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Spill over effect of technological innovation on CO2 emissions in China's construction industry

Abstract

Given the leading role of the construction industry in fossil fuel consumption, it is essential to identify the drivers responsible for carbon emission in that sector. Based on the panel data of 30 provinces in China in the period between 2000 and 2015, this study estimated the spatial distribution and driving innovation factors of construction carbon emissions (CCE) by using Moran's I index and spatial econometric models as underlying methods. The empirical results show that there were significant spatial dependence and clustering characteristics in provincial CCE. The net value of machinery and equipment, labor productivity, technical renovation input, construction gross domestic product, and the total construction profit prohibit greater emission reductions. Specifically, the economy related performance indicators cause smaller positive impacts on emission growth than the machinery- and labor-related factors. In addition, it is also noted that proportion of technical personnel and the ratio of technical equipment have significantly positive effects on CCE abatement. The findings of this study would be beneficial for local government to adopt stratified and effective emission reduction methods in the provincial construction industry.

Acronyms

CCE Construction carbon emissions
CGDP Construction gross domestic product FE Fixed effects
GDP Gross domestic product HH High-high clustering type HL High-low clustering type
LH Low-high clustering type LL Low-low clustering type LM Lagrange multiplier
LP Construction labor productivity
LR The joint likelihood ratio
ME Net value of machinery and equipment in construction industry
OLS Ordinary least squares
PA Patent application counts in high-tech industry
PR Total construction profit
R&D Research and development RE Random effects
SAR Spatial autoregressive model SDM Spatial Durbin model SEM Spatial error model
SLM Spatial lag model
TE Ratio of technical equipment in construction industry
TP The proportion of technical personnel
TR Technical renovation input TWFE Two-way fixed effects

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1. Introduction

As a major factor leading to global warming, CO_2 emissions have received global attention. According to the Intergovernmental Panel on Climate Change (IPCC) report, the global temperature will increase by 1.1 C–6.4 C by 2100 [1]. Against this backdrop, many countries reached an agreement to control global average temperature increases below 2 C above the pre-industrial levels at the 2015 Paris Climate Change Conference [2].

China, as the world largest CO_2 emitter, contributed about one quarter of world's total CO_2 emissions in 2013 [3,4], which was 1.5 times than that of the United States. According to Zhu and Dabo [3], China's CO_2 emissions will continue to increase further by over 50% from 2015 to 2030 unless specific reduction policies are implemented. The Chinese government has released a plan for controlling CO_2 peak emissions by 2030 by reducing 60%–65% CO_2 emissions per unit of Gross Domestic Product (GDP) at 2005 level [5].

A vast body of work demonstrates that the construction industry in China is energy intensive, that was the main contributor to the overall CO_2 emissions in China [6–10]. As a crucial pillar industry of the Chinese economy, the construction industry accounted for 7% of China's GDP [11,12] but was responsible for approximately 30% of the total CO_2 emissions in China [13]. This was mainly because the building materials consumed on construction sites, such as cement, steel, glass, and aluminum, were manufactured in energy-intensive manners and generated a large amount of CO_2 emissions during their manufacturing. Such indirect CO_2 emissions accounted for more than 90% of the total construction CO_2 emissions (CCE) [14–17]. Thus, cutting CCE is beneficial for achieving emission reduction targets in China.

Given China's burgeoning economic situation and ongoing process of urban industrialization, the present economic vibrancy in the construction industry is likely to continue [9]. Compared with reducing CO_2 emissions by controlling economic growth, strengthening technical innovations in the construction industry is a more rational approach to decreasing CO_2 emissions. Many studies have uncovered the positive

