken as the undesirable output. The input and output calculation indicators of the dependent variable are displayed in Table 11. To reduce heteroscedasticity and maintain data stability, we take the logarithm of GEE in the regression analysis (Sha et al., 2021).

Figure 2 is two representative years of GEE in 2003 and 2019 to analyze the spatial pattern. The first and last years of the study period in this paper are 2003 and 2019, which are chosen to characterize the changes in GEE. From the temporal perspective, we find that the level of China's GEE has gradually improved from 2003 to 2019, and the number of cities with higher GEE also increases. From the spatial perspective, GEE has obvious spatial agglomeration characteristics. Specifically, the GEE of cities along the southeastern coast, the lower area of the Yangtze River Delta, and the lower area of the Yellow River Basin are significantly higher than that of other cities. This is because these cities have a higher development level of economic, pay more attention to environmental protection, and gradually moved toward green development (Liu & Dong, 2021).

Low-carbon innovation (LCI) is identified as the independent variable. R&D expenditures and patent counts are widely used to measure technology innovation. The former presents the input of innovation activity, while the latter is regarded as the output (Popp, 2012). In comparison to R&D data, patent data not only can be segmented into low-carbon technology categories but also provides an appropriate measurement for large sample analysis, particularly using international standards for cross-regional comparison of technology development (Cui et al., 2018). Therefore, we choose patent data to measure the city's LCI. Based on previous studies, patent technologies already have an impact on enterprises during the application process. Since the patent application is more objective, trustworthy, and timely than the granted patent data, we choose the low-carbon patent application data in this study. Given that larger cities usually create more innovation projects, the overall number of patents is biased when used to determine a city's level of LCI. Hence, we employ the number of low-carbon patent applications per 10^4 people to represent the city's LCI level. Figure 3 presents the spatial distribution evolution of LCI. The level of LCI has continued to improve from 2003 to 2019, but the overall level of LCI needs to be improved. In addition, LCI decreases from eastern China to western China because eastern China has vast resources for innovation, such as high-level labor, sufficient capital, and well-developed infrastructure, which facilitates the advancement of LCI. Specifically, we use the most recent Climate Change Mitigation Technologies (CCMTs) code in the Cooperative Patent

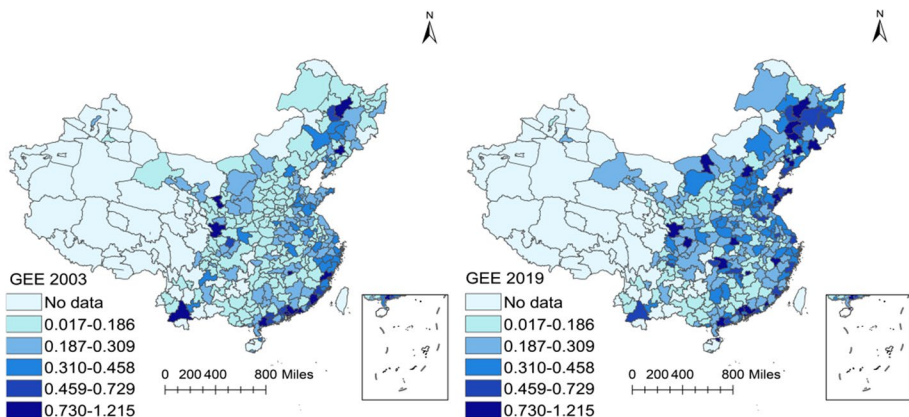


Fig. 2 The changing pattern of GEE in China. Data source: The authors used MATLAB software to calculate the GEE value of 285 cities, and then drew this map based on ArcGIS10.5 software. The vector map is from the National Geomatics Center of China

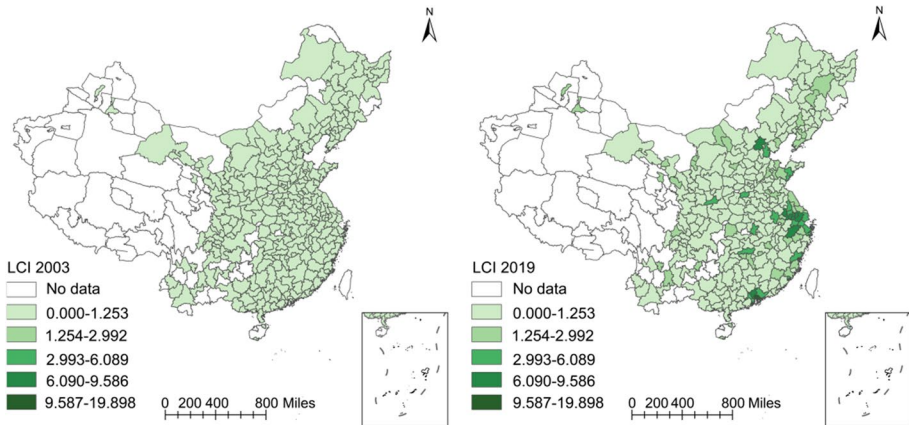


Fig. 3 The changing pattern of LCI in China. Data source: The authors manually collected low-carbon patent data for 285 cities based on *Incopat database*, and then drew this map based on ArcGIS 10.5 software. The vector map is from the National Geomatics Center of China

Classification (CPC) issued by the European Patent Office and United States Patent and Trademark Office, to retrieve the number of patents classified by Y02, which has structural and systematic characteristics and can characterize the dynamic evolution progress of LCI. It includes farming, animal husbandry and economic activities (*FARM*), building (*BUILD*), greenhouse gas treatment (*GHG*), information and communication (*INCOMM*), energy (*ENERGY*), commodity production and processing (*CPP*), transportation (*TRANS*), sewage and pollutant treatment (*SPT*). The specific classification and definition can be seen in Table 12.

We analyze three channels of LCI affecting GEE. (1) Industrial structure (*IS*). Industrial upgrading can promote the reallocation of labor, capital, and other factors, and the effective allocation of resources can improve the GEE (Zhu et al., 2019). In addition, the demand for low-carbon development drives the industry to shift from emission-intensive and pollution-intensive to clean and low-carbon production. Without losing generality, the industrial structure effect is estimated by the logarithm value of the rate of the added values of the service and secondary industries. (2) Energy consumption structure (*ECS*). The latest *China Energy Statistical Yearbook* shows that coal consumption accounts for more than half of total energy consumption. There is no data on city's energy consumption. Following existing literature (Meng et al., 2014), we employ corrected nighttime light data to estimate the city's energy consumption data. The logarithm value of the proportion of coal consumption to total energy consumption is used to measure the energy consumption structure. (3) Human capital (*HC*). The new growth theory introduces human capital into the growth model and believes that accumulating specialized human capital is the new source of sustained economic growth. Furthermore, the increased awareness of emission reduction and energy-saving among highly educated people can affect environmental quality, thereby promoting GEE (Hao et al., 2021). To verify this channel, human capital is represented by the logarithm value of the number of researchers as a percentage of the total population.

