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# The impact of LCTI on China's low-carbon transformation from the spatial spillover perspective

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## Abstract

China has conducted a long-term low-carbon technology innovation (LCTI), but there was a faster increase of $CO_2$ emission in 2017 and 2018 than in 2016, which has lead scholars to doubt the effect of LCTI on $CO_2$ emission. This paper builds a spatial auto regression (SAR) model with provincial panel data from 2011 to 2017 to calculate the spatial spillover effect of China's LCTI on regional $CO_2$ emission. The results show that regional LCTI can reduce the local $CO_2$ emission, but will increase the $CO_2$ emission of adjacent regions due to spatial spillover effect. This produces the uncertainty of the promotion effect of LCTI on China's low-carbon transformation. Therefore, this paper suggests innovation resources should be appropriately and evenly distributed among regions to avoid their agglomeration in few regions.

## Introduction

There will be only ten years left for China to honor the pledge to peak its emissions by 2030. Low-carbon technology innovation is highly anticipated in China, where many policies have been carried out to promote low-carbon technology innovation (LCTI). Technological patents are the core of LCTI, while low-carbon project revenue reflects the commercial value of the technology innovation. Recently, low-carbon technology patents and the low-carbon project revenue (environmental project) in China have increased a lot (Fig 1), especially in the field of new energy power generation, new energy vehicle, green sharing technology and etc.

As shown in Fig 1, a few regions generally have more innovations than other regions. Specifically, Beijing, Guangdong and Jiangsu are taking the lead in terms of the numbers of patents and revenue. Despite the increasing innovation, the growth of China's $CO_2$ emission is higher in 2017 and 2018 than in 2016. Therefore, this article mainly focuses on the counterintuitive relations between LCTI and $CO_2$ emission. The research conclusion shows that the spatial spillover effect of LCTI in adjacent regions increases the carbon emission in this region, leading to ineffective curb on China's carbon emission. Based on this, relevant policy suggestions are proposed for the development of China's low-carbon technology innovation.

## Literature review

In China, the national and some regional carbon emission is decreasing [1]. However, there is altogether a large amount of $CO_2$ emission in China, most of which is from traditional

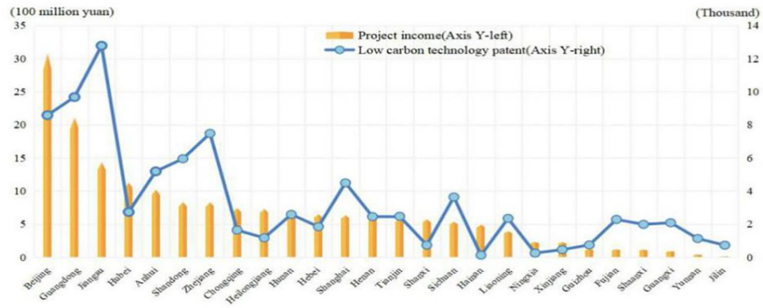


**Fig 1. Regional low-carbon technology patents and environmental project income.** Data sources: Tonghuashun database (http://www.51ifind.com/ Accessed 14 March 2020) & incopat database (https://www.incopat.com/ Accessed 13 March 2020.). Notice: there are only 26 regions, as five other regions lacking the project income data.

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industries [2]. To achieve the emission peak in 2030, China needs to reduce 12.5Gt $CO_2$ emission relative to 2015 [3].

Previous studies have proposed various suggestions on carbon emission reduction from different perspectives. From the perspective of energy consumption, low-carbon transformation can be realized by reducing the proportion of coal consumption and increasing the proportion of natural gas and renewable energy consumption [4]. From the perspective of industrial structure, developing low-carbon industries [5] and eliminating enterprises with high energy consumption in traditional industries [6] are the main paths to control $CO_2$ emission. From the perspective of market trading, the construction of the carbon trading market can achieve a win-win situation of economic growth and low-carbon transformation [7]. From the perspective of environmental regulation, imposing heavy taxes on enterprises with high-energy consumption can make them exit the market [8].

All the literature conclusions above admite that the technology innovation is important to reduce $CO_2$ emission: without economic alternative technology, it is difficult to reduce the proportion of coal consumption. Without the core technologies of the low-carbon industry, it is difficult to develop low-carbon industries and reduce backward production capacity. Without carbon productivity improvement, it is difficult for the carbon quota seller to make profits. Without specific low-carbon technology for traditional industries, environmental regulation can only restrict economic development rather than achieve low-carbon transformation.