role of technologies on emission reduction. From a macro-level perspective, Zhang, Peng, Ma and Shen [18] showed that most environmental innovation measures can reduce CO_2 emission in China. Zhu and Dabo [3] estimated that adopting strict low-carbon strategies such as improving production efficiency and using renewable energies and natural gas would remove 30 Gt of CO_2 emissions from China between 2015 and 2030. Nataly Echevarria Huaman and Xiu Jun [19] insisted that the advancement of carbon capture and storage (CCS) technologies, such as low-carbon technology is a decisive piece in the fight against global warming. According to Du, Li and Yan [11], green technology upgrades considerably contribute to reducing CO_2 emissions of the countries above a certain income level. At industrial level, Tian, Chang, Tanikawa, Shi and Imura [20] found that both energy intensity reduction and structural upgrade were important in the decarbonization in Beijing. Ouyang and Lin [21] indicated that progress in technologies in the construction industry ensured consistently energy savings. Borghesi, Cainelli and Mazzanti [22] examined the positive role of the European Emissions Trading Scheme for CO_2 decline in the manufacturing industry. From a micro-level angle, Lee and Min [23] affirmed the presence of a negative relationship between green research and development (R&D) and carbon emissions by investigating Japanese manufacturing firms. Hazarika and Zhang [24] demonstrated that adopting advanced techniques and implementing eco-innovation in production plants can significantly lessen the ill environmental impacts induced by construction products. Menyhart and Krarti [25] assessed the potential energy conservation of dynamic insulation materials (DIMs) for residential buildings and found that DIM technology could conserve up to 42% energy. In summary, progress in technologies is beneficial for emission reduction at multi-scales. Despite China having greatly improved in energy-saving technologies pertaining to fossil fuels [26], the total primary energy demand has nonetheless increased by more than 160% from 2000 to 2016 [27]. Moreover, the energy saved by improvements on technologies was partially offset by energy demand increase [28–31].

McKinsey Global Institute (2016) concluded that technology and management innovations in construction industry were insufficient, where the research and development (R&D) investment accounted only for less than 1% of the total income. Given the backward role of the construction industry in technical innovation, it is necessary to inspect the potential of technical progress for CCE mitigation.

With respect to the methods for estimating the driving factors of carbon emissions, structural decomposition analysis (SDA), index decomposition analysis (IDA), and spatial econometric model were normally adopted. The SDA method mainly employs input-output data to decompose factors that impact carbon emissions or energy consumption [32–34], whereas the IDA method primarily practices time series data to decompose the changes in carbon emissions into different factors, which is more applicable for evaluating the temporal changes of these factors [35–37]. The first two approaches suffer weaknesses in revealing spatiality and fail to explore the spatial dependence in geographically adjacent regions [38,39]. More specifically, the spatial panel-data econometric model is widely used as a precise estimation by considering both temporal and spatial characteristics [40–42]. As a consequence, the spatial econometric model is often employed to evaluate the complex relationship between CO_2 emissions and driving factors. For example, Wang and Wang [43] used energy technology patents to measure technical progress and explored its positive impact on CO_2 emission reductions by applying the spatial lag model (SLM). At the industry level, Long, Shao and Chen [44] revealed that energy efficiency and technical innovation had significant positive effects on carbon productivity by using spatial panel data models. Cheng, Li and Liu [45], Cheng, Li and Liu [46] used a dynamic spatial panel model to demonstrate the effect of technical progress on carbon emissions due to the rebound effect. To the best of our knowledge, many researchers have paid attention to the driving factors of carbon emissions reduction using spatial econometric model, but only a few studies have focused on the relationship between technology innovations and CO_2 emissions in the construction industry with due consideration also being given to spatial spillover effects.

To fill such gaps in existing knowledge, this study firstly analyzed the spatial agglomeration characteristics of CO_2 emissions in China's construction industry between 2000 and 2015. Secondly, based on panel data obtained from 30 regions in China, we applied the spatial econometric model to estimate the spatial spillover effect of CCE and explore its driving factors. Theoretically, examining spatial heterogeneity and the spillover effects of technical innovation on industrial-level carbon reduction is beneficial because it would allow the government to adopt stratified and effective emission reduction methods. Practically, the establishment of a CCE database from a spatiotemporal perspective provides a solid foundation for systematically understanding the trajectory of CCE changes, which can facilitate authorities' attempts to create benchmarks for carbon emission reduction in provincial construction industries.

2. Methods and data

This section firstly presents the method for CO_2 emission quantification, which is a data foundation for the following spatial regression analysis. Subsequently, the explanatory variables are explained in detail. Thirdly, several spatial analysis methods, including global spatial autocorrelation, local spatial autocorrelation, and spatial panel-data econometric model, are introduced.