Eight Control variables are introduced to the regression model: (1) Economic development level (*EDL*) is measured by the logarithm value of GDP per capita. The improvement in the economic development level can provide a material basis for green development

through the scale effect. (2) Population density (*PD*) is estimated by the logarithmic value of the population per unit area. Population growth increases the overuse of resource, and also cause environmental damage through agglomeration effects, which is detrimental to the GEE. (3) Ownership structure (*OS*) is measured by the ratio of domestic private enterprise employees to the total number of local employees. The reform of the ownership structure not only reallocates capital and labor but also promotes regional economic efficiency (Song et al., 2011). (4) Financial development (*FD*) is measured by the logarithm value of the year-end loan balance of financial institutions as a percentage of GDP. The quality and composition of financial development directly increase financial assets and spawn economic growth (Menyah et al., 2014). (5) Marketization level (*ML*) is determined by the ratio of government expenditures to GDP. Limited government market intervention can regulate the allocation of resources and improve GEE. Conversely, it disturbs the market order and is not conducive to the improvement in GEE (Xu et al., 2021). (6) Education level (*EL*) is represented by the logarithm value of the ratio of the number of college students to the total population. The improvement in education level means a higher quality labor force that can inspire higher production efficiency and stricter environmental quality requirement, ultimately increasing GEE (Balaguer & Cantavella, 2018). (7) Opening degree (*OD*) is calculated by the ratio of foreign direct investment (FDI) to GDP (Zhang et al., 2022a). According to the pollution halo and pollution paradise hypotheses, while FDI contributes to the technological progress in the host countries, it also transfers excess capacity to the host country through industrial transfer. (8) Environmental regulation (*ER*) is represented by the industrial solid waste utilization rate. Environmental regulation can stimulate enterprises to use more clean energy and contribute to GEE in the long run.

3.4.2 Data description

Considering the availability of the data and representativeness of the study, 285 prefecture-level cities in China from 2003 to 2019 are selected as the study sample. The low-carbon patent data is mainly retrieved from the *Incopat database*, and the patent search is carried out based on the classification number in the CPC, city name, and application time. Other data are mainly collected from the *China City Statistical Yearbook* and *CEIC China Economic Database*. Night-time light data are compiled from the *Harvard Dataverse*. To eliminate the influence of inflation, all economic variables related to monetary values are deflated using 2003 as the base period. Some missing data are supplemented according to the provincial statistical yearbooks and statistical bulletins, others are filled by the interpolation method. The results of descriptive statistics can be seen in Table 1.

4 Empirical results

4.1 Analysis of spatial autocorrelation

We apply the Stata17.0 software to calculate the global Moran's indexes and draw the scatterplots of the local Moran's indexes. Table 13 shows the global spatial autocorrelation test results of LCI and GEE from 2003 to 2019 under W_1 and W_2 . We can observe that all global Moran's indexes are significantly positive at the 1% level, implying that LCI and GEE have a positive spatial correlation among cities.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
GEE	4845	-1.563	0.641	-4.075	0.218
LCI	4845	0.498	1.345	0.001	22.279
EDL	4845	10.028	0.848	7.545	12.488
PD	4845	5.717	0.914	1.547	7.882
OS	4845	1.011	0.668	0.052	7.504
FD	4845	0.644	1.201	-3.929	3.937
ML	4845	0.168	0.101	0.031	1.936
OD	4845	0.019	0.022	0	0.376
EL	4845	4.258	1.677	-6.226	7.290
ER	4845	0.779	0.235	0.001	1.350
IS	4845	-0.208	0.469	-3.627	4.989
ECS	4845	-0.440	0.654	-2.745	2.311
HC	4845	-6.749	0.973	-9.377	-1.480

Figure 4 and Fig. 5 show the scatterplots of the local spatial autocorrelation test for GEE and LCI in 2003 and 2019. The horizontal and vertical axes represent the standardized variable values and spatial lag values, respectively, and these two lines divide the study sample into four quadrants. Scattered points in the first (high-high agglomeration) and third quadrants (low-low agglomeration) denote positive spatial correlation, while those in the second (low-high agglomeration) and fourth quadrants (high-low agglomeration) demonstrate negative spatial correlation. As displayed in Fig. 4 and Fig. 5, more than half of