Once a low-carbon technology patent has commercial value, it will impose effects on the low-carbon transformation with other factors such as the industrial structure, per capital GDP, energy structure, foreign investment, public concern and etc. [9–17]. However, such a development mode is controversial [18]. Although it forms the agglomeration of low-carbon technology innovation resources and accelerates the low-carbon transformation [19], it leads to an unbalanced allocation of low-carbon technology innovation resources [20]. The article proposes the hypothesis that the regional agglomeration effect of LCTI offsets its inhibition effect on $CO_2$ emission, that is, the spatial spillover effect of LCTI on $CO_2$ emission is positive. It is because the innovation resources of low-carbon technology are transferred to the agglomeration region, making adjacent regions unable to make full use of the innovation resources to reduce their $CO_2$ emission. If the positive spillover effect is significant, China's low-carbon transformation may be restrained. On this basis, the article conducts an empirical analysis to verify the above hypothesis. The research framework is as follows (Fig 2).

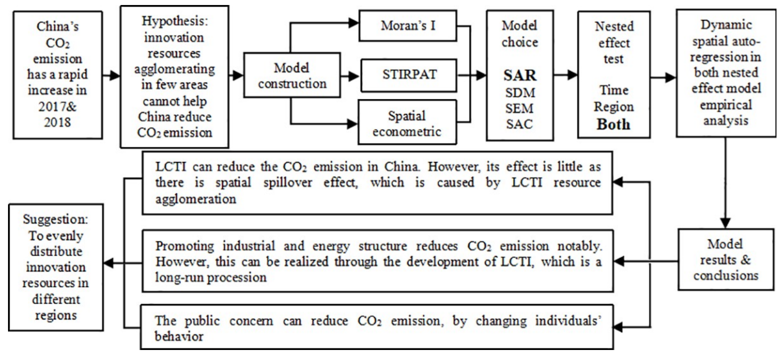


**Fig 2. The research framework diagram.**

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## Methodology

To explore whether there exists the LCTI spatial spillover effect on $CO_2$ emission, the article should test whether there are spatial autocorrelation in LCTI and $CO_2$ emission. Therefore, the article calculates the Moran's Index to test whether there is spatial autocorrelation between LCTI and $CO_2$ emission at first, and then the spatial econometric model about LCTI spatial spillover effect on $CO_2$ emission is constructed based on Stochastic Impacts by Regression method on Population, Affluence, and Technology (STIRPAT). To avoid the mismatch between the geographical and economical contiguity, the article chooses economic spatial weight matrix (Eq 1) to calculate the Moran's Index.

$$\begin{cases} \overline{Y} = \dfrac{\sum_{i=1}^{n}\sum_{t=t_0}^{t_1} Y_{i,t}}{n(t_1 - t_0 + 1)}; \overline{Y_i} = \dfrac{1}{(t_1 - t_0 + 1)\sum_{t=t_0}^{t_1} Y_{i,t}} \\ w = w_i diag(\dfrac{\overline{Y_1}}{\overline{Y}}, \dfrac{\overline{Y_2}}{\overline{Y}}, \cdots, \dfrac{\overline{Y_n}}{\overline{Y}}) \end{cases} \quad (1)$$

In Eq 1, $w$ is the spatial weight matrix, $w_i$ is the spatial weight matrix of geographic distance, and $\overline{Y_i}$ is the weighted average GDP of the region ($i$). $t_0$ & $t_1$ is the initial year and the end year of the sample, and $\overline{Y}$ is the weighted average GDP of all regions. Furthermore, the Moran's Index ($Moran'sI$) is measured, and the specific formula is shown in Eq 2:

$$Moran'sI = \frac{\sum_{i=1}^{n}\sum_{c=1}^{n} w_{i,c}(CE_i - \overline{CE})(CE_c - \overline{CE})}{S^2 \sum_{i=1}^{n}\sum_{c=1}^{n} w_{i,c}}, Moran'sI \in [-1, 1] \quad (2)$$

In Eq 2, $CE_i$ & $CE_c$ represent the $CO_2$ emission of region $i$ & $c$, $\omega_{ic}$ is the spatial weight matrix, which shows regional and correlation characteristics between the regions $i$ & $c$, and $\overline{CE}$ is the average $CO_2$ emission in all the regions. In Eq 2, $S$ represents the geographic coordinate distance between capitals of region $i$ and $c$ (this article regards municipality itself as the provincial capital). For calculating the LCTI Moran's Index, $CE$ should be substituted with $LP$ (low-carbon patent). The spatial agglomeration is stronger when the Moran's Index is closer to 1. Moran's Index reveals the global spatial autocorrelation, and exponential scatter diagram reveals local spatial autocorrelation. If the spatial autocorrelation exists, the article will

construct the basic panel data model in nested effect (Eq 3).

$$\begin{aligned} \ln CE_{it} = \beta_0 + \beta_1 \ln LP_{it} + \beta_2 \ln IS_{it} + \beta_3 \ln GDP_{it} + \beta_4 \ln ES_{it} + \beta_5 \ln FI_{it} + \\ \beta_6 \ln PC_{it} + \beta_7 \ln EGI_{it} + \beta_8 \ln SC_{it} + \lambda_t + \mu_\varphi + \varepsilon_{it} \end{aligned} \tag{3}$$