2.1. CO_2 emission quantification

Although there is a debate about the allocation of carbon emissions responsibility in research

communities, this study follows the principle that whoever consumes the resource should take the charge. Therefore, the responsibility of CCE from material production, electricity generation, and heat production should be allocated to consumer regions instead of producer regions. Given the material conservation method used by Feng, Wang and Liu [47], it can be concluded that the total emissions consist of direct emissions from onsite construction process and indirect emissions from the upstream supply chain. Considering construction practices, the direct emissions are mainly from 17 types of fossil fuels (see Appendix Table A1) and the indirect emissions primarily result from the use of electricity, heat, and five main building materials (see Tables A2-A3 in the appendix). This study focuses on the provincial CCE of China's construction sector from 2000 to 2015 (Tibet, Hong Kong, Macao, and Taiwan are excluded). This is a period which covers three time intervals of Five-Year Plans, namely 2000–2005, 2006–2010, and 2011–2015, and is therefore an appropriate length of study because China organizes its socioeconomic development targets in every five years. The CCE can be defined as Eq. (1):

$$CCE = CCE_{dir} + CCE_{ind} = \sum_{i=1}^{17} C_i NCV_i \; CC_i \; O_i \; 44/12 + C_h \alpha_h + C_e \alpha_e + \sum_{m=1}^{5} C_m \alpha_m (1 - \beta_m) \qquad (1)$$

$m¼1$

In this formula, CCE_{dir} and CCE_{ind} separately represent the direct and indirect emissions, i and m is the category of fossil fuel and building materials, respectively. C_i, C_h, C_e and C_m refers to the amount of fossil fuel, heat, electricity, and building materials. NCV_i is the net caloric value, O_i is the oxygenation efficiency, 44=12 denotes the molecular weight ratio of carbon dioxide to carbon. α_h, α_e, and α_m are the carbon emission factors, β_m is the cycling coefficient of building material m.

The consumption data of 17 types of fossil fuels, electricity, and heat was obtained from the *China Energy Statistical Yearbook*. The quantity data of the five primary building materials was collected from the *China Statistical Yearbook on Construction*. The coefficients of direct emissions are provided by Shan, Guan, Zheng, Ou, Li, Meng, Mi, Liu and Zhang [48] and China Emission Accounts and Datasets (*CEADs*). The electricity conversion coefficients are in line with *The Guidelines to Make Provincial Lists of Greenhouse Gas Inventory*, which classifies China's power grids into North China, Northeast China, East China, Central China, Northwest China, Southern China and Hainan. The building material emission coefficients and recycling coefficients are based on Zhang [49]. In general, all CO_2 emission factors listed in Appendix Table A1-A4.

2.2. Explanatory variables

To explore the spatial interaction mechanism of the provincial CCE, this study measures the technical innovations of the construction industry from four aspects: economy development, innovation performance, innovation investment, and output. As depicted in Table 1, the innovation related indicators are the construction gross domestic product (CGDP), the net value of machinery and equipment (ME), labor productivity (LP), the ratio of technical equipment (TE), technical

Table 1
Basic profile of variables.

renovation input (TR), the proportion of technical personnel (TP), patent application counts (PA), and total profit (PR). The variables are detailed as follows.

CGDP represents the gross output value of the construction industry [50]. It is an economic upholder for technology development, and this is assumed to be positive with CCE. ME is the main energy consumer in the building construction process [51], and is determined by the quantity and scale of construction projects. Since innovation activities can directly improve LP [52], it follows that, to an extent, LP indirectly reflects the level of innovation. We should maximize the productivity of labor resources as site workers account for a large proportion of the direct capital cost of construction projects [53]. TE, reveals technical inputs to the construction industry, and is highly related to the energy efficiency of construction machinery and equipment [50,54]. TR measures the equipment renovation investment in the construction industry. The physical condition and production efficiency of machinery and equipment significantly affect energy consumption on construction sites [18,50]. PA is commonly used to denote innovation output [55]. For instance, Zhang, Peng, Ma and Shen [18] demonstrated that the effect of patent output on carbon emission reductions in China was significant between 2006 and 2013. PR is an important innovation output depicting the effectiveness of technical progress. Table 2 shows the results of the descriptive analysis for these variables. The panel Ordinary Least Squares (OLS) model can be expressed as Eq. (2):