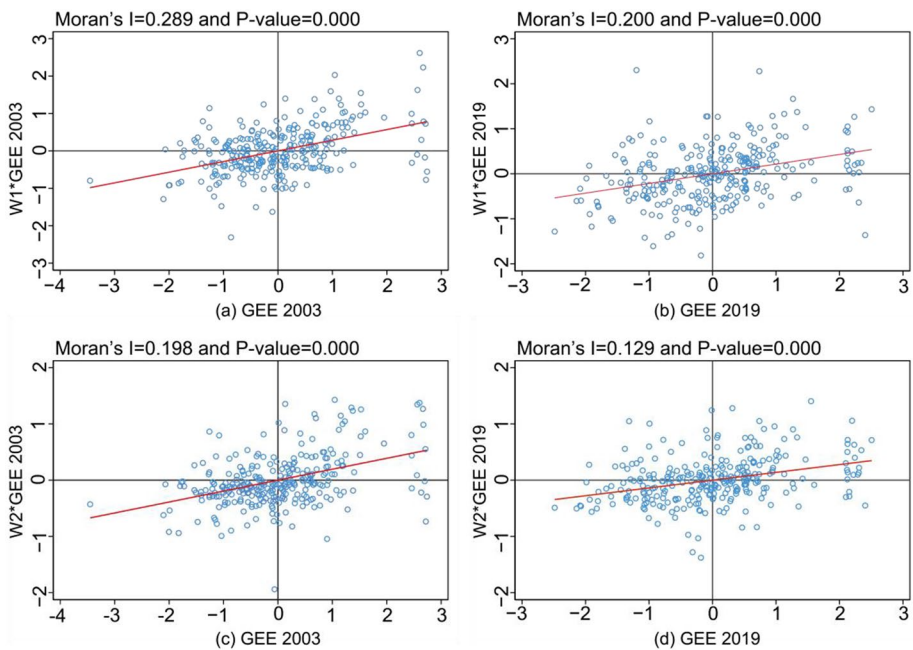


Fig. 4 Scatterplots of the local Moran's indexes of GEE

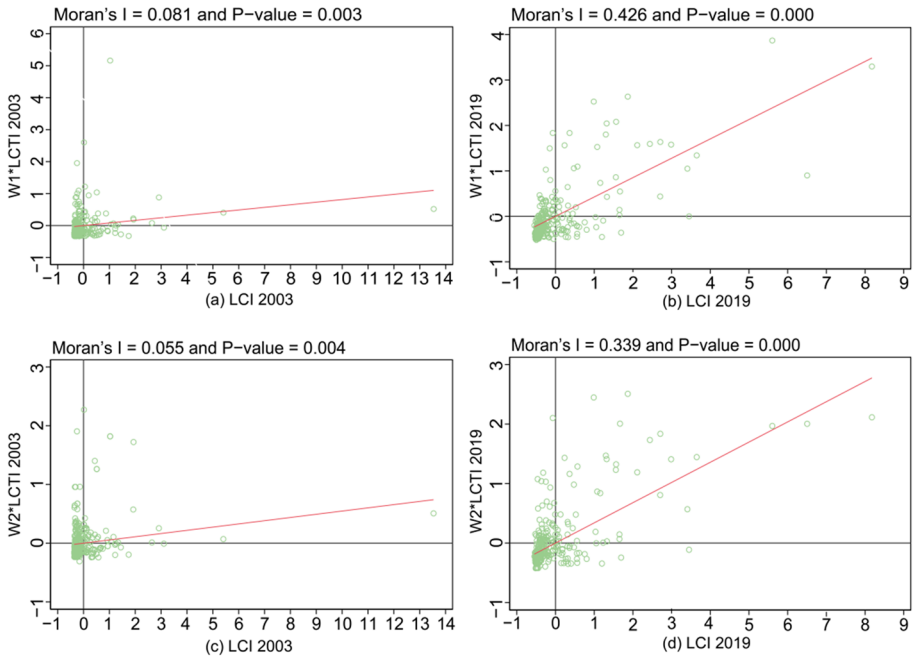


Fig. 5 Scatterplots of the local Moran's indexes of LCI

the cities are in the first and third quadrants, further confirming that LCI and GEE are positively correlated in space, which is in-line with the respective global Moran's index. Therefore, the spatial econometrics model is deemed reliable for analyzing the effect of LCI on GEE.

4.2 Benchmark regression and spatial effect results

To identify the specific form of the spatial econometric model, we use LM and LR tests according to Elhorst (2014). Specifically, the LM test is applied to determine the most suitable model between SLM and SEM, and the LR test is employed to judge whether the SDM would simplify into SLM or SEM (Le Sage and Pace, 2009). Table 2 presents the test results. For both matrices, all results of the LM and LR tests reject the null hypothesis, demonstrating that SDM is most suitable for analyzing the relationship between LCI and GEE. The results of the LR test also prove that the space and time fixed effects are jointly significant. Furthermore, we use Akaike Information Criterion (AIC) to assess the goodness of fit of the three spatial econometric models. AIC supports the goodness of data fitting and minimizes overfitting, so the preferred model should be the one with the smallest AIC value. The results further indicate that the SDM has the lowest AIC value and is the best fit. Thus, SDM with a two-way fixed effect is selected to explore the spatial effects of LCI on GEE.

Table 2 also reports the estimation results of the benchmark regression. To facilitate the comparison, the results for the OLS estimation, SLM, and SEM with space and time

Table 2 Benchmark regression and test results

Variables	OLS (1)	SDM(W_1) (2)	SEM(W_1) (3)	SLM(W_1) (4)	SDM(W_2) (5)	SEM(W_2) (6)	SLM(W_2) (7)
LCI	0.043*** (5.802)	0.019** (2.500)	-0.009 (-1.454)	-0.010* (-1.760)	0.013* (1.867)	-0.006 (-1.052)	-0.010* (-1.741)
EDL	0.267*** (18.088)	0.848*** (10.522)	0.763*** (10.402)	0.703*** (10.030)	0.925*** (11.695)	0.809*** (10.897)	0.712*** (10.187)
PD	0.029** (2.573)	-0.024 (-0.271)	-0.118 (-1.413)	-0.137* (-1.689)	0.026 (0.294)	-0.084 (-0.985)	-0.123 (-1.516)
OS	0.151*** (11.413)	0.065*** (6.611)	0.067*** (6.701)	0.068*** (6.856)	0.068*** (6.918)	0.070*** (7.088)	0.069*** (7.001)
FD	-0.111*** (-12.185)	-0.094*** (-4.200)	-0.107*** (-5.067)	-0.105*** (-5.159)	-0.106*** (-4.686)	-0.112*** (-5.255)	-0.107*** (-5.271)
ML	-0.010 (-0.097)	-0.419*** (-4.372)	-0.377*** (-3.983)	-0.351*** (-3.784)	-0.422*** (-4.372)	-0.383*** (-4.054)	-0.360*** (-3.880)
OD	1.169*** (2.815)	-0.232 (-0.604)	0.264 (0.777)	0.270 (0.835)	-0.784** (-2.140)	0.042 (0.122)	0.154 (0.475)
EL	-0.032*** (-5.288)	0.032*** (5.003)	0.033*** (5.172)	0.033*** (5.170)	0.031*** (4.810)	0.032*** (5.007)	0.033*** (5.052)
ER	0.268*** (6.820)	-0.025 (-0.823)	-0.032 (-1.029)	-0.033 (-1.075)	-0.020 (-0.637)	-0.024 (-0.789)	-0.029 (-0.932)
$W \times LCI$		-0.059*** (-4.695)			-0.055*** (-3.795)		
ρ		0.146*** (7.649)		0.143*** (7.605)	0.240*** (7.694)		0.262*** (8.588)
λ			0.153*** (7.946)			0.293*** (9.475)	
LM			408.215***	431.148***		539.868***	466.848***
Robust LM			3.565*	26.499***		74.894***	1.874
LR			66.390***	71.390***		91.510***	105.350***
LR-space		216.770***			142.360***		
LR-time		5901.250***			5979.260***		
AIC		1956.592	2004.979	2009.987	1908.936	1982.449	1996.284
City fixed effect		Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect		Yes	Yes	Yes	Yes	Yes	Yes
Constant	-4.603*** (-28.802)						
R^2	0.187	0.056	0.057	0.056	0.054	0.056	0.054
N	4845	4845	4845	4845	4845	4845	4845

***, **, and *Represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are t statistics

fixed effects estimation are also shown. Columns (2)-(4) and (5)-(7) are the regression results using W_1 and W_2 . This study mainly focuses on the estimation results in columns (2) and (5). The empirical results suggest that the coefficients of LCI are all significantly positive, preliminarily indicating that the enhancement in LCI of a city exerts a positive

influence on its GEE. Moreover, the significant spatial autoregressive coefficient suggests the positive spatial correlation consistent with the conclusions in the previous analysis.

The positive regression coefficient of EDL indicates that the higher economic development level, the more conducive to GEE. OS is significantly positive, showing that a higher level of private enterprises contributes to higher GEE. This can also be deduced from the significantly negative regression coefficient of ML, demonstrating that excessive government intervention inhibits the GEE. The coefficients of FD are negative, verifying that the effect of financial development on economic progress is not visible. In addition, the impact of EL on GEE is significantly positive, suggesting that a higher quality labor force contributes to GEE. In this study, the regression coefficients of three control variables are insignificant, because the effect of control variables on the GEE of different subsamples in the overall sample regression could offset each other (Xu et al., 2021). Therefore, we further discuss the regional heterogeneity in Sect. 4.5.2.

Due to the feedback effect, marginal effects estimated by spatial econometric models are biased. Here, we reveal the impact of LCI on GEE from direct, indirect, and total effect coefficients, that is, from the perspectives of intra-city, inter-city, and the whole city. Specifically, the direct effect reflects the influence of LCIs on the GEE of local cities. The indirect effect represents the impact of LCI on the GEE of neighboring cities. The sum of the above two is the total effect. The decomposition results of the three effects are displayed in Table 3. It can be observed that the decomposition results of the two matrices are almost similar, indicating the robustness of baseline regression results. Since the spatial effects of control variables are not the focus of this paper, this section mainly analyzes the spatial effect of LCI on GEE.

As illustrated in Table 3, the direct effect of LCI is significantly positive, suggesting that the increase in LCI promotes local GEE. The main reason is that LCI improves local GEE primarily by stimulating enterprise innovation compensation (Liu & Zhang, 2021), incentivizing the energy structure to shift from non-renewable energy to relatively sustainable energy sources, and encouraging human capital to develop advanced environmental technology. However, the indirect effect is significantly negative, showing that the increase in LCI restrains GEE in neighboring cities, which is consistent with the findings of Wang et al. (2021a). The reason for this result is, on the one hand, that the LCI efforts in each city of China still work for themselves, and the synergistic cooperation and linkage effect of LCI among cities is insufficient (Wang et al., 2018; Zhang et al., 2022c). On the other hand, the progress of LCI requires the support of professional researchers and large amounts of R&D funds. Cities with a good LCI base tend to have a siphon effect and crowding-out effect on low-carbon resources in the neighboring cities, while cities with a poor LCI base have a mismatch between their absorption capacity and technology spillover (Shao et al., 2022), which eventually leads to a negative indirect effect. Furthermore, the negative indirect effect of LCI is larger than the positive direct effect, resulting in negative total effects. This finding concurs with Li et al. (2021). This is mainly because the clustering of LCI resources makes developed cities greener, which encourages the flow of more innovative resources to these cities. Instead, green development in less-developed cities will be slowed down by the loss of LCI resources, which is detrimental to China's overall green development. Additionally, due to the obvious regional differences in LCI in China (Fig. 3), a small number of cities in China have successfully developed LCI, which makes it challenging to significantly improve GEE nationwide.

Table 3 Decomposition results of spatial effects

Variables	W ₁			W ₂		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
LCI	0.018** (2.314)	-0.064*** (-4.523)	-0.046*** (-4.204)	0.012* (1.724)	-0.067*** (-3.645)	-0.055*** (-3.407)
EDL	0.836*** (10.951)	-0.278** (-2.108)	0.558*** (4.440)	0.907*** (12.100)	-0.828*** (-3.598)	0.078 (0.360)
PD	-0.031 (-0.377)	-0.549*** (-3.079)	-0.580*** (-3.189)	0.016 (0.191)	-0.999*** (-3.704)	-0.983*** (-3.685)
OS	0.067*** (6.924)	0.047** (2.313)	0.113*** (5.001)	0.067*** (7.017)	-0.044 (-1.158)	0.024 (0.598)
FD	-0.094*** (-4.450)	0.008 (0.204)	-0.086** (-2.248)	-0.104*** (-4.901)	0.089 (1.428)	-0.015 (-0.248)
ML	-0.403*** (-4.314)	0.387* (1.926)	-0.017 (-0.081)	-0.408*** (-4.376)	0.460 (1.075)	0.051 (0.123)
OD	-0.215 (-0.547)	0.649 (0.932)	0.434 (0.686)	-0.722* (-1.922)	3.452*** (2.762)	2.730** (2.306)
EL	0.032*** (5.056)	-0.014 (-0.825)	0.018 (0.972)	0.031*** (4.971)	0.021 (0.868)	0.052** (2.032)
ER	-0.024 (-0.786)	-0.048 (-0.728)	-0.072 (-0.972)	-0.019 (-0.638)	-0.148 (-1.151)	-0.167 (-1.242)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	4845	4845	4845	4845	4845	4845

***, **, and *Represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are *t* statistics

4.3 Robustness and endogeneity tests

To verify the robustness of the benchmark results, a series of auxiliary tests were conducted. First, the robustness can be verified by adopting the economic geographic nested spatial weight matrix to re-estimate the effect of LCI on GEE (Yuan et al., 2020). Based on column (1) in Table 4, it can be seen that the estimated coefficients of the three effects are consistent with the benchmark regression results. Second, we re-estimate Eq. (6) by replacing the values less than 1% and greater than 99% of all variables with the corresponding quartile values to avoid the impact of outliers. The result in column (2) suggests that the coefficient is also highly consistent with the benchmark estimation results. Third, due to the special administrative status, regressions are performed after removing the municipalities sample to eliminate the estimation bias caused by sample selection (Yang et al., 2019). The results in column (3) show that LCI does promote GEE without considering the results bias caused by the municipalities. Finally, referring to the study by Li et al. (2022), we use the first-order and second-order lag terms of LCI as the core independent variables for regression analysis to avoid the endogeneity problem caused by reciprocal causality. The results in columns (4) and (5) show that the lag

Table 4 Robustness test results

	Dependent variable: GEE				
	(1)	(2)	(3)	(4)	(5)
Direct effect	0.015** (1.975)	0.030*** (2.980)	0.019** (2.290)	0.018** (2.093)	0.022** (2.328)
Indirect effect	-0.141*** (-3.188)	-0.051*** (-2.985)	-0.071*** (-4.786)	-0.069*** (-4.425)	-0.078*** (-4.434)
Total effect	-0.125*** (-3.140)	-0.021 (-1.502)	-0.052*** (-4.664)	-0.051*** (-4.361)	-0.056*** (-4.273)
City fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
N	4845	4845	4777	4560	4275

***, **, and *Represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are *t* statistics

terms of LCI do not change the spatial impact of LCI on GEE, which again validates the core findings. Overall, the above robustness tests largely support our findings.

The instrumental variable approach is chosen to further test the endogeneity. Valid instrumental variables need to satisfy both exogeneity and relevance conditions. The number of fixed telephones and the number of post offices in 1984 is selected as the instrument variables for two considerations. First, the sample time of the instrumental variables (1984) is different from this study period (2003–2019), which means that the historical number of post offices and fixed telephones can hardly affect the present GEE. Second, post offices and fixed telephones represent the degree of information flow in a city. If the number of post offices and fixed telephones is high, knowledge flow and technology exchange between cities will increase, which helps to promote the potential for LCI. Because the sample in this study is balanced panel data, using only cross-sectional data for the instrumental variables mentioned above would be difficult to measure due to the application of fixed effect model. Given this, this study draws on Nunn and Qian (2014) to construct interaction terms for the number of fixed telephone calls per 100 people (TEL) and the number of post offices per million people in 1984 (POST) and national science and technology investment in the previous year at the prefecture-level, respectively, as instrumental variables for LCI. Table 5 reports the 2SLS regression results. Panel A reflects the first-stage regression results of POST and TEL on the LCI and indicates that POST and TEL are significantly correlated with the LCI, which is consistent with our expectations. Moreover, we find that the F-statistics is greater than 10, rejecting the hypothesis of “weak instrument variable”. Panel B also shows that LCI significantly improved GEE. In sum, the results of endogeneity tests indicate that benchmark conclusions are credible and robust.

4.4 Channel identification

The benchmark model results demonstrate that LCI improves GEE significantly, but what factors cause this effect? Therefore, the fundamental channels must be identified. We anticipate that LCI will impact GEE through the energy consumption structure, industrial structure, and human capital channels. To verify whether the factors mentioned above can

Table 5 2SLS results of instrumental variables

	LCI	GEE	LCI	GEE
Panel A: first-stage				
POST	0.092*** (7.681)			
TEL			0.420*** (16.829)	
Panel B: second-stage				
LCI		0.418*** (5.477)		0.177*** (6.645)
City fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
R ²	0.312	0.028	0.344	0.066
F-statistics	17.470		18.580	

***, **, and *Represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are *t* statistics

serve as channels, the following SDM model is constructed to ensure the coherence of our benchmark model:

$$Z_{it} = \rho \sum_{i=1}^N w_{ij}Z_{it} + \beta X_{it} + \theta \sum_{j=1}^N w_{ij}X_{it} + \varphi_i + \tau_t + \delta_{it} \tag{12}$$

where Z_{it} refers to three channels (*IS*, *ECS*, *HC*). φ , τ , δ represent city fixed effect, year fixed effect, and random disturbance term, respectively. The remaining variables are consistent with Eq. (6).

Table 6 shows the regression results of channels. Columns (1) and (4), columns (2) and (5), and columns (3) and (6) are the estimation results of *IS*, *ECS*, and *HC* based on

Table 6 Channel analysis results

Variables		W ₁			W ₂		
		IS	ECS	HC	IS	ECS	HC
LCI	Direct effect	0.019*** (3.995)	-0.082*** (-14.996)	0.070*** (9.834)	0.019*** (4.266)	-0.087*** (-16.876)	0.072*** (10.923)
	Indirect effect	-0.022* (-1.950)	0.043*** (3.247)	0.028** (2.121)	-0.038** (-2.090)	0.089*** (3.727)	0.043** (2.516)
	Total effect	-0.002 (-0.253)	-0.039*** (-3.309)	0.098*** (9.431)	-0.018 (-1.071)	0.002 (0.099)	0.115*** (7.712)
City fixed effect		Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect		Yes	Yes	Yes	Yes	Yes	Yes
Control variables		Yes	Yes	Yes	Yes	Yes	Yes
N		4845	4845	4845	4845	4845	4845

***, **, and *Represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are *t* statistics

Eq. (12). Since channel identification emphasizes the influence of independent variable on three channels, we primarily focus on the influence of direct effects. In detail, the results of models (1) and (4) show that the direct effects of the industrial structure are significantly positive, indicating that improving a city's LCI level accelerates industrial structure upgrading, thereby improving the GEE. In models (2) and (5), the coefficients of the energy consumption structure are significantly negative, implying that optimizing the energy consumption structure can improve a city's GEE. The direct effects of human capital are also significantly positive in models (3) and (6), indicating that an increase in human capital provides solid intellectual support for GEE. Therefore, it can be concluded that LCI affects GEE via the channels of industrial structure, energy consumption structure, and human capital.

4.5 Heterogeneity analysis

4.5.1 Difference in low-carbon innovation

Considering that the technology biases of different patent types differ, this study reveals the heterogeneous effects of LCI on GEE. Specifically, the number of low-carbon technology patent applications per 10^4 people in eight subcategories are used as the independent variables and are substituted into the model (6) for regression analysis. Table 7 lists the heterogeneous results of different LCIs. The direct effects of building, greenhouse gas treatment, transportation, and sewage and pollutant treatment are significantly positive with W_1 and W_2 , implying that all four categories of LCIs significantly promote the city's GEE. Theoretically, these four subcategories of LCI are closely associated with green transformation and conform to the development concept. In practice, local governments prioritize the layout of these four LCI fields in the green development process, directing innovation resources toward them and providing financial and human support for the relevant LCIs, thereby promoting local GEE. However, regarding indirect effects, eight subcategories of LCIs on GEE are significantly negative, demonstrating that LCIs have no synergistic effect on improving the GEE in local and neighboring cities.

4.5.2 Difference in geographical location

To examine whether the LCI exerts equal influence on GEE across different regions, the research samples are classified as eastern China, central China, western China, and north-eastern China. Table 8 shows the regression results for the four regions. The direct effect of LCI on the GEE in eastern China is significantly positive with the spatial matrix of W_2 . However, this positive effect is not observed in central and northeastern China cities. This could further deepen the GEE gap between these regions in China. This is because LCI in eastern China is highly specialized and more advanced, allowing for the relatively easy diffusion of LCIs throughout the region, thus facilitating GEE (Liu & Dong, 2021). It is worth noting that the direct effect in western China is also significantly positive under the spatial weight matrix of W_1 . On the one hand, western China is relatively backward in terms of infrastructure and technological innovation, pays more attention to technological innovation for replacing physical capital input, and urgently needs the progress of LCI. On the other hand, with the in-depth implementation of national strategies such as the "Western Development" and "the Belt and Road", advanced low-carbon technologies in eastern China are transferred to western region (Wang et al., 2021a), and western China

Table 7 Heterogeneity analysis of low-carbon innovation

Matrices	Effects	FARM	BUILD	GHG	INCOMM	ENERGY	CPP	TRANS	SPT
W ₁	Direct effect	0.002 (0.042)	0.185*** (4.149)	2.802*** (3.206)	-0.043 (-0.693)	-0.010 (-0.586)	0.031 (1.104)	0.1148*** (2.615)	0.328*** (3.411)
	Indirect effect	-0.214*** (-2.836)	-0.466*** (-5.277)	-5.821*** (-3.009)	-0.309** (-2.162)	-0.064** (-2.107)	-0.190*** (-3.723)	-0.587*** (-4.921)	-0.939*** (-5.555)
	Total effect	-0.212*** (-3.106)	-0.282*** (-3.852)	-3.019 (-1.364)	-0.351*** (-2.589)	-0.074*** (-3.106)	-0.159*** (-3.765)	-0.438*** (-4.033)	-0.611*** (-4.309)
W ₂	Direct effect	-0.007 (-0.179)	0.160*** (3.747)	2.220*** (2.577)	-0.052 (-0.883)	-0.006 (-0.415)	0.020 (0.786)	0.134** (2.405)	0.242*** (2.595)
	Indirect effect	-0.155 (-1.409)	-0.405*** (-3.896)	-9.092* (-1.957)	-1.268*** (-4.826)	-0.108*** (-2.609)	-0.217*** (-3.127)	-0.696*** (-4.045)	-0.782*** (-3.348)
	Total effect	-0.163 (-1.595)	-0.245*** (-2.640)	-6.873 (-1.435)	-1.319*** (-5.013)	-0.114*** (-3.090)	-0.196*** (-3.122)	-0.562*** (-3.481)	-0.540*** (-2.599)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4845	4845	4845	4845	4845	4845	4845	4845	4845

***, **, and * Represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are *t* statistics

Table 8 Heterogeneity analysis of geographical location

Variable	Effects	W ₁					W ₂				
		EastGEE	CentralGEE	WestGEE	NortheastGEE	NortheastGEE	EastGEE	CentralGEE	WestGEE	NortheastGEE	
LCI	Direct effect	0.007* (1.690)	0.002 (0.585)	0.009** (2.116)	-0.000 (-0.140)	-0.000 (-0.140)	0.007* (1.953)	-0.001 (-0.173)	0.005 (1.331)	0.000 (0.024)	
	Indirect effect	-0.005 (-0.693)	-0.019** (-2.272)	-0.032*** (-4.179)	-0.009 (-1.379)	-0.009 (-1.379)	-0.010 (-0.918)	-0.021 (-1.369)	-0.038*** (-3.668)	-0.008 (-0.889)	
	Total effect	0.001 (0.220)	-0.017** (-2.275)	-0.023*** (-3.926)	-0.009* (-1.765)	-0.009* (-1.765)	-0.003 (-0.295)	-0.022 (-1.454)	-0.033*** (-3.596)	-0.008 (-0.977)	
City fixed effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Year fixed effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Control variables		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
N		4845	4845	4845	4845	4845	4845	4845	4845		

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are *t* statistics

imitates the advanced LCIs, thus promoting GEE. Consistent with the benchmark regression results, the indirect effects in the four regions are all negative, indicating that LCI resources lack coordination with neighboring areas, limiting green development.

4.5.3 Difference in city development level

Considering that the impact of LCI on GEE varies with the development levels of different cities, according to the classification criteria of the Institute of Chinese New First-tier Cities, cities are divided based on five dimensions. The classification reflects the city's comprehensive development level and LCI potential. A total of 285 prefecture-level cities in China are categorized and merged, resulting in a new ranking of first- through fifth-tier cities. Referring to *Chinese Cities' Business Attractiveness 2021 Ranking*, the research sample in this study is divided into 19, 30, 70, 81, and 85 from first- to fifth-tier. Table 9 reports the estimation results for different city development levels. The direct effects of first- and second-tier cities are significantly positive, demonstrating that LCI has greater GEE promotion effects in first- and second-tier cities. In contrast, the direct effects of other cities are negative, one possible reason is that limited LCI capabilities and high pollution governance costs have led to a decline in GEE in third-, fourth-, and fifth-tier cities. The findings imply that LCI only promotes GEE when the city's development level reaches a particular level, which is similar to that of Du and Li (2019). Meanwhile, the indirect effect of third-tier cities is insignificantly positive, while the indirect effect of other cities is negative, which can be supported by Brabazon's (2014) view. The siphon effect and the crowding-out effect in neighboring cities could explain why the projected indirect effect has yet to manifest.

5 Conclusions and policy implications

5.1 Conclusions

The development concept of an innovation-driven economy has undoubtedly become one of the focuses in recent years. While scholars have extensively discussed the relationship between technological innovation and green development, knowledge is limited regarding how LCI drives green development in China. To address this void in the literature, we use the low-carbon patent dataset of 285 prefecture-level cities in China, measure the GEE by applying the super-SBM model with undesirable outputs, and estimate the effect of LCI on GEE using the spatial econometric model. Based on the spatial effects, the channels of LCI to GEE are further verified. Finally, a heterogeneity analysis is constructed considering the differences between LCIs, regional development, and city development levels.

We find the following main conclusions. First, advances in LCI and some subcategories have positively affected GEE in China. Specifically, LCIs in building, greenhouse gas treatment, transportation, and sewage and pollutant treatment categories have improved GEE under the spatial matrices of location adjacency and geographic distance. Second, LCI has significant positive spatial effects on GEE but negative spatial effects on neighboring cities. The positive direct effects on GEE are offset by negative indirect effects due to the lack of spatial linkage effect and the existence of the siphon and crowding-out effects among cities. The indirect negative effect of LCI is greater than the direct positive effect, mainly because the clustering of LCI resources makes developed cities greener and accelerates

Table 9 Heterogeneity analysis of city development level

Variable	Effects	First-tier GEE	Second-tier GEE	Third-tier GEE	Fourth-tier GEE	Fifth-tier GEE
LCI (W ₁)	Direct effect	0.021*** (9.887)	0.012*** (5.730)	-0.008* (-1.914)	-0.006 (-1.528)	-0.002 (-0.371)
	Indirect effect	-0.034*** (-10.146)	-0.014*** (-3.940)	0.009 (1.339)	-0.001 (-0.201)	-0.019** (-2.194)
	Total effect	-0.012*** (-5.790)	-0.002 (-0.928)	0.001 (0.283)	-0.008 (-1.425)	-0.020*** (-3.297)
LCI (W ₂)	Direct effect	0.013*** (6.395)	0.012*** (6.379)	-0.005 (-1.486)	-0.004 (-0.984)	-0.002 (-0.495)
	Indirect effect	-0.019*** (-5.394)	-0.022*** (-5.424)	0.013 (1.525)	-0.012 (-1.307)	-0.021** (-1.998)
	Total effect	-0.006** (-2.495)	-0.011*** (-3.114)	0.007 (1.054)	-0.015** (-2.064)	-0.023*** (-2.594)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	4845	4845	4845	4845	4845	4845

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; the values in parentheses are *t* statistics

the flow of more resources to these cities, while the green development of less-developed cities slows down by the loss of LCI resources, the gap between the green development of a small number of developed cities and the majority of less-developed cities is gradually growing, which ultimately leads to a negative overall effect. Third, LCI promotes GEE via industrial structure, energy consumption structure, and human capital channels. Fourth, the impacts of LCI on GEE are heterogeneous: the GEE promotion effect is significant in eastern China and western China, particularly in first- and second-tier cities. However, the LCI of cities in first- to fifth-tier and cities in four regions inhibit GEE in neighboring cities.

5.2 Policy implications

Based on the above conclusions, this study offers some policy implications for Chinese cities' green development planning. First, the government should continue to improve LCI capabilities and give full attention to the leverage role of low-carbon technological progress on green development. LCI is a multi-dimensional and systematic project, which requires not only the government to strengthen policy support for LCI activities but to stimulate LCI power through environmental regulation policies. Specifically, one is to provide special tax preferential policies and financial subsidies for low-carbon patents and invest sufficient social capital in developing LCIs. The other is to guide enterprises to replace old growth drivers with new ones by raising environmental access thresholds and promoting capital flow to greener, low-carbon industrial sectors.

Moreover, it is essential to build a multi-sectoral and multi-regional coordination mechanism to form a regional synergy for low-carbon technological progress and green development. The policies adopted by a city government to achieve low-carbon progress inevitably have spatial spillover effects on other cities' GEEs through geographic distance or location adjacency, suggesting the need to build a regional community of green development. Authorities should encourage inter-city low-carbon technology sharing and co-construction, create a cross-regional high-level talent mobility mechanism in the field of low-carbon technology, coordinate the forces of government authorities, enterprises, and universities, and promote the integration and construction of inter-city low-carbon technology knowledge sharing platforms.

To promote GEE, attention should be paid to industrial structure, energy consumption structure, and human capital. First, the governments should eliminate backward production capacity, strengthen environmental constraints on high-pollution industries, promote the transfer of production factors to cleaner industries, and establish a green industrial structure system. Second, policymakers should encourage and support the utilization of renewable energy, and guide enterprises to cultivate new kinetic energy for green development by increasing the mass production of LCIs, thereby reducing the path dependence and lock-in effect brought by resources. Third, authorities should expedite the training of talents for LCIs, cultivate and introduce high-level talents in the low-carbon technology domains, and improve the integration of technology and education. This way, optimizing the industrial structure and energy consumption structure, and promoting human capital can be achieved, thus promoting GEE.

Finally, distinct low-carbon technology-driven green development strategies should be developed in China based on the different conditions of the cities. Policymakers should foster and guide the low-carbon technology positive externalities of first- and second-tier cities, and exert radiation and demonstration effects on third-, fourth-, and fifth-tier cities. Besides, the central government should increase investment in scientific research and

the intensity of policy inclination in central, western, and northeastern China to create a favorable atmosphere for the transfer of resources for low-carbon technology from eastern China. What needs our attention is that the different categories of low-carbon patents are uneven in China, especially energy, information and communication LCIs. The local government should assist enterprises in researching and developing LCIs.

This study has some limitations, which should be addressed in future research. As a preliminary study, we investigate the LCI on GEE using prefecture-level city data. To understand this effect completely, it would be useful to expand the scope of future research to the macro- and micro-levels. At the macro-level, an in-depth study at the county level can provide useful information about China's low-carbon development and green transformation. At the micro-level, data at the enterprise level can be used in future research to explore the impact of LCI adopted by enterprises on GEE. Furthermore, due to the systematic nature of LCI, other channels, such as market demand, carbon reduction, and resource allocation, are not considered in this research. Future studies could consider these channels to expand on this research area.

Appendix

Appendix A

See Tables 10, 11, 12 and 13.

Table 10 Abbreviations

Symbol	Meaning	Symbol	Meaning
GEE	Green economic efficiency	LCI	Low-carbon innovation
EDL	Economic development level	PD	Population density
OS	Ownership structure	FD	Financial development
ML	Marketization level	EL	Education level
OD	Opening degree	ER	Environmental regulation
IS	Industrial structure	ECS	Energy consumption structure
HC	Human capital	CCMTs	Climate change mitigation technologies
FARM	Farming, animal husbandry and economic activities	BUILD	Building
GHG	Greenhouse gas treatment	INCOMM	Information and communication
ENERGY	Energy	CPP	Commodity production and processing
TRANS	Transportation	SPT	Sewage and pollutant treatment
SFA	Stochastic frontier approach	DEA	Data envelopment analysis
SBM	Slacks-based measure	CPC	Cooperative patent classification
DMU	Decision-making unit	OLS	Ordinary least squares
SLM	Spatial lag model	SDM	Spatial durbin model
POST	The number of post offices per million people	SEM	Spatial error model
TEL	The number of fixed telephone calls per 100 people	AIC	Akaike information criterion

Table 11 Description of input–output indicators in dependent variable

Type	Measure	Indicator	Unit
Input	Labor force	Number of employees at year-end	10 ⁴ people
	Capital stock	Total stock of fixed assets investment	10 ⁸ yuan
	Energy	Total energy consumption	10 ⁴ ton standard coal
Desirable output	Economy	Real gross domestic product	10 ⁸ yuan
	Undesired output	Environmental pollution	Industrial wastewater effluent
Industrial sulfur dioxide emissions			Ton
Industrial soot emissions			Ton
		CO ₂ emission	Million tons

Table 12 Detailed description of the LCI classification

Type	Symbol	Description
Farming, animal husbandry and economic activities	FARM	LCIs are related to water conservation, efficient water supply and use, infrastructure or operation protection, agriculture, forestry, livestock or agroalimentary production, and human health protection
Building	BUILD	LCIs are related to the integration of renewable energy sources in buildings, energy efficiency in lighting, heating, ventilation, air conditioning, home appliances, elevators, end-user side electric power consumption, and improvement in the thermal performance of buildings
Greenhouse gas treatment	GHG	LCIs are related to capture or disposal of greenhouse gases
Information and communication	INCOMM	LCIs are related to energy-efficient computing and reduction of energy consumption in communication networks
Energy	ENERGY	LCIs are related to energy generation through renewable energy sources, combustion technologies with mitigation potential, energy generation of nuclear origin, efficient electrical power generation, transmission or distribution, and production of fuel of non-fossil origin
Commodity production and processing	CPP	LCIs are related to metal processing, chemical industry, oil refining and petrochemical industry, the processing of minerals, agriculture, livestock or agroalimentary industries, and the production process for final industrial or consumer products
Transportation	TRANS	LCIs are related to road transport and railway of goods or passengers, aeronautics or air transport, and maritime or waterways transport
Sewage and pollutant treatment	SPT	LCIs are related to wastewater treatment and solid waste management

Table 13 Global spatial autocorrelation test results

Year	W_1				W_2			
	GEE Moran' I	Z(I)	LCI Moran' I	Z(I)	GEE Moran' I	Z(I)	LCI Moran' I	Z(I)
2003	0.289***	7.351	0.081***	2.815	0.198***	8.046	0.055***	3.070
2004	0.304***	7.730	0.110***	4.362	0.218***	8.855	0.064***	4.123
2005	0.280***	7.136	0.089***	4.459	0.204***	8.277	0.057***	4.667
2006	0.306***	7.775	0.103***	4.576	0.209***	8.486	0.073***	5.197
2007	0.289***	7.354	0.171***	6.789	0.188***	7.642	0.099***	6.381
2008	0.270***	6.883	0.199***	7.232	0.175***	7.126	0.108***	6.301
2009	0.291***	7.417	0.230***	8.126	0.198***	8.042	0.130***	7.365
2010	0.344***	8.746	0.311***	10.178	0.220***	8.958	0.168***	8.820
2011	0.291***	7.423	0.326***	10.107	0.190***	7.750	0.204***	10.114
2012	0.317***	8.065	0.352***	10.461	0.215***	8.746	0.218***	10.357
2013	0.289***	7.365	0.344***	9.873	0.179***	7.295	0.215***	9.869
2014	0.279***	7.100	0.386***	10.517	0.183***	7.472	0.252***	10.987
2015	0.284***	7.226	0.418***	11.306	0.177***	7.232	0.294***	12.668
2016	0.290***	7.373	0.462***	12.620	0.166***	6.773	0.314***	13.665
2017	0.225***	5.741	0.478***	12.916	0.141***	5.773	0.337***	14.517
2018	0.203***	5.177	0.457***	12.240	0.124***	5.091	0.345***	14.731
2019	0.200***	5.107	0.426***	11.309	0.129***	5.280	0.339***	14.354

***Represents significance levels of 1%. Z(I) is the z-score of Moran's index

Appendix B

MATLAB code for measuring the GEE.

```

clc;
clear;
data=xlsread('D:\matlab\GEE.xlsx','2019'); %Retrieve variable data
%%
x =data(:,[2,3,4]);%Input indicator data
y =data(:,[5]);%Desirable output data
z =data(:,[6,7,8,9]);%Undesired output data
X =x';
Y =y';
Z =z';
%%
[m,n]=size(X);
s=size(Y,1);
q=size(Z,1);
D=1./(m*X');
E=1./((s+q)*Y');
F=1./((s+q)*Z');
A=[];b=[];
LB=zeros(n+m+s+q+1,1);UB=[];
theta=zeros(n,1);
w=zeros(n+m+s+q+1,n);
for i=1:n
f1=[zeros(1,n) -D(i,:) zeros(1,s+q) 1];
A1=[];b1=[];
Aeq1=[X eye(m) zeros(m,s+q) -X(:,i)
      Y zeros(s,m) -eye(s) zeros(s,q) -Y(:,i)
      Z zeros(q,m) zeros(q,s) eye(q) -Z(:,i)
      zeros(1,n+m) E(i,:) F(i,:) 1];
beq1=[zeros(m,1)
      zeros(s,1)
      zeros(q,1)
      1];
[w1(:,i) theta(i)]=linprog(f1,A1,b1,Aeq1,beq1,LB,UB);

if abs(theta(i)-1)<0.00001
f=[zeros(1,n) D(i,:) zeros(1,s+q) 1];

```

```

A=[[X(:,1:i-1),zeros(m,1),X(:,i+1:n)] -eye(m) zeros(m,s+q) -X(:,i)
    - [Y(:,1:i-1),zeros(s,1),Y(:,i+1:n)] zeros(s,m) -eye(s) zeros(s,q) Y(:,i)
    [Z(:,1:i-1),zeros(q,1),Z(:,i+1:n)] zeros(q,m+s) -eye(q) -Z(:,i)];
b=zeros(m+s+q,1);
Aeq=[zeros(1,n+m) -E(i,:) -F(i,:) 1];
beq=1;
[w(:,i) theta(i)]=linprog(f,A,b,Aeq,beq,LB,UB);
end
end
theta;%GEE

```

Acknowledgements This work is supported by the National Planning Office of Philosophy and Social Science Foundation of China (22BJL030) and Cultivation Project of the Major Research for Medium and Long-term Research in Philosophy and Social Sciences of Northeast Normal University (22FR006).

Authors contributions HR contributed to writing—original draft, methodology, software. GG contributed to conceptualization, funding acquisition, and supervision. HZ contributed to methodology, writing—review and editing, validation, and supervision.

Data availability The datasets generated or analyzed during this study are available from the first author on reasonable request.

Declarations

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

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