In Eq 3, $i$ represents the region, $t$ represent the time, and $CE$ represents the $CO_2$ emission. The core explanatory variable $LP$ represents LCTI level. The other explanatory variables are industrial structure ($IS$), regional per capita GDP ($GDP$), energy structure ($ES$), foreign investment ($FI$), public concern index of environmental pollution ($PC$), environmental government invest per GDP ($EGI$), and regional sewage charges ($SC$). Meanwhile, the time nested variable is $\lambda_t$, the regional nested variable is $\mu_\varphi$, and error is $\varepsilon_{it}$. At last, this article can construct the spatial panel model (Eq 4) based on Eq 3.

$$\begin{cases} CE_{it} = \tau CE_{i,t-1} + \rho \omega_i' CE_t + x_{it}'\beta + d_i' X_i \delta + \lambda_t + \mu_\varphi + \varepsilon_{it} \\ x_{it}'\beta = \beta_1 \ln LP_{it} + \beta_2 \ln IS_{it} + \beta_3 \ln GDP_{it} + \beta_4 \ln ES_{it} + \beta_5 \ln FI_{it} + \\ \beta_6 \ln PC_{it} + \beta_7 \ln EGI_{it} + \beta_8 \ln SC_{it} \\ \varepsilon_{it} = \lambda m_i' \varepsilon_i + v_{it} \end{cases} \tag{4}$$

In Eq 4, the term $d_i' X_i \delta$ is the explanatory variable of the spatial lag effect, and the term $\rho \omega_i' CE_t$ is the explained variable of the spatial lag effect of. $d_i'$, $\omega_i'$ and $m_i'$ represent the line $i$ in spatial weighted matrix of explanatory variable, explained variable, and perturbation term. The variables $\tau$, $\rho$, $\delta$, and $\lambda$ are the determination coefficients: If $\lambda = 0$, Eq 4 is a Spatial Durbin Model; If $\lambda = 0$ & $\delta = 0$, Eq 4 is a Spatial Autoregressive Model; If $\tau = 0$ & $\delta = 0$, Eq 4 is a Spatial Autocorrelation Model; If $\tau = \rho = 0$ & $\delta = 0$, Eq 4 is a Spatial Error Model.

### Ethics statement

The data of this paper comes from authoritative data sets such as China Statistical Yearbook and China logistics yearbook, which can be found on the open website.

## Variables and data

### Core variables

There are two core variables in this article: $CO_2$ emission and LCTI. As the team of China Emission Accounts and Datasets (CEADs) calculated the $CO_2$ emission of China from 17 kinds of energy and 47 industries, so the article uses the CEADs' $CO_2$ emission data of China [20].

The article uses the number of technology patents classified by Y02 in the Cooperative Patent Classification (CPC) published in the incopat database in October 2017 to represent the level of LCTI (Table 1). The retrieval scope covers all the patents applied in China from 2011

**Table 1. The classification of low-carbon technology patents.**

| Codes | Name | Codes | Name |
|---|---|---|---|
| Y02B | Building-related low-carbon technologies | Y02T | Transportation-related low-carbon technologies |
| Y02C | Technologies of the capture, storage, storage or disposal of greenhouse gases | Y02W | Low-carbon technologies related to wastewater treatment or waste management |
| Y02E | Low-carbon technologies of energy generation, transmission and distribution | Y02P | Low-carbon technologies of goods production and processing of goods |

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to 2017, and the retrieval formula is ((CPC = (Y02) AND (AP-COUNTRY = (CN)) AND (AD = 2011)).

### Other variables

In addition to LCTI, $CO_2$ emission is also affected by other factors. Based on the existing research results, the article also considered the following explanatory variables: (1) Environmental Regulation. Studies have shown that under the heterogeneous environmental regulations, the agglomeration scale and $CO_2$ emission of various manufacturing sectors present an inverted U-shaped trend [21]. This article measures the environmental regulation intensity of each region from three dimensions: government, enterprise, and public. The proportion of environmental pollution control investment to GDP represents the intensity of environmental regulation from the government. The total amount of pollutant charges in each region represents the intensity of environmental regulation from the enterprise. The index of public attention to environmental pollution represents the intensity of environmental regulation from residents. (2) Industrial Structure. Low-carbon industrial structure transformation can help build a sustainable industrial system, which can solve the problems of environmental pollution and economic slowdown [22, 23]. The article uses the proportion of the secondary industry to GDP to represent the $CO_2$ emission status of the industrial structure in each region. (3) Economic Development and Market Opening. In addition to technological progress and industrial structure, economic development & foreign investment are the main factors affecting carbon emissions [24, 25], because $CO_2$ emission in most regions of China has not decoupled with economic growth and foreign investment [26]. The article uses per capita GDP and foreign direct investment to represent economic development and market opening. (4) Energy Structure. The optimization of energy consumption structure is the main way to reduce carbon emission intensity [27]. The article uses the ratio of renewable energy consumption to total energy consumption to represent the energy structure.