$$\ln CCE_{it} = \alpha + \beta_1 \ln CGDP_{it} + \beta_2 \ln PST_{it} + \beta_3 \ln PA_{it} + \beta_4 \ln PR_{it} + \beta_5 \ln CTER_{it} + \beta_6 \ln LP_{it} + \beta_7 \ln ME_{it} + \beta_8 \ln TR_{it} + \varepsilon_{it} \quad (2)$$

where i refers to the category of province, t denotes the year, α is a constant, β represents the estimated elasticity coefficient, and ε_{it} donates the random error term.

2.3. Spatial analysis methods

The attributes of spatial correlation are largely driven by the absolute location and relative location among the regions [32]. Spatial correlation can manifest spatial interaction effects, such as the spillover and diffusion of technical innovation, the omission of which may lead to biased estimations. Consequently, the spatial econometric models is feasible for capturing spatiality of carbon emissions [64]. To explore the spatiality of technical innovation in emission reduction, this study employed a series of spatial analysis methods. Generally, spatial econometric analysis involves two steps. The first step is to demonstrate the existence of spatial dependence. This then allows the second step to be achieved in which spatial econometric models are determined. Where this is not the case, the traditional econometric model should be adopted [65,66].

2.3.1. Global spatial autocorrelation

To test the presence of spatial autocorrelation, we adopt the global Moran's I index [67], as shown in Eq. (3):

	Variable	Explanation	Reference	Data resource
Explained variable	CCE	Construction CO_2 emissions	[47,56,57]	Calculation in this paper
Economy development	CGDP	Construction gross domestic product	[50]	China Statistical Yearbook on Construction
	ME	Net value of machinery and equipment in construction industry	[51]	China Statistical Yearbook on Construction
Innovation performance	LP	Construction labor productivity	[52,53,58,59]	China Statistical Yearbook on Construction
	TE	Ratio of technical equipment in construction industry	[50,54]	China Statistical Yearbook on Construction
Innovation investment	TR	Construction technical renovation input	[50]	China Statistical Yearbook on High Technology Industry
	TP	The proportion of technical personnel in construction industry	[18,60]	China Statistical Yearbook on Science and Technology

Output	PA	Patent applications in high-tech industry	[18,55,60–62]	China Statistical Yearbook for High Technology Industry
	PR	Total construction profit	[11,63]	China Statistical Yearbook on Construction

Table 2
Statistical description of the variables.

	Variable	Unit	Mean	Std. Dev.	Min	Max	Obs.
Explained variable	CCE	10^4 tons	2448	3663	47	36558	480
	CGDP	10^2 million Yuan	932	1038	27	6601	480
Economy development	ME	10^2 million Yuan	117	136	2	1553	480
Innovation performance	LP	Yuan/person	34532	19148	10998	107462	480
Innovation investment	TE	Yuan/person	12417	9993	728	154930	480
	TR	10^4 Yuan	80673	139661	0	1225605	480
	TP	Percentage	0.12	0.07	0.01	0.64	480
Output	PA	Number	2029	6048	0	58119	480
	PR	10^2 million Yuan	87	131	5	985.39	480

$$I = \frac{\sum_{i=1}^{30}\sum_{j=1}^{30} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{S^2\sum_{i=1}^{30}\sum_{j=1}^{30} w_{ij}}; (i \neq j) \quad (3)$$

where y_i and y_j is the CCE of province i and j, separately, $\bar{y}$ stands for the average value of y_i, $S^2 = \frac{1}{30}\sum_{i=1}^{30}(y_i-\bar{y})^2$ refers to the variance of y_i. w_{ij} is the degree of spatial correlation between region i and j in the spatial economic weight matrix which is row-standardized, and the specific formula is given as follows:

$$w_{ij} = \frac{\frac{1}{|\overline{GDP_i}-\overline{GDP_j}|}}{\sum_{j=1}^{30}\frac{1}{|\overline{GDP_i}-\overline{GDP_j}|}} \quad (4)$$

where $\overline{GDP_i}$ and $\overline{GDP_j}$ represents the average value of GDP in province i and j from 2000 to 2015, respectively. Since the spatial weight matrix is normalized, the values of the global Moran's I index range from 1 to 1. If $I > 0$, a positive spatial dependence exists; the larger the value, the stronger the dependence of spatial distribution; If $I < 0$, a negative spatial dependence exists, and if $I = 0$, there is no spatial dependence and it exhibits a random spatial distribution.

2.3.2. Local spatial autocorrelation index

As the Global Moran's I index only reflects global spatial associations, the local Moran's I scatter diagram was also used because it indicates the detailed dependence between the observed regions and their neighbors [68]. The local Moran's I index can be expressed as Eq. (5):

$$I_i = \frac{(y_i - \bar{y})}{S^2} \sum_{j \neq i}^{30} w_{ij} (y_j - \bar{y}) \tag{5}$$

The Moran's I index scatter plot can be divided into four quadrants, the meanings of which are described in Table 3.

2.3.3. Spatial panel-data econometric model

Compared with the panel OLS mentioned above, the spatial econometric model is an extension of the traditional regression model which integrates spatial effects. The two most regularly used spatial econometric models are the spatial lag model (SLM) (also known as SAR) and

Table 3

Explanation of four spatial clustering types.

Quadrant	Clustering type	Implication
I	High–High (HH)	Spatial positive association; provinces with high values are surrounded by provinces with high values
II	Low–High (LH)	Spatial negative association; provinces with low values are surrounded by provinces with high values
III	Low–Low (LL)	Spatial positive association; provinces with low values are surrounded by provinces with low values

IV	High–Low (HL)	Spatial negative association; provinces with high values are surrounded by provinces with low values

the spatial error model (SEM). SLM involves endogenous interaction effects with the dependent variable, which is employed to a scenario that the economic activity of a local region is influenced by that of neighboring regions in consequence of the spillover effects. SEM consists of interaction effects among the error terms, which is applied to a case where these effects are induced by neglected variables that impact both the local and neighboring regions [69]. As mentioned by Anselin, Gallo and Jayet [70], SLM integrates a spatially lagged dependent variable on the basis of the panel OLS. This can be specified as:

$$\ln CCE_{it} = \alpha + \rho \sum_{j=1}^{N} w_{ij} \ln CCE_{it} + \beta_1 \ln CGDP_{it} + \beta_2 \ln PST_{it} + \beta_3 \ln PA_{it} + \beta_4 \ln PR_{it} + \beta_5 \ln CTER_{it} + \beta_6 \ln LP_{it} + \beta_7 \ln ME_{it} + \beta_8 \ln TR_{it} + \gamma_i + \phi_t + \varepsilon_{it};\ \varepsilon_{it} \sim N\left(0; \delta^2 I_N\right) \quad (6)$$

where α is the constant term, $i = 1;2;\ldots;N$; $t = 1;2;\ldots;T$, ε_{it} is an error term which is independently and identically distributed with zero mean and variance δ^2, ρ denotes spatial autoregressive coefficient, β represents the coefficient of determinant. γ_i is a spatial specific effect and ϕ_t is a temporal specific effect.

SEM contains spatially autoregressive effects among the error terms. The model can be expressed as follows:

$$\begin{cases} \ln CCE_{it} = \alpha + \beta_1 \ln CGDP_{it} + \beta_2 \ln PST_{it} + \beta_3 \ln PA_{it} + \beta_4 \ln PR_{it} + \beta_5 \ln CTER_{it} + \beta_6 \ln LP_{it} + \beta_7 \ln ME_{it} + \beta_8 \ln TR_{it} + \gamma_i + \phi_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda \sum_{j=1}^{N} w_{ij} \varepsilon_{it} + \mu_{it};\ \mu_{it} \sim N\left(0; \delta^2 I_N\right) \end{cases} \quad (7)$$

where ε_{it} represents the spatial error autocorrelation, λ is the spatial autocorrelation coefficient of error term, μ_{it} is the random error term. The meanings of other variables and parameters are mentioned above.

For the SLM and SEM, the static panel data estimation methods including fixed effects (FE) and random effects (RE). The Lagrange Multiplier (LM) test, robust LM test, Wald test, and the joint likelihood ratio (LR) test need to be adopted to determine the appropriate econometric models. In addition, this study follows the process adopted by LeSage and Pace [71] in dividing the spatial spillover effects of explanatory variables into direct, indirect, and total effects.

3. Results analysis

Firstly, this section summarizes spatial characteristics of the provincial CCE based on the results of CCE quantification. Secondly, the spatiality of CCE and its dynamics are explored. Thirdly, after determining the most appropriate spatial econometric model, the estimation results are presented.

3.1. Spatial characteristics of the provincial CCE

The national CCE has increased dramatically from 0.25 billion tons in 2000 to 1.49 billion tons in 2011 along with the country's rapid economic development and urbanization (see Table 4). For instance,

Table 4

The statistics of China's provincial construction CO_2 emissions from 2000 to 2015 (in million tons).

No.	Regions	Mean	Rank	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	201
R1	Beijing	16.7	15	7.2	9.9	10.2	10.4	10.9	12.1	11.1	13.4	15.4	21.7	24.8	26.0	21.6
R2	Tianjin	12.7	20	3.2	3.6	4.0	4.6	5.6	5.0	6.2	9.0	10.2	13.7	14.2	18.3	18.5
R3	Hebei	64.3	3	12.4	14.8	14.5	14.9	15.2	20.2	33.5	20.5	26.4	28.3	68.6	283.5	270
R4	Shanxi	15.2	17	9.4	6.7	7.5	7.2	9.0	11.0	9.9	12.0	17.9	18.9	26.9	19.9	20.4
R5	Inner Mongolia	9.3	22	3.9	3.8	4.4	5.0	6.0	5.2	6.0	7.8	16.2	11.8	15.0	14.4	13.1
R6	Liaoning	31.1	8	9.9	11.7	12.0	12.5	12.8	12.6	14.1	16.3	21.9	32.3	37.7	60.9	48.8
R7	Jilin	15.4	16	4.3	5.0	7.1	9.0	10.7	2.2	5.6	5.7	7.5	9.5	9.4	10.4	60.3
R8	Heilongjiang	6.6	27	4.7	5.0	5.0	4.9	4.9	4.0	4.2	4.8	6.1	6.5	8.0	10.2	9.4
R9	Shanghai	14.3	18	7.3	9.3	11.0	11.6	12.5	14.6	14.1	14.3	15.3	16.7	17.0	17.8	16.6
R10	Jiangsu	93.8	2	28.9	35.9	36.6	37.6	38.5	44.5	50.2	62.9	79.3	81.3	91.0	365.6	165
R11	Zhejiang	101.4	1	33.0	42.9	46.1	49.6	53.0	66.1	77.0	80.3	98.1	104.2	120.9	147.7	158
R12	Anhui	18.4	12	6.7	9.3	9.2	9.1	9.0	9.4	11.1	14.2	15.3	17.9	25.0	27.8	28.0
R13	Fujian	26.9	9	4.6	6.5	6.2	6.0	5.9	10.1	14.4	12.0	22.6	27.5	34.1	34.5	43.0
R14	Jiangxi	10.6	21	2.2	3.0	3.7	4.5	5.1	6.1	7.7	7.2	8.4	10.0	11.0	17.6	17.3
R15	Shandong	42.8	5	18.1	25.9	26.1	20.8	26.5	32.1	35.0	30.4	43.1	52.4	48.3	47.9	105
R16	Henan	31.3	7	8.7	10.3	10.6	10.9	11.1	11.7	16.2	23.1	26.3	32.6	40.6	41.6	51.2
R17	Hubei	37.9	6	9.8	12.3	12.6	13.1	14.1	19.3	19.7	22.8	21.1	26.1	25.6	50.6	89.8
R18	Hunan	26.5	10	6.5	10.6	15.6	20.6	25.7	17.3	21.1	22.7	24.6	29.8	33.1	31.3	36.1
R19	Guangdong	26.4	11	16.2	19.3	18.8	18.3	18.2	21.9	23.4	23.0	23.6	25.8	34.4	50.8	3.4
R20	Guangxi	7.2	25	3.6	4.1	4.5	4.9	5.4	5.1	5.9	5.8	6.1	8.1	9.8	11.1	15.5
R21	Hainan	1.4	30	0.8	0.7	0.5	0.6	0.6	0.7	0.7	0.8	1.1	1.4	1.5	2.5	2.5
R22	Chongqing	18.3	13	9.1	11.7	11.1	10.5	9.1	9.8	10.3	12.5	15.7	14.5	27.4	27.9	26.4
R23	Sichuan	47.1	4	16.6	18.7	17.2	15.9	14.7	15.5	17.8	20.6	23.5	29.6	66.0	77.9	126
R24	Guizhou	8.2	23	2.8	3.7	4.0	4.2	4.4	3.7	4.3	4.7	5.3	8.6	5.3	8.1	9.7
R25	Yunnan	14.0	19	8.3	7.3	6.7	6.2	5.1	6.4	8.6	8.1	10.1	11.3	14.9	14.1	16.5
R26	Shaanxi	17.1	14	4.9	6.0	6.0	6.2	6.3	8.3	9.3	11.7	20.4	20.6	23.0	37.6	25.1
R27	Gansu	7.0	26	2.9	3.6	3.8	4.1	4.4	4.5	5.2	4.2	9.1	6.2	6.3	13.0	8.7
R28	Qinghai	1.9	29	0.9	0.9	1.0	1.0	1.1	0.9	0.9	1.3	2.0	2.6	3.7	2.3	2.6
R29	Ningxia	2.6	28	0.9	1.4	1.3	1.2	1.2	1.4	1.6	1.8	2.4	2.8	3.4	4.1	3.9
R30	Xinjiang	7.9	24	4.4	4.0	5.9	6.7	6.2	3.3	6.3	4.7	5.3	5.6	6.9	19.0	12.3
	Total	734.5		252.2	308.0	323.2	331.9	353.1	385.0	451.2	478.5	600.5	678.4	853.6	1494.4	142

Jiangsu (R10) emitted the maximum amount of CCE (0.366 billion tons) in 2011, with indirect CCE of 0.361 billion tons being mainly attributable to building materials production which accounted for over 98% of the total CCE. After reaching a peak in 2011, the national CCE has declined slowly from 1.49 to 1.1 billion tons by 2015. This is mainly because national economic growth rates have slowed down since 2011, with the growth rate of GDP reducing from 9.3% to 6.9% between 2011 and 2015.

To depict the spatial characteristics of the provincial CCE distributions, this study calculated the average values of the provincial CCE from 2000 to 2015 (See Fig. 1). Obviously, the regions with high CCE were predominantly concentrated in eastern China. The distribution of CCE followed a sequence from the eastern area to the southern and northern areas, and thence to the western area. The three regions with the highest CCE were all located in the eastern area; Zhejiang (R11) (101.4 million tons), Jiangsu (R10) (93.8 million tons), and Hebei (R3) (64.3 million tons), while the three regions with the lowest CCE were Hainan (R21) (1.4 million tons), Qinghai (R28) (1.9 million tons), and Ningxia (R29) (2.6 million tons). In summary, the CCE presented a large spatial heterogeneity in China.

3.2. Spatial autocorrelation and its dynamics

Aforementioned analysis demonstrates the spatial characteristics of CCE distribution. To systematically investigate spatial clustering, the global Moran's I index was used to test the spatial autocorrelation of China's provincial CCE. As specified in Table 5, the Moran's I statistics were statistically significant with values ranging from 0.087 to 0.292; indicating a significantly geographical autocorrelation of CCE among different regions.

To further detect the spatial dependence in local areas, this study conducted a Moran's I scatter plot analysis. Four sectional data (2000, 2005, 2010, and 2015) were chosen to represent the local spatial correlations. As illustrated in Fig. 2, 24 provinces (80%), 26 provinces (87%), 27 provinces (90%), and 26 provinces (87%) were kept in both HH and LL quadrants. This indicates that most of the provinces exhibited a highly spatial agglomeration of CCE.

To intuitively understand the spatial clustering of CCE, this study depicted geographical distribution maps for selected years to examine the spatial agglomerations from a temporal perspective (See Fig. 3). It can be seen from this figure that most of the eastern coastal regions were HH clustering types whilst most of the northern and southwestern areas were located in the LL clustering group. For instance, Hebei (R3),

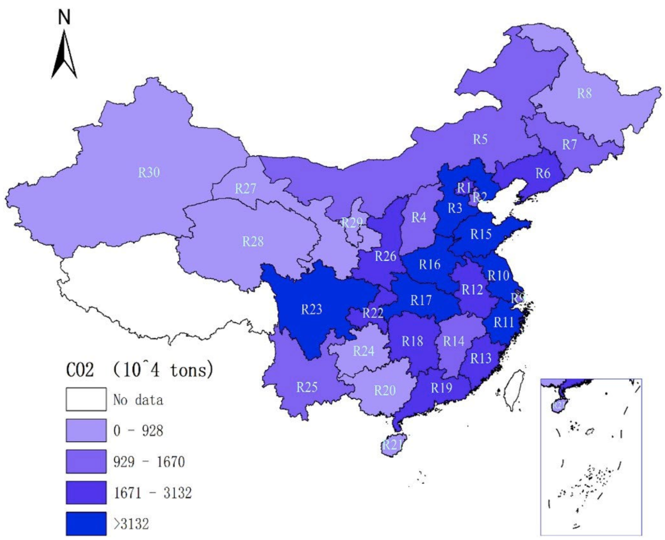

Fig. 1. Spatial distribution of the average of the provincial CCE from 2000 to 2015.

Table 5

Global Moran's I index of China's provincial CCE concentrations.

Year	Moran's I	Z-stat value	P-value	Year	Moran's I	Z-stat value	P-value
2000	0.272***	3.873	0.000	2008	0.210***	3.334	0.000
2001	0.292***	4.150	0.000	2009	0.250***	3.774	0.000
2002	0.284***	4.114	0.000	2010	0.242***	3.494	0.000
2003	0.245***	3.708	0.000	2011	0.087**	1.740	0.041
2004	0.251***	3.748	0.000	2012	0.141**	2.280	0.011
2005	0.247***	3.809	0.000	2013	0.215***	3.091	0.001
2006	0.242***	3.738	0.000	2014	0.222***	3.122	0.001
2007	0.225***	3.544	0.000	2015	0.168***	2.706	0.003

***Notes:** ***; **; * denote significant at 1%, 5%, 10% level of significance, respectively.*

Jiangsu (R10), Zhejiang(R11), and Shandong (R15) were spatially adjacent in the HH clustering group. In the LL clustering group, Inner Mongolia (R5), Heilongjiang (R8), Shaanxi (R26), Gansu (R27), Qinghai (R28), Ningxia (R29), and Xinjiang (R30) were geographically neighboring in northern China, whilst Guangxi (R20), Chongqing (R21), Guizhou (R24), and Yunnan (R25) were spatially clustered in southern China. The results indicate an obvious spatial agglomeration trend in China's CCE.

In addition, Table 6 presents the distributive transitions of CCE during the observation period. It is noteworthy that most of regions, including Liaoning (R6), Shanghai (R9), Henan (R16), and Hubei (R17), have frequently changed their clusterings. This is mainly because these regions are located in hub places – places which are regarded as bonds that linking with different areas of China. For instance, Henan (R16) and Hubei (R17) are located in the central area, which is an immediate zone bridging the highly developed eastern coastal areas with inland developing western areas. By excluding these status-unstable regions, five regions represented a trend concentrating on the HH and LL categories while only one region (Beijing) changed its role from LL to LH. In summary, the spatial distribution of the provincial CCE exhibited an obvious pole growth effect; regions were inclined to agglomerate in either HH or LL categories.

3.3. Results of spatial econometric regression

There are several common econometric methods including; panel ordinary least squares (OLS), the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). To determine the appropriate econometric models, a series of tests need to be conducted.

First, the results of the Hausman test (χ^2 ¼ 18.32, p ¼ 0.0189) rejected the null hypothesis that there is no fixed effect. Given the objects investigated in this study, the fixed effect (FE) is more rational than the random effect (RE). Secondly, the Lagrange Multