Original Research

Does Technical Progress Stimulate the Low-Carbon Transformation Process in China? A Provincial Aspect

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Abstract

How to stimulate technical progress development among provinces is of great significance in order for China to achieve high-quality economic development. Spatial statistical methods are applied to analyze their spatial characteristics of technical progress and its influential effect on carbon dioxide emissions. Results are as follows: (1) Moran index and Moran scatter diagram are used to analyze spatial distribution features among provinces in terms of technical progress. It presents a significant, positive spatial cluster state and is dominated by the 'Lower-Lower' (L-L) type. Spatial spillover effects should not be ignored. (2) Spatial Durbin model (SDM) is applied to analyze technical influential effects on carbon dioxide emissions. Technical progress impacts itself in a negative way. Cleaner technical progress among provinces is dominated during the whole research period. Its indirect effects on neighbors are positive and insignificant. Total effect is close to zero. 'L-L'-dominated spatial distribution of technical outputs is not beneficial for stimulating reduction effects by technical spillovers among provinces. (3) When regional technical development incentive policies are arranged to accelerate low-carbon transformation, green technical progress should be placed in the priority order. Their spatial optimization also puts more focus upon it. The Yangtze River Delta, Pearl River Delta and Beijing-Tianjin-Hebei regions should be the first R&D centers to accelerate spatial transmissions.

Keywords: technical progress; carbon dioxide emissions; spatial distribution, spatial Durbin model

Introduction

Low carbon transformation has become an important subject to realize high quality development for China nowadays. Its carbon dioxide emissions occupied 27.3 percent of the world in 2016, which exceeded the sum of emissions from US and EU and were 7.65 times the emissions in Japan [1]. International calls for more responsibilities for carbon emissions exert more and more pressure on the low-carbon transformation process. How to accelerate this process and realize absolute emissions reduction are the best choice for central government to answer for international calls and improve economic development quality. On one hand, technical progress is the core driving force to realize low-carbon transformation [2]. Low-carbon

energy supply, industrial sectors' production and their structure arrangement rely on technical progress finally. Thus, how to stimulate technical development is a great significant subject to accelerate the low-carbon transformation process. Such measures as R&D funds input, technical outputs and spatial structures, etc., should be considered in detail. Especially, green technical progress development should be given the priority. On the other hand, inadequate and imbalanced development problems are apparent in terms of technical progress among regions. These have become an obstacle to accelerate the transformation process. Spatial distribution optimization can save R&D resource input, and spillovers among regions can give full paly to emissions reduction effects. Since 2000, technical progress in China has been developing at high speed. For instance, annual growth rate of authorized patent output in China was greater than 20 percent during 2001-2016. Meanwhile, regional disparities among regions in terms of technical development also cannot be neglected. Provincial disparity in terms of authorized patent per capita among provinces kept more than 20 times during the period. In 2003, it peaked 56.6 times. Spatial disparity features should be considered in detail during technical development arrangements for the central government. According to the first geography economics laws (Tobler, 1979), there exist close relationships among adjacent regions [3]. Spatial autocorrelation is also included in policy arrangement. Based on the above analysis, spatial clusters and heterogeneity characters should be evaluated before considering its effects upon carbon dioxide emissions. Therefore, this research is carried out from spatial distribution characters among provinces in China during the research period and then its influences upon carbon dioxide emissions will be considered in detail. Suggestions shall be made for central governments' references in terms of identifying the prior development provinces and improving spatial spillover effects among 30 provinces in order to accelerate the whole transformation process in China.

In the literature, technical influences on pollutant emissions has become a key subject for researchers today. Most literature focuses on technical progress evaluation and its transmission mechanism analysis. In technical progress evaluation research, data envelopment analysis (DEA) and Malmquist index methods are applied in order to obtain technical progress information. In this framework, economic output is regarded as expected output, and carbon dioxide emissions are included as the unexpected output. Han C. (2018) applied 'DEA+Malmquist index decomposition' framework to the low-carbon technical progress index values and explore its reduction effects of industrial sectors [4]. Zhang B. (2017) [5], Xie B. and Song Y. (2017) [6], Cheng et al. (2017) [7], Sun X. et al. (2016) [8], Jin P. (2017) [9], Ji K. and Qu R. (2012) [10] et al. used this framework to evaluate technical trends and further analyzed their influential effects in China. Besides, some researchers use such statistical indexes as

R&D funds input, human resources input or technical output indexes to reflect technical trends. Zhang C. and Zhang Z. (2015) utilized FDI, R&D fund input, human capital input and authorized patent indexes to evaluate technical progress trends in China [11]. Wei W. and Yang F. (2010), Huang J. and Ding G. (2014), Yin J. et al. (2015), Zhou H et al. (2016), Zhou Z. et al. (2017), Zhao Q.Z. and Yan Q.Y. (2018) employed patent output index to evaluate technical trends [12-17]. When DEA framework is utilized, evaluation results are concluded based on the relative efficiency compared with production frontiers, and they are much dependent on sample selection. Therefore, results are sensitive to abnormal values and have poor stability. To avoid the result stability problem, more researchers have chosen statistical indicators to reveal technical trends. Compared with technical input indicators, technical output indicators can supply more exact information. Thus, an authorized patent output indicator is selected in this research in order to evaluate technical development trends among provinces in China.

In terms of technical influence on carbon emissions research, the two main directions are mechanism and empirical analysis. With respect to influential mechanisms, Jaffe (2002) pointed out that technical progress may lead to pollutant emissions rising or decreasing [18]. Shen M. et al. (2012) divided its influence effects into two ways: direct and indirect effects [19]. The direct effect was the path of 'technical progress $\rightarrow$ carbon dioxide emissions' and it meant that technical progress directly inflects emissions. An undirected effect was referred to the way 'technical progress $\rightarrow$ economic growth $\rightarrow$ carbon dioxide emissions' and technical progress stimulated emissions change by economic growth. Technical progress had path dependence and depended on its initial technical structure. Acemoglu et al. (2009) classified technical progress into two types: pollutant and clean technology [20]. When pollutant technical progress dominated, technical progress pushed pollutant sectors to expand at a higher speed and promote carbon dioxide emissions ascending. Otherwise, when cleaner technical progress dominated technical progress, it stimulates clean sectors to produce more goods and edge out pollutant goods. At the end, less fossil energy is consumed and fewer emissions are produced. Yan Z.M. and Deng X.L. (2016) analyzed direct effect and possible indirect effects on industrial carbon dioxide emissions, from theoretical mechanism and empirical model aspects [21]. In summary, there is much uncertainty surrounding technical influences on carbon dioxide emissions and it depends on transmission path and technology structure of the economics.

Decomposition methods and econometric models are used in the influential factor analysis in current literature. IDA (index decomposition analysis) and SDA (structural decomposition analysis) are the two widely used decomposition methods. LMDI (logarithmic mean divisia index) is the most popular IDA method,

which is widely used in recent energy or emissions analysis. Sun N. (2010) used LMDI to analyze the main factors that influence manufacturing sectors' carbon emissions in China and pointed out the driving effects from technical progress [22]. Liao and Xu (2017) and Dong F. et al. (2018) decomposed the driving effects in carbon dioxide emissions with SDA framework [23-24]. Under decomposition method framework, the accidental factor is not taken into consideration and conclusions may deviate from reality. In the econometric model, accidental factor is included in the model as random variable ε. Influential effects can be evaluated by parameter estimation results and statistical tests. As panel data supply individual and dynamic information simultaneously, panel data econometric models are widely utilized by many researchers during factor analysis. Common panel data econometric model and spatial panel data econometric model are often constructed to explore technical progress effect on carbon emissions. [25-29] applied the panel data econometric model to analyze technical progress factor's influence on carbon dioxide emissions. They mainly differ in explained variable selection and parameter estimation results.

In a summary, current research mainly focuses on technical progress trends under DEA framework and results have poor stability. A statistical indicator can provide precise data information and its results can be more stable and referable for implementing low carbon incentives. The main contributions of this research are as follows. Firstly, authorized patent indicator is chosen as the evaluation indicator to reveal technical progress information among provinces. Moran's index (Moran I) and Moran scatter diagram (MSD) are used to reveal its spatial characteristics. Secondly, the spatial econometric model is constructed to analyze its influence on carbon dioxide emissions and technical progress is the core variable. Results can explain not only its direct effects, but also the indirect effects to its neighbors' emissions. Conclusions will provide detailed references for the central government to stimulate technical development incentive policies and coordinate regional low-carbon transformation plans in China.

Material and Methods

Spatial Character Analysis

Moran I and MSD are the usually used statistical methods to analyze the spatial distribution character of a sample. Moran I is obtained according to Eq. (1), and it varies within the range [-1, 1]. When it is positive, it indicates a wholly positive spatial cluster character. When it is negative, it shows a negative spatial cluster character. When it ranges at zero, it reveals that there are no spatial autocorrelations and no clusters in a whole among individuals. Its significance test is to examine whether it is a significant effect for this variable. When it

is rejected, it means spatial cluster character is important and it should not be neglected from consideration. In Eq. (1), W is defined as spatial adjacency matric and W_{ij} reveals the spatial adjacency features among the two individuals. When they are spatial neighbors, it is 1 and otherwise it is given zero. $\bar{X}$ and S^2 are the mean and variance of indicator X:

$$Moran\ I = \frac{\sum_{i,j} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i,j} W_{ij}} \quad (1)$$

MSD is utilized to analyze local spatial heterogeneity characters by its four quadrants. Four quadrants reveal four types and they are 'H-H', 'L-H', 'L-L' and 'H-L' types, respectively. 'H-H' and 'L-L' reveal positive spatial clusters locally. 'H-H' shows both higher properties for two neighbors. And if they are of 'L-L' type, they represent both lower properties. 'L-H' and 'H-L' types reveal a locally negative cluster state. Of 'L-H' type, individuals with lower values are spatially adjacent to those with higher values. On the above analysis in terms of technical progress, spatial heterogeneity character among provinces can be concluded.

Spatial Panel Data Econometric Model

The econometric model is used to explain influences with its parameter estimation results and statistical test conclusions. Panel data can provide individual and timing information simultaneously of the sample. The econometric model with panel data is defined as panel data econometric model (PDEM) and widely applied to factor analysis in current research. It is classified into two types: common panel data econometric model (CPDEM) and spatial panel data econometric model (SPDEM). In CPDEM, individuals are assumed to be independent and inter-individual interaction is neglected. In SPDEM, spatial adjacency matric (W) is included into the model to reveal interactions among individuals. SPDEM is further divided into three sub-types: spatial lag model (SLM), spatial error model (SEM) and spatial durbin model (SDM). In SLM, spatial lag variable Wy is introduced into the model. In SEM, $W\varepsilon$ is included into the model as an explanatory variable. Wy and $W\varepsilon$ are both introduced into the model in SDM. SDM is usually constructed when spatial spillover effect is considered. Statistical test results are helpful for confirming whether it is converted into SLM or SEM.

A series of statistical tests should be carried out to obtain reliable parameter estimation results and obtain analysis conclusions. They are mainly panel unit root tests, panel co-integration tests, models form selection tests, significance tests and robust tests, etc.

Firstly, panel unit root tests and co-integration tests are implemented before the econometric model

is constructed. They are intent on examining stable, long-term equilibrium relationship existence among variables. Panel unit root tests are to explore the stability features for variables and mainly conclude LLC, Fisher ADF and Fisher PP tests. The null hypothesis is that there is a general unit root in LLC test and it is an effective unit root in the other two tests. Only when variables have the same order stable property can panel co-integration tests be implemented to examine whether there is a long-term equilibrium relationship among variables. Otherwise, false regression results may be obtained. Kao test is used in the co-integration test. Its null hypothesis assumes that there is no long-term co-integration relationship among variables. If the null hypothesis is refused, stable long-term equilibrium relationships among variables exist and the econometric model should be constructed.

The second type of statistical test is about fixed effect model forms of selection tests. There are four fixed effect model forms and they are models with fixed effects: mixed fixed, individual fixed, time fixed and dual fixed effect. Statistical tests mainly conclude R square (R^2), log-likelihood test (Log-L), and Lagrange multiplier (LM-lag, LM-error, robust LM-lag and robust LM-error). The third type of statistical test is to examine how SDM should be converted into SLM or SEM. The conclusion is based onstatistics, Wald test (*Wald_spatial_lag*, *Wald_spatial_error*) and likelihood ratio test (*LR, LR_spatial_ lag* and *LR_spatial_error*) results.

Finally, robust tests of parameter estimation results in the model should be implemented to confirm that results are robust by variables or data change. In this section, two substitute variables for the core explanatory variable are chosen to explore out the robustness results. Besides, the middle part of the research period (2005-2012) is chosen to estimate parameters and examine the robust results of the model.

All variables are converted into the logarithm forms in order to eliminate the heteroscedasticity phenomena among variables in the model and they are represented by *ln*(·).

Results and Discussion

Spatial Distribution Characters of Technical Progress

In this section, an authorized patent indicator is chosen to reveal their spatial characters and dynamic trends during 2001-2016. Moran indexes and MSDs are obtained during the period and they are shown in Table 1 and Fig. 1.

From Table 1, Moran Index turned from an insignificant indicator to significant one and the critical year was 2007. Before 2007, it was not wholly significant and it revealed that spatial effect was not an important factor in terms of technical development. During 2007-2016, spatial effect among provinces was an important influential factor and should be considered when technical policies were implemented. Moreover, Moran index was kept positive during the whole period. Positive spillovers dominated among the provinces in terms of tehcincal progress. It kept an apparently rising trend and increased by 28.89 percent totally during 2007-2016. In 2016, it was 0.2311 and still located at a lower level. In summary, technical progress represents a positive, lower-level spatial cluster character among 30 provinces.

Fig. 1(a-b) are the MSDs in 2011 and 2016, respectively. With comparison, spatial heterogeneity trends are analyzed. In Fig. 1b), 6 provinces are located in the first quadrant and 17 provinces in the third quadrant. They occupied 20% and 56.67% of 30 provinces, respectively. 'L-L' is the dominant spatial cluster type and reveals that many provinces with lower technical output form spatial clusters in China. It is not suitable for technical spillovers among them. 'L-H' and 'H-L' types occupied 13.33% and 10%, respectively. Compared with MSD in 2011, a few provinces took spatial transition during 2011-2016. For instance, Fujian Province is located in the secondary quadrant in 2011 and changed to the first quadrant in 2016. Sichuan Province transferred from the third to fourth quadrant, which indicates that

Table 1. Moran I values of technical progress during 2001-2016 ($\alpha = 5\%$).

Year	*Moran I*	p-value	Sig. test	Year	*Moran I*	p-value	Sig. test
2001	0.0664	0.1470	No	2009	0.2442	0.0240	Yes
2002	0.0829	0.0990	No	2010	0.2530	0.0230	Yes
2003	0.1612	0.1340	No	2011	0.2747	0.0150	Yes
2004	0.0861	0.1130	No	2012	0.2640	0.0130	Yes
2005	0.0966	0.0930	No	2013	0.2481	0.0190	Yes
2006	0.1367	0.0700	No	2014	0.2376	0.0220	Yes
2007	0.1793	0.0440	Yes	2015	0.2352	0.0180	Yes
2008	0.1853	0.0480	Yes	2016	0.2311	0.0200	Yes

a)

b)
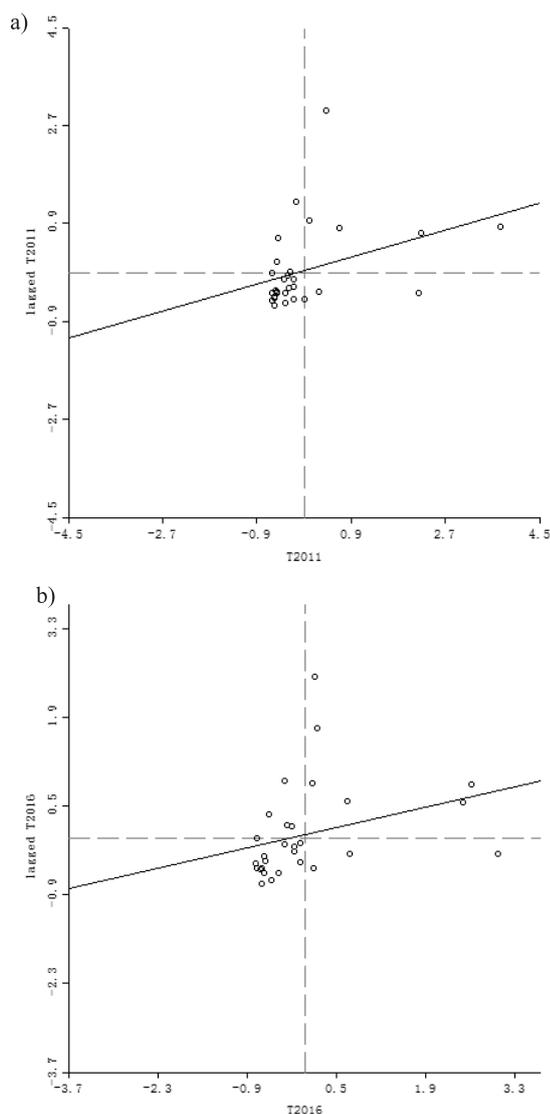
Fig. 1. MSD in terms of authorized patent in a) 2011, b) 2016.

Anhui, Fujian, Shanghai and Shandong provinces. They are mainly located in the Yangtze River Delta and only Shandong surrounds the Beijing-Tianjin-Hebei region in China. The Yangtze River Delta has become a technical output center.

Econometric Model Estimation Results

Variables and Descriptions

In this research, carbon dioxide emission is chosen as the explained variable of the model to reveal the low carbon transformation process in China. Provincial emission is obtained based on Intergovernmental Panel on Climate Change (IPCC), and carbon emission coefficients of energy types are from its annual report (IPCC 2006) [30]. Eight energy types are considered to estimate carbon dioxide emissions: coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil and natural gas (Table 2).

In Table 2, seven variables are introduced into the econometric model as the explanatory variables. Among them, authorized patent scale is regarded as the core variable to reveal technical influences on carbon dioxide emissions in the model. Data are from the China Statistical Yearbook on Science and Technology [31]. GDP is concluded in the model to reveal economic growth influence on emissions. To avoid price fluctuations, it is converted into real values at the fixed price in the year 2000. Population scale is also chosen into the model. It is a timing indicator and population scale of year t is the average value at the end of the year t and t–1. Industrial structure and energy consumption structure are both concluded into the model to indicate structural adjustment influences during the research period. Industrial value-added proportion in *GDP* is used to reveal economic structure adjustment. Coal proportion in energy consumption is used to reveal energy structure state in the model. Foreign spillovers are referred to the technologies accompanied with foreign investment and trades. Foreign direct investment (*FDI*) is introduced into the model as an explanatory variable. Technology

technical progress effects in the upper reaches of the Yangtze River Economic Delta has gradually formed and plays a role, taking Sichuan as the center. In MSD of 2016, the first quadrant includes Jiangsu, Zhejiang,

Table 2. Variable definitions and descriptive statistics.

Variable	Definition	Unit	Mean	Std. Dev.	Min	Max
CO_2	Carbon dioxide emissions	10^4 tons	32389	24981	1164	147193
GDP	Gross domestic production	10^8 RMB	9469	9221	292	50976
Pop	Population scale	10^4 persons	4380	2635	521	10924
IS	Economic structure	Percent	46	8	19	62
ES	Energy consumption structure	Percent	68	17	10	98
Pat	Granted patent scale	Piece	1353	42261	70	269944
FDI	Foreign direct investment	10^4 dollars	519975	659586	1495	3575956
Tim	Imported technology value	10^4 dollars	75347	146096	0.02	971292

Table 3. Stability test results of the eight variables.

Variables	LLC Test		Fisher-ADF Test		Fisher-PP Test		Conclusions
	$ln(\cdot)$	$d\,ln(\cdot)$	$ln(\cdot)$	$d\,ln(\cdot)$	$ln(\cdot)$	$d\,ln(\cdot)$	
$lnCO_2$	1.044	-11.927***	11.748***	195.105***	9.482	248.171***	I(1)
$lnGDP$	9.677	-5.514***	9.177	76.155*	7.471	189.089***	I(1)
$lnPop$	-4.661***	-12.948***	60.131	215.031***	78.995**	364.279***	I(1)
$lnFDI$	0.147	-16.770***	65.607	178.364***	78.036*	230.287***	I(1)
$lnPat$	2.702	-13.650***	10.456	175.925***	11.453	272.132***	I(1)
$lnTim$	3.652	-16.877***	17.069	301.576***	14.976	432.259***	I(1)
$lnES$	-1.119	-14.210***	27.657	220.108***	25.404	302.789***	I(1)
$lnIS$	-0.6302	-14.357***	25.659	173.134***	22.808	249.595***	I(1)

Note: ***, ** and * represent α = 1%, 5% and 10%.

purchase scale is also an explanatory variable to reveal technology import investment scale of provinces. Data are mainly from the China Statistical Yearbook 2017 and China Energy Statistical Yearbook 2017 [32-33].

Stability and Co-Integration Test Results

Table 3 is stability test results for all eight variables in this model. $dln(\cdot)$ is the first-order difference sequence of variables. According to LLC, Fisher ADF and Fisher PP tests results, eight variables are not stable in their logarithm form at 10% confidence level. The first-order difference sequences for variables have turned into stable state and they are in the same order in stable tests. Thus, the co-integration test can be implemented to decide whether the econometric model should be constructed in this section. Table 4 is the Kao test results for co-integration test for all variables. Based on ADF statistic values in the Kao test, its p-value is 0.0005 and null hypothesis should be refused. There exist stable long-term equilibrium relationships among eight variables, and the econometric model can be constructed. Thus the economic model is suitable to estimate factor analysis on carbon dioxide emissions and the basis model is as follows in Eq. (2). ε is a random variable to explain the accidental variable's influence:

$$lnCO_2 = f(ln\,GDP, ln\,Pop, ln\,IS, ln\,ES, ln\,Pat, ln\,FDI, ln\,Tim) + \varepsilon$$

(2)

Table 4. Panel data co-integration test results.

Test method	Statistic	Statistic value	p-value
Kao test	ADF	-3.3072	0.0005

Statistical Tests for Model form Selection

Table 5 is the result of the fixed-effect model form selection for panel data econometric model. Main statistics are R^2, *Log-L*, *LM-lag*, *LM-error*, *robust LM-lag* and *robust LM-error* in this section. Based on R^2 statistic values of models (1)-(4), R^2 in models (2) and (4) are 0.9731 and 0.9763, which are higher than those in models (1) and (3). Test results indicate that models (2) and (4) have more goodness of fit than that in the other two. During *Log-L* results in Table 5, values in models (2) and (4) are more than the others. It also proves that models (2) and (4) are a better choice among the four forms. Among the four LM test results, three statistics of model (2) are significant, while the four LM statistics of model (4) are not significant. Thus, model (2) should be chosen as the common panel data econometric model.

With Table 6 and Table 7 test results, spatial effects characters are implemented into the common panel data model and converted into spatial panel data model. Table 6 is the Moran index significance test results for carbon dioxide emissions during 2001-2016. It kept 'rising→peak→decline' trends and was a significant variable at 1% confidence level. Spatial spillover effects should not be ignored from influential factors, and the spatial econometric model should be constructed in this section. With results in Table 7, R^2 and *Log-L* statistical values are more than results of model (2) in Table 5, and model fitness degree becomes more. With results in *Wald* and *LR* tests, null hypotheses are all rejected. These indicate that SDM cannot be converted into SLM or SEM in this research, and its estimation results have better statistical features. In summary, SDM under individual fixed effect form is the most proper economic model in order to analyze influential effects upon emissions in this research. The SDM with seven explanatory variables are as follows in Eq. (3):

Table 5. Statistical test results for fixed-effect form selection in panel data model.

Test statistics	Model (1)	Model (2)	Model (3)	Model (4)
R^2	0.7819	0.9731	0.7867	0.9763
Log-L	-227.9276	274.5369	-222.6154	305.0197
LM-lag	0.2467	1.2630	29.0815***	0.2425
Robust LM-lag	0.9030	6.1683***	1.0521	1.8681
LM-error	44.2480***	18.0501***	44.6008***	1.1433
robust LM-error	44.9043***	22.9555***	16.5713***	2.7689

Note: Model (1)-(4) represents mixed, individual, time and dual fixed effect model forms, respectively; ***, ** and * represent confidence level α = 1%, 5% and 10%.

$$lnCO_2 = \alpha + \lambda W \ln CO_2 + \beta_1 lnPat + \beta_2 lnGDP + \beta_3 lnPop + \beta_4 \ln IS + \beta_5 lnES$$
$$+ \beta_6 lnFDI + \beta_7 lnTim + \delta_1 WlnPat + \delta_2 WlnGDP + \delta_3 WlnPop + \delta_4 W \ln IS$$
$$+ \delta_5 WlnES + \delta_6 WlnFDI + \delta_7 WlnTim + \varepsilon$$

(3)

Parameter Estimation Results and Analysis

Parameters of SDM in Eq. (3) are estimated with maximum likelihood estimation (MLE) method [34]. With the aid of Matric Laboratory (Matlab) software, parameter estimation results are obtained and shown in Table 8. In comparison, estimation results in CPDEM are also shown in Table 8. There are significant differences among the two model estimation results.

In SDM, β_i indicates the regional effect upon its own carbon dioxide emissions and δ_i reveals its impacts on its neighbors' carbon dioxide emissions. Lesage and Pace (2009) proposed a partial differential method to estimate the indirect effects and total effects of each factor [35] and they are shown in Table 9. There is little difference between the direct effect results under partial differential method and the parameter estimations in SDM. The indirect effects for all variables in SDM are apparently different from estimation results with Lesage's method. Total effect of a variable is the sum of direct and indirect effects and they reveal the influential effect of an explanatory variable in a whole. Influential effect analysis is mainly based on them.

As the core explanatory variable, technical progress influences carbon dioxide emissions in a complex way. Firstly, it influences its own carbon dioxide emissions in a negative direction. According to Table 8, its direct effect is -0.0414. When technical output increased by one percent, it leads to 0.0414 percentage decline in carbon dioxide emissions of its own. Compared with the estimator in CPDEM, it is -0.0789. The absolute value of direct effect is lower than the estimator in CPDEM. The influential effect of technical progress upon its carbon dioxide emissions is overestimated under CPDEM framework. In terms of estimator significance test, it is not significant even at a confidence level of 10% in Table 8. In SDM estimation results, -0.0430 is significant at confidence level 10%. Its estimation result -0.0789 in CPDEM is a significant estimator at confidence level 1%. In summary, technical progress of a province leads to a negative effect on its own emissions in a weak way. This conclusion revises the former conclusions under the CPDEM framework. When we neglect spatial spillovers among provinces, its effect is overestimated. Meanwhile, the technical output structure is weakly dominated by clean technical output. The R&D investment in green technical progress field should be continuously expanded in order to exert its

Table 6. Moran I significance test of provincial carbon dioxide emissions (α = 5%).

Year	Moran I	p-value	Significance Test	Year	Moran I	p-value	Significance Test
2001	0.2618	0.015	Yes	2009	0.2849	0.007	Yes
2002	0.2556	0.013	Yes	2010	0.2856	0.006	Yes
2003	0.2409	0.024	Yes	2011	0.2872	0.005	Yes
2004	0.2784	0.009	Yes	2012	0.2712	0.010	Yes
2005	0.3050	0.005	Yes	2013	0.2656	0.007	Yes
2006	0.2995	0.005	Yes	2014	0.2544	0.015	Yes
2007	0.2946	0.008	Yes	2015	0.2555	0.013	Yes
2008	0.3044	0.005	Yes	2016	0.2404	0.015	Yes

Table 7. Statistical tests results of SDM.

Test statistics	Statistical value	p-value	Conclusions
R^2	0.9821	—	Good
Log-L	367.32	—	Apparent improved
Wald_spatial_lag	220.85	0.000	Reject H_0
Wald_spatil_error	116.70	0.000	Reject H_0
LR_spatial_lag	185.26	0.000	Reject H_0
LR_spatial_error	157.45	0.000	Reject H_0

emission reduction driving effects in the future. The inadequacy feature of technical development is apparent in the current stage. Especially clean technical progress development is the most potential driving factor to accelerate low carbon transformation in China.

Secondly, the parameter estimator of is 0.0426 in Table 8 is not significant even at confidence level 10%. This indicates that technical output increases by one percent, leading to a 0.0426% rise in its neighbor's carbon dioxide emissions. They vary in the same direction. Based on Table 8, the total indirect effect is 0.0406 and is not significant, either. The total effect of technical progress is -0.0008 and is close to zero. These results indicate that technical progress influences other provinces' emissions by technical progress spillovers. Though technical progress spillovers among provinces are significant, their indirect effects on emissions are

not significant. The whole effect of technical progress on emissions in China is almost zero. This proves that regional technical progress leads not only to declining emissions of its own and others in this stage of China.

From analysis in Section 1, the technology output of most regions in China has developed at a higher speed during the research period. Why did technical progress not bring about emissions reduction? The answer lies in its spatial features. Based on MSD of provincial authorized patent output, it is a lower-level, positive spatial distribution state. Although it is significant, most provinces are located in the 'L-L' type of the MSD. These indicate that most provinces of lower technical progress outputs are spatial clusters, and this spatial distribution state is not in favor of technical progress spillover among provinces. There are only a few southeastern provinces which are

Table 8. Parameter estimation results of SDM and CPDEM (individual fixed effect form).

Explanatory variables		SDM			CPDEM		
		Parameters	t-statistics	p-value	Parameters	t-statistics	p-value
Core variables	β_1	-0.0430*	-1.6804	0.0929	-0.0789***	-3.2666	0.0012
	δ_1	0.0426	1.2579	0.2084	——	——	——
Controlled variables	β_2	1.3358***	19.5526	0.0000	0.8231***	15.7874	0.0000
	β_3	-0.2946*	-1 .7013	0.0889	-0.0529*	-0.3328	0.7385
	β_4	0.2710***	3.5033	0.0005	0.7418***	9.2244	0.0000
	β_5	0.0914*	1.8603	0.0628	0.0926*	1.7406	0.0824
	β_6	-0.0079	-0.6567	0.5114	-0.0230	-1.6289	0.1040
	β_7	-0.0021	-0.4466	0.6551	0.0139*	1.7953	0.0733
	δ_2	-0.6996***	-6.9355	0.0000			
	δ_3	0.6637*	1.8931	0.0583			
	δ_4	0.7760***	5.3708	0.0000			
	δ_5	0.4467***	3.5453	0.0004			
	δ_6	-0.1270***	-5.1566	0.0000			
	δ_7	-0.0085	-1.0064	0.3142			
	λ	0.2880***	5.1205	0.0000			

Note: ***, ** and * represent confidence level $\alpha = 1\%$, 5% and 10%.

Table 9. Direct, indirect and total effects of explanatory variables.

Explanatory variables	Direct effects		Indirect effects		Total effects	
	Estimator	t-statistics	Estimator	t-statistics	Estimator	t-statistics
lnPat	-0.0414	-1.6363	0.0406	1.0230	-0.0008	-0.0194
lnGDP	1.3141***	19.6749	-0.4185***	-3.8768	0.8956***	9.2988
lnPop	-0.2512	-1.4919	0.7717*	1.7821	0.5204	1.2810
lnIS	0.3323***	4.4145	1.1510***	6.6040	1.4833***	7.9708
lnES	0.1230**	2.4201	0.6337***	3.6286	0.7567***	3.7342
lnFDI	-0.0165	-1.3267	-0.1735***	-4.8070	-0.1900***	-4.5583
lnTim	-0.0030	-0.6106	-0.0129	-1.1112	-0.0159	-1.1318

Note: ***, ** and * represent confidence level α = 1%, 5% and 10%.

divided into 'L-L' type in terms of technical progress. In 2016, there are 4 and 3 provinces which belong to the 'L-H' and 'H-L' types. These two types are beneficial to optimize spatial distribution with respect to technical progress. During 2001-2016, the quantity of the two types is rising and they are in the minority among the provinces in China. The spatial distribution state restricts its reduction effects on carbon dioxide emissions by technology diffusion mechanism in China. According to technical progress research by Aghion (1992) [36], technical progress is classified into two categories: dirty and clean technical progress. Dirty technical progress points to new technologies characterized by pollutant emissions rising of some industrial production sectors in the economy. Clean technical progress refers to some certain new technologies and they will produce fewer pollutant emissions. When technology output of an economic entity is dominated by clean technical progress, technical progress leads to fewer emissions. Otherwise, dirty technology progress will cause emissions to rise in the economic entity.

In summary, the clean character of technical progress is appearing up and it is still a weak factor for reducing carbon emissions among provinces at this stage. Technical progress remains unstable and its influential elasticity coefficient is about -0.0414. The indirect effect is approximately 0.0406 through spatial spillovers from other provinces and it is a weak, positive factor in terms of carbon dioxide emissions. To sum up, total effects on carbon dioxide emissions from technical progress is almost close to zero. This means that technical progress cannot exert significant effects upon carbon emissions whether of its own or of its neighboring provinces. The inadequacy and unbalanced development characters in terms of technological progress are becoming more and more obvious in China. In the future, how to promote technical progress to develop at a higher speed and to optimize its spatial distribution should be the most potential factor to accelerate low-carbon transformation in China.

Among the other explained variables, regional economic growth has significant influences on whether on its own carbon emissions or on others' emissions. Its direct effect is 1.3141 and indirect effect is -0.4185. It is underestimated in the CPDEM framework. Economic development of a province drives its carbon dioxide emissions in the same direction while it drives other emissions in a negative direction. In total, economic growth leads to rising emissions significantly. Meanwhile, spatial distribution optimization in terms of economic development is beneficial for China to accelerate its low carbon emission transformation process. At the same time, economic growth quality is being improved during the research period.

Based on estimation results in Table 9, industrial structure has a positive and significant impact on carbon dioxide emissions. Total effect is 1.4833 and is much higher than the direct effect 0.3323. For every percentage down in industrial structure, 0.3323 percentages of carbon emissions result from it. In addition, it plays more reduction effects upon their neighbors' emissions by economic structure adjustment. It shall be an important potential direction to reduce carbon emissions.

In Table 9, energy consumption type structure is a significant explanatory variable at confidence level 10%. Meanwhile, it also impacts a more indirect effect on their neighbors through spatial spillovers among provinces. They vary in the same directions. Reducing coal consumption in China can greatly accelerate carbon dioxide emissions downward. How to stimulate cleaner energy consumption is a good choice whether in goods production or in life. To accelerate clean energy technology development is essential to realizing energy consumption transformation.

For population scale variable, its indirect effect is a significant estimator in Table 9. The direct and total effects are not significant. The population growth doesn't lead to carbon emissions rising apparently, while population mobility among provinces maybe stimulates carbon dioxide emissions of neighbors. Foreign direct

Table 10. Robust test results of SDM.

Explanatory variables		Robust test 1		Robust test 2		Robust test 3	
		Parameters	p-value	Parameters	p-value	Parameters	p-value
Core variables	β_1	-0.0028	0.9009	0.0220	0.2575	-0.0140	0.6128
	δ_1	0.0457	0.1601	0.0089	0.7420	0.0083	0.8376
Controlled variables	β_2	1.2743***	0.0000	1.2211***	0.0000	1.3811***	0.0000
	β_3	0.2195	0.2057	-0.1527	0.3458	-0.2705	0.2752
	β_4	0.2903***	0.0002	0.3107***	0.0001	0.0476	0.6789
	β_5	0.0982**	0.0464	0.1097**	0.0293	-0.2123**	0.0109
	β_6	-0.0090	0.4559	-0.0076	0.5312	-0.0021	0.8999
	β_7	-0.0016	0.7262	-0.0006	0.8980	-0.0034	0.6340
	δ_2	-0.7205***	0.0000	-0.6566***	0.0000	0.6185***	0.0001
	δ_3	0.5847*	0.0937	0.4568	0.1683	0.1637	0.7614
	δ_4	0.7867***	0.0000	0.7202***	0.0000	0.1311***	0.0015
	δ_5	0.4742***	0.0002	0.4778***	0.0002	0.5057**	0.0361
	δ_6	-0.1240***	0.0000	-0.1185***	0.0000	-0.1328***	0.0000
	δ_7	-0.0078	0.3481	-0.0070	0.4029	-0.0352**	0.0210
	λ	0.2860***	0.0000	0.2740***	0.0000	0.1520*	0.0785

investment (FDI) leads to indirect and total effects upon carbon emissions significantly. The effects of FDI are negative and FDI influences carbon dioxide emissions in a negative direction. Pollution heaven phenomenon does not happen in China during 2001-2016. Conversely, FDI relieves environmental pressure by technological progress spillovers from other countries.

Robust Tests of Model Results

To test parameter estimation results robustness, three robust tests were implemented in this section. And the results are presented in Table 10. Tests 1 and 2 are two substitute variables for the core explanatory variable chosen to explore results robustness. They are domestic application for patent received indicator for provinces and invention granted by regions during 2001-2016. Test 3 is chosen for the middle part of the research period (2005-2012) and all parameters are estimated. Based on test results, parameter estimators of core variables are insignificant at 10% confidence level in the three tests and accord with the above conclusion in Table 9. Its spatial lag coefficients are also insignificant at 10% confidence level. Technical progress doesn't play a significant role in carbon emissions for provinces in China. For the other six explanatory variables, significance tests keep in accordance with that in SDM. Moreover, signs of parameters in the three tests are in the same with that in SDM. Upon the above analysis, parameters in SDM are robust and the corresponding analysis is reliable to convert into conclusions.

Conclusions and Implications

Main Conclusions of this Research

Based on the above empirical analysis, the main conclusions are as follows:

Firstly, parameters estimation results under SDM have revised original results under the CPDEM framework. They can reflect the influential effects of technical progress on carbon dioxide emissions in China more accurately. Based upon Moran I significance test results of carbon dioxide emissions among 30 provinces, they represent significant, lower positive distribution states during 2001-2016. Spatial effects should be introduced into CPDEM, and SPDEM is a better choice to analyze its influential factors of carbon dioxide emissions. From statistical tests, SDM cannot be converted into SLM or SEM. Parameter estimation results show good statistical property and are more suitable to analyze carbon dioxide emissions factors in this research. According to estimation results, the direct effect of technical progress is -0.0414 and is lower than that in CPDEM (0.0789). Technical progress is a negative driving force to influence provincial carbon dioxide emissions. Its indirect effect is 0.0406 and is not significant. The total effect of technical progress on emissions is -0.0008 and much closer to zero. Technical progress didn't play a significant role in driving the low carbon dioxide transformation process during 2001-2016.

Secondly, inadequate and imbalanced development in terms of technical progress is a barrier to promote

its carbon emission reduction effects at this stage. How to develop technical progress among provinces is the most potential force to realize low carbon transformation targets in the future. On one hand, technical progress has a negative impact on its own carbon dioxide emissions. As it is lower and insignificant, inadequate development of technical progress is much more apparent among regions in China. Especially green technical progress development should be given increasing effort in the future. Although technical progress has significant spatial spillovers among provinces, it still plays a weak positive role on neighbors' carbon dioxide emissions in the research period. The spatial distribution state is lower, positive 'L-L' type and is maybe the cause of hampering technical spillover effects. This mechanism is not beneficial for provinces to spatial spillovers among the low carbon transformation process.

Policy Recommendations

Firstly, it is an important step to energetically accelerate cleaner technical progress in order to strengthen its reduction effects on carbon dioxide emissions. Especially low carbon technology should be given more and more effort for stimulating its development in the future. Only by this way does technical progress convert it into a more significant factor to push the transformation process in China. Pollution technologies characterized by high energy consumption and high pollutant emissions should be strictly controlled from the whole process. This should be the long-term technical development strategy in China. In order to promote low-carbon technology development, three aspects should be paid more focus. They are divided into types and are no carbon technologies, carbon reduction technologies and de−carbonation technologies. No carbon emission technology intends to control carbon emissions from the source. Clean energy types emitting zero emissions and replacing fossil energies with clean energy types is the best choice for low-carbon transformation. Solar, wind or geothermal energies are good examples for developing technologies. Carbon reduction technologies are a kind of process control technology. This kind of technology is intended to improve efficiency and lower emissions during goods production and consumption. Technologies as integrated gasification combined cycle (IGCC), combined heat and power (CHP), and purification catalyst technologies for volatile organic compounds (VOC) are the types of technologies in power generation and petroleum sectors. De−carbonation technology is a kind of technology to capture, store or recycle carbon dioxide. Carbon Capture and Storge (CCS) is a good example of this type. For these technologies, R&D fund input, technology output and transformation should be given more incentive policies to stimulate them to develop wholly.

Secondly, spatial distribution optimization of technical progress should be considered and given more focus on when technical development policies

are arranged. By this way, cleaner technical spillovers among provinces will accelerate emission reduction effect transmissions. In the end, it will save R&D funds input and accelerate the whole low carbon transformation process in China. In the current stage, this technical progress distribution state is dominated by 'L-L' spatial cluster mode, which is not suitable for provinces to have technical spillovers among them. Provinces of 'H-H' type are mainly located in the Yangtze River Delta region of China and they are Shanghai, Zhejiang and Jiangsu provinces. These provinces are the most developed economic region in China and are rich in R&D resources. This region also develops quickly with respect to regional coordinated development. As the preferential development regions in regional coordinated development, although such regions as Yangtze River Delta, Pearl River Delta and Beijing-Tianjin-Hebei have some technology agglomeration, they haven't formed high-level technical clusters and related industrial sector clusters. Spatial spillovers in clean technology fields do not radiate well into their outside regions. As the central nodes of technical progress transmission network in China, more R&D resources and incentive policies should be given to these regions and more resources should be input into clean technical progress research of the regions. More incentive policies are made to stimulate technology transmission among regions and these will enlarge technical spillover effects during the low-carbon transformation process.

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Conflict of Interest

The authors declare no conflict of interest.

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