### Data

The research period of the article is 2011–2017, with 30 regions (except Tibet) involved. The low-carbon patent data of each region was from the incopat patent database. $CO_2$ emission data was from CEADs. The proportion of the secondary industry, foreign direct investment and per capita GDP data were from <China Statistical Yearbook>. The data on energy structure was from <China Energy Statistical Yearbook>. The data on the investment in environmental pollution control was from <China Environmental Yearbook>. The data of sewage charges were from <China Environmental Yearbook> and some regional environmental yearbooks [28]. The data of public concern on environmental pollution were from the official website of Baidu Index [29].

## Empirical analysis

### Spatial autocorrelation

To measure the spatial autocorrelation between LCTI and $CO_2$ emission, the article calculates the global Moran's Index (Table 2) and draws Moran's Index scatter diagram of both LCTI (Fig 3) and $CO_2$ emission (Fig 4) in 30 regions.

The global Moran's Index of both LCTI and $CO_2$ emission are positive (Table 2), which means there are spatial autocorrelation in both LCTI and CO2 emission. In Fig 3, most regions are agglomerating in the third quadrant. It shows that although the agglomeration of LCTI is comparatively high, the quality of agglomeration is low. And a few regions have a better LCTI

**Table 2. The global Moran's Index of LCTI and $CO_2$ emission from 2011 to 2017.**

| LCTI | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|
| Moran's I | 0.257 | 0.287 | 0.278 | 0.286 | 0.331 | 0.327 | 0.296 |
| Z-value | 2.590 | 2.807 | 2.698 | 2.772 | 3.111 | 3.113 | 2.963 |
| P-value | 0.005 | 0.003 | 0.003 | 0.003 | 0.001 | 0.001 | 0.002 |
| $CO_2$ emission | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| Moran's I | 0.240 | 0.232 | 0.224 | 0.225 | 0.217 | 0.206 | 0.176 |
| Z-value | 2.338 | 2.219 | 2.139 | 2.148 | 2.091 | 1.998 | 1.785 |
| P-value | 0.010 | 0.013 | 0.016 | 0.016 | 0.018 | 0.023 | 0.037 |

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agglomeration, such as Jiangsu (JS), Shandong (SD), Zhejiang (ZJ), and Shanghai (SH). In Fig 4, most regions agglomerate in the first and the third quadrant, with high-emission regions in the first quadrant and low-emission regions in the third quadrant. Meanwhile, there are some differences in few regions. Zhejiang (ZJ) and Guangdong (GD) can help neighbor regions reduce $CO_2$ emission, whereas Beijing (BJ) and Shanghai (SH) increase neighbor regions' $CO_2$ emission. On this basis, a spatial econometric model is set up. There are four kinds of spatial econometric models: Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), and Spatial Autocorrelation Model (SAC). The article compares Log-likelihood Index, Moran's Index, Lagrange Multiplier, and Robust Lagrange Multiplier of these four models by model error test (Table 3). In Table 3, compared with other three models, the SAR model can be chosen for better coefficients.

## Spillover effect of LCTI on carbon emissions

The article uses the maximum likelihood regression to calculate the LCTI's impact on $CO_2$ emission of China from 2011 to 2017. As the nested effect has a better result than the random effect in the Hausman test, the article chooses the nested effect SAR model to run the data. There are three kinds of nested effect model: time nested, region nested, and both nested, and the article should choose one of them by comparing their fitting results (Table 4). In Table 4, the results of the basic panel model in the nested effect and static SAR model are compared with the results of the dynamic SAR model.

In Table 4, In the dynamic SAR model, the coefficient of the lag term of lnCE is positive, and are significant at 1% level, indicating that China's inter-provincial carbon dioxide emissions have a strong cumulative effect. SAR model can not only verify the spatial correlation of carbon dioxide emissions among provinces, making the estimation of the model more reliable, but also estimate the spillover effect of province-internal LCTI (direct effect), inter-provincial LCTI and overall LCTI (total effect) on China's carbon dioxide emissions respectively.

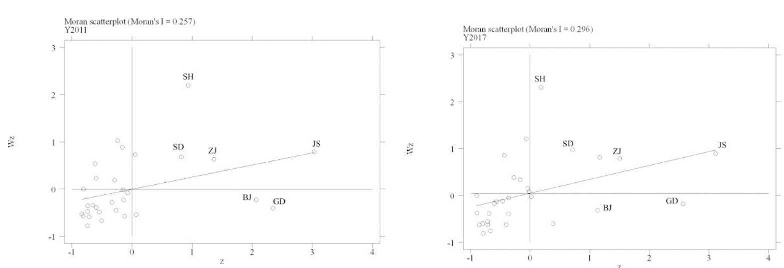


**Fig 3. The Moran's Index scatter diagram of LCTI in 2011 and 2017.**

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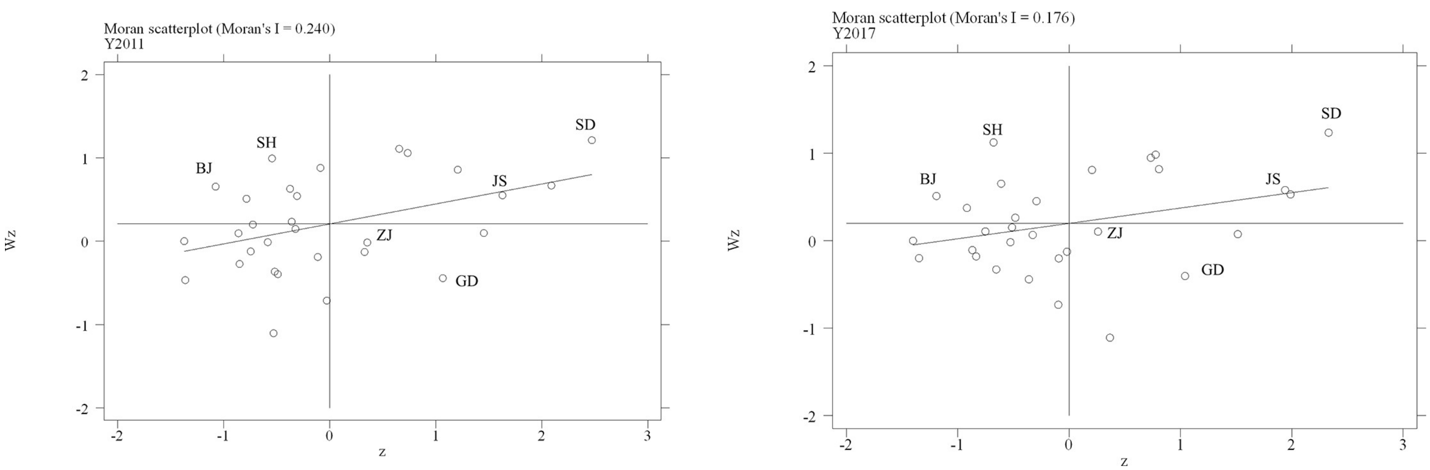


**Fig 4. The Moran's Index scatter diagram of $CO_2$ emission in 2011 and 2017.**

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The w*lnCE coefficient is positive in the dynamic SAR model, which proves the positive spillover effect of the neighbor region on the local region. As a result, the dynamic SAR model in the both nested effect has better fitting coefficients (see p-value in the bracket). However, whether the nested effect exists depends on the both nested effect test (Table 5).

In Table 5, the both nested effect exists, and the explanatory variables of the local region (Local effect) and neighbor region (Spillover effect) jointly affect the local region's carbon emissions. As explanatory variables are hard to change in the short term, the article makes regression analysis in the short term and long term separately (Table 6).

In Table 6, the total effect of LCTI on $CO_2$ emission is -0.003 in the short term and -0.009 in the long term. This means the LCTI can reduce the $CO_2$ emission, and with the promotion of the industrial & energy structure, the reduction effect will be increased. However, compared with other explanatory variables, the reduction effect of LCTI is uncertain. Meanwhile, the spillover effect of LCTI on $CO_2$ emission is 0.001 in the short term and 0.011 in the long term. It shows that the LCTI in neighbor regions increases the $CO_2$ emission in the local region, especially in the long run. The results proved the assumption of the article: the $CO_2$ emission in local region, will increase with the development of LCTI in neighbor regions.

Besides LCTI, there are other explanatory variables, and the analysis results of these explanatory variables are similar to those reported in the literature in Part 1, so the article will not repeat them here. However, the industrial (IS) and energy structure (ES) have a strong total effect on $CO_2$ emission. This is because considering stability, safety and economy, energy consumption relies on fossil energy, especially the manufactory industry. Moreover, LCTI can promote the industrial & energy structure as reported in literature review. Meanwhile, the public concern about environmental pollution (PC) has a certain inhibitory effect on carbon emissions.

**Table 3. Results of spatial econometric model error test.**

| | SAR (dynamic) | SEM (static) | SDM (dynamic) | SAC (static) |
|---|---|---|---|---|
| Log-likelihood | 323.43 | 312.12 | 232.45 | 310.13 |
| Moran's Index | none | $43.53^{***}$ (0.000) | none | none |
| Lagrange multiplier | $25.47^{***}$ (0.001) | 1.98 (0.096) | none | none |
| Robust Lagrange multiplier | $23.75^{***}$ (0.000) | 0.753 (0.271) | none | none |

Notice: data in the bracket is P-value.

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**Table 4. SAR model results of time-space spillover effect.**

| Variables | Basic panel model in nested effect | Static SAR model | Dynamic SAR model in time nested effect | Dynamic SAR model in region nested effect | Dynamic SAR model in both nested effect |
|---|---|---|---|---|---|
| $LnCE_{t-1}$ | | | 1.055*** (0.013) | 0.706*** (0.047) | 0.693*** (0.048) |
| w*lnCE | | 0.052 (0.240) | 0.295*** (0.040) | 0.317** (0.151) | 0.445* (0.268) |
| lnLP | -0.109*** (0.026) | 0.110*** (0.026) | -0.012 (0.011) | -0.015 (0.020) | -0.003*** (0.001) |
| lnIS | 0.118 (0.081) | 0.118 (0.079) | 0.043* (0.024) | 0.127** (0.057) | 0.183** (0.086) |
| lnGDP | -0.161* (0.087) | -0.160* (0.085) | 0.039** (0.017) | 0.033 (0.057) | -0.026 (0.067) |
| lnES | 0.188** (0.082) | 0.188** (0.081) | 0.009 (0.018) | -0.063 (0.060) | -0.114* (0.064) |
| lnFI | 0.036 (0.025) | 0.036 (0.024) | -0.004 (0.009) | 0.051*** (0.015) | 0.028 (0.018) |
| lnPC | 0.002 (0.010) | 0.002 (0.010) | -0.023** (0.011) | -0.021* (0.012) | -0.030 (0.022) |
| lnEGI | 0.028 (0.018) | 0.028 (0.018) | 0.018* (0.010) | -0.013 (0.013) | -0.011 (0.012) |
| lnSC | -0.015 (0.015) | -0.015 (0.024) | -0.023** (0.010) | -0.013 (0.009) | -0.011 (0.000) |
| error | | 0.004*** (0.000) | 0.003*** (0.000) | 0.002*** (0.000) | 0.001*** (0.000) |
| Log-likelihood | | 297.232 | 279.727 | 330.928 | 281.122 |
| R-sq | 0.294 | 0.293 | 0.998 | 0.985 | 0.983 |
| consant | 4.594*** (0.465) | | | | |
| Obs | 210 | 180 | 180 | 180 | 180 |

Notice
* $p<0.1$
** $p<0.05$
*** $p<0.01$, and data in the bracket is standard error.

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## Conclusions and suggestions

The article tests the impact of low-carbon technology innovation on $CO_2$ emission by building a dynamic spatial auto-regression model with the panel data of 30 regions in China from 2011 to 2017. Conclusions and suggestions are as follows:

1. Low-carbon technology innovation can curb regional $CO_2$ emissions, but its overall effect is weak at the national level. The regions with a good innovation environment attract low-carbon technological innovation resources from neighboring regions, which will lead to the improvement of low-carbon technological innovation in this region but increase $CO_2$ emission in neighboring regions for lack of innovation resources. This indicates that the gathering of technology innovation resources can promote the rapid development of low-carbon technology innovation in a few regions at the beginning. However, at a certain stage of development, resources are excessively concentrated in a few regions, which slow down the innovation and development of low-carbon technologies in many other regions. Consequently, the transition of China's low-carbon economy will slow down and the $CO_2$ emission will increase (e.g. in 2017 and 2018).

**Table 5. The both nested effect test of the SAR model.**

| Likelihood-ratio test | LR chi2(10) = 19.68 |
|---|---|
| (Assumption: region nested in both) | Prob > chi2 = 0.0003 |
| Likelihood-ratio test | LR chi2(10) = 879.63 |
| (Assumption: time nested in both) | Prob > chi2 = 0.0000 |

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**Table 6. The spatial effect of explanatory variables on $CO_2$ emission.**

| Explanatory variables | Short term | | | Long term | | |
|---|---|---|---|---|---|---|
| | Local effect | Spillover effect | Total effect | Local effect | Spillover effect | Total effect |
| lnLP | -0.004*** (0.007) | 0.001*** (0.000) | -0.003*** (0.008) | -0.020*** (0.004) | 0.011*** (0.003) | -0.009*** (0.001) |
| lnIS | 0.194** (0.083) | -0.055** (0.024) | 0.139** (0.069) | 0.666*** (0.023) | -0.316** (0.095) | 0.350** (0.092) |
| lnGDP | -0.030*** (0.002) | 0.008** (0.003) | -0.022** (0.010) | -0.110* (0.061) | 0.059** (0.021) | -0.050* (0.031) |
| lnES | -0.116* (0.062) | 0.032** (0.011) | -0.084* (0.050) | -0.388** (0.101) | 0.179** (0.069) | -0.209** (0.102) |
| lnFI | 0.029* (0.005) | -0.008 (0.007) | 0.021 (0.015) | 0.101* (0.060) | -0.043 (0.123) | 0.058 (0.130) |
| lnPC | -0.030** (0.012) | 0.009*** (0.001) | -0.021*** (0.009) | -0.108*** (0.005) | 0.059*** (0.003) | -0.049 *** (0.003) |
| lnEGI | -0.012** (0.006) | 0.003** (0.001) | -0.008* (0.005) | -0.040 (0.061) | 0.020 (0.077) | -0.020 (0.066) |
| lnSC | -0.010*** (0.002) | 0.003** (0.001) | -0.007*** (0.001) | -0.036** (0.031) | 0.017 (0.039) | -0.019 (0.038) |

Notice

* $p<0.1$

** $p<0.05$

*** $p<0.01$, and data in the bracket is standard error.

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2. In the long run, the optimization of industrial and energy structure has an important impact on curbing $CO_2$ emission. However, it is difficult to optimize the industrial and energy structure in the short term significantly without low-carbon technological innovations.
3. The residents' awareness of a low-carbon life has an impact on $CO_2$ emission. The awareness can promote the low-carbon transformation by changing the consciousness of the public, such as changing their consumption behavior, motivating them to prevent the emission from enterprises and propagandize the importance of low-carbon development to the society.
4. Based on the above conclusions, the article proposes that innovation resources should be appropriately and evenly distributed among regions to guide the transfer of talents and capital from the regions with abundant resources to other regions. The publicity and education should be intensified to call on the public to pay more attention to the ecological environment so that the public's low-carbon awareness will be improved and can play a greater role in the economic low-carbon transformation.
5. The government should strengthen and improve the democratic system in all aspects, increase the channels for citizens' environmental supervision, and improve relevant laws and regulations to protect citizens' environmental demands and environmental rights and interests. By improving the credibility of the government, the public will pay more attention to carbon emissions and participate in environmental governance, and the goal of carbon dioxide emission reduction can be achieved.

According to the results above, the optimization of industrial and energy structure has an important impact on curbing $CO_2$ emission. In the literature review, we show that the LCTI can promote the industrial and energy structure. However, this paper has a limitation in data collection (at least 15–20 years' data is needed, but the low-carbon data starts from 2011) to prove the mechanism. Therefore, the next step is to prove the mechanism that LCTI can promote the industrial and energy structure transition by collecting enough data.

## Limitation, and future work

However, this paper has some limitations in data selection and classification. Due to the availability of data, this paper takes the provincial area as the research object, which makes the amount of data relatively limited.

How to use low-carbon technology innovation to drive the low-carbon transformation of industrial and energy structure is a key point that needs further research.

## Supporting information

**S1 Table. The data of all variables.**
(DOCX)

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## References

1. Liu Y, Zhao G, Zhao Y. An analysis of Chinese provincial carbon dioxide emission efficiencies based on energy consumption structure. Energy Policy. 2016; 96:524–33. https://doi.org/10.1016/j.enpol.2016.06.028.
2. Huang L, Krigsvoll G, Johansen F, Liu Y, Zhang X. Carbon emission of global construction sector. Renewable and Sustainable Energy Reviews. 2018; 81:1906–16. https://doi.org/10.1016/j.rser.2017.06.001.
3. Chen H, Yang L, Chen W. Modelling national, provincial and city-level low-carbon energy transformation pathways. Energy Policy. 2020; 137:111096. https://doi.org/10.1016/j.enpol.2019.111096.
4. Liu G, Hao Y, Zhou Y, Yang Z, Zhang Y, Su M. China's low-carbon industrial transformation assessment based on Logarithmic Mean Divisia Index model. Resources, Conservation and Recycling. 2016; 108:156–70. https://doi.org/10.1016/j.resconrec.2016.02.002.
5. Busch J, Foxon TJ, Taylor PG. Designing industrial strategy for a low carbon transformation. Environmental Innovation and Societal Transitions. 2018; 29:114–25. https://doi.org/10.1016/j.eist.2018.07.005.
6. Zhang S, Li H, Zhang Q, Tian X, Shi F. Uncovering the impacts of industrial transformation on low-carbon development in the Yangtze River Delta. Resources, Conservation and Recycling. 2019; 150:104442. https://doi.org/10.1016/j.resconrec.2019.104442.
7. Wang H, Chen Z, Wu X, Nie X. Can a carbon trading system promote the transformation of a low-carbon economy under the framework of the porter hypothesis?—Empirical analysis based on the PSM-DID method. Energy Policy. 2019; 129:930–8. https://doi.org/10.1016/j.enpol.2019.03.007.
8. Du W, Li M. Influence of environmental regulation on promoting the low-carbon transformation of China's foreign trade: Based on the dual margin of export enterprise. Journal of Cleaner Production. 2020; 244:118687. https://doi.org/10.1016/j.jclepro.2019.118687.
9. Su B, Ang BW. Structural decomposition analysis applied to energy and emissions: Some methodological developments. Energy Economics. 2012; 34(1):177–88. https://doi.org/10.1016/j.eneco.2011.10.009.
10. Meng F, Su B, Thomson E, Zhou D, Zhou P. Measuring China's regional energy and carbon emission efficiency with DEA models: A survey. Applied Energy. 2016; 183:1–21. https://doi.org/10.1016/j.apenergy.2016.08.158.
11. Wang H, Ang BW, Su B. Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. Energy Policy. 2017; 107:585–99. https://doi.org/10.1016/j.enpol.2017.05.034.

**12.** Shuai C, Chen X, Wu Y, Tan Y, Zhang Y, Shen L. Identifying the key impact factors of carbon emission in China: Results from a largely expanded pool of potential impact factors. Journal of Cleaner Production. 2018; 175:612–23. https://doi.org/10.1016/j.jclepro.2017.12.097.

**13.** Yao X, Kou D, Shao S, Li X, Wang W, Zhang C. Can urbanization process and carbon emission abatement be harmonious? New evidence from China. Environmental Impact Assessment Review. 2018; 71:70–83. https://doi.org/10.1016/j.eiar.2018.04.005.

**14.** Li JS, Zhou HW, Meng J, Yang Q, Chen B, Zhang YY. Carbon emissions and their drivers for a typical urban economy from multiple perspectives: A case analysis for Beijing city. Applied Energy. 2018; 226:1076–86. https://doi.org/10.1016/j.apenergy.2018.06.004.

**15.** Ma X, Wang C, Dong B, Gu G, Chen R, Li Y, et al. Carbon emissions from energy consumption in China: Its measurement and driving factors. Science of The Total Environment. 2019; 648:1411–20. https://doi.org/10.1016/j.scitotenv.2018.08.183 PMID: 30340286

**16.** Nguyen KH, Kakinaka M. Renewable energy consumption, carbon emissions, and development stages: Some evidence from panel cointegration analysis. Renewable Energy. 2019; 132:1049–57. https://doi.org/10.1016/j.renene.2018.08.069.

**17.** Yu B. Industrial structure, technological innovation, and total-factor energy efficiency in China. Environ Sci Pollut Res Int. 2020; 27(8):8371–8385. https://doi.org/10.1007/s11356-019-07363-5 Epub 2020 Jan 4. PMID: 31902075.

**18.** Helveston J, Nahm J. China's key role in scaling low-carbon energy technologies. Science. 2019; 366 (6467): 794–796. https://doi.org/10.1126/science.aaz1014 PMID: 31727813

**19.** Guo Q, Zhou M, Liu N, Wang Y. Spatial Effects of Environmental Regulation and Green Credits on Green Technology Innovation Under Low-Carbon Economy Background Conditions. Int J Environ Res Public Health. 2019 Aug 21; 16(17):3027. https://doi.org/10.3390/ijerph16173027 PMID: 31438575; PMCID: PMC6747161.

**20.** Shan Y, Huang Q, Guan D, Hubacek H. China CO2 emission accounts 2016–2017. Sci Data. 2020; 7: 54. https://doi.org/10.1038/s41597-020-0393-y PMID: 32054849

**21.** Wang Y, Yan W, Ma D, Zhang C. Carbon emissions and optimal scale of China's manufacturing agglomeration under heterogeneous environmental regulation. Journal of Cleaner Production. 2018; 176:140–50. https://doi.org/10.1016/j.jclepro.2017.12.118.

**22.** Li Z, Sun L, Geng Y, Dong H, Ren J, Liu Z, et al. Examining industrial structure changes and corresponding carbon emission reduction effect by combining input-output analysis and social network analysis: A comparison study of China and Japan. Journal of Cleaner Production. 2017; 162:61–70. https://doi.org/10.1016/j.jclepro.2017.05.200.

**23.** Wang K, Wu M, Sun Y, Shi X, Sun A, Zhang P. Resource abundance, industrial structure, and regional carbon emissions efficiency in China. Resources Policy. 2019; 60:203–14. https://doi.org/10.1016/j.resourpol.2019.01.001.

**24.** Du L, Wei C, Cai S. Economic development and carbon dioxide emissions in China: Provincial panel data analysis. China Economic Review. 2012; 23(2):371–84. https://doi.org/10.1016/j.chieco.2012.02.004.

**25.** Behera SR, Dash DP. The effect of urbanization, energy consumption, and foreign direct investment on the carbon dioxide emission in the SSEA (South and Southeast Asian) region. Renewable and Sustainable Energy Reviews. 2017; 70:96–106. https://doi.org/10.1016/j.rser.2016.11.201.

**26.** Zhou X, Zhang M, Zhou M, Zhou M. A comparative study on decoupling relationship and influence factors between China's regional economic development and industrial energy–related carbon emissions. Journal of Cleaner Production. 2017; 142:783–800. https://doi.org/10.1016/j.jclepro.2016.09.115.

**27.** Xiao HW, Ma ZY, Zhang P, Liu M. Study of the impact of energy consumption structure on carbon emission intensity in China from the perspective of spatial effects. Natural Hazards. 2019; 99(3): 1365–1380. https://doi.org/10.1007/s11069-018-3535-1.

**28.** China national knowledge internet. (2020). http://tongji.cnki.net/kns55/Dig/dig.aspx/ Accessed 15 March 2020.

**29.** Baidu Index. (2020). http://index.baidu.com/v2/index.html#/ Accessed 15 March 2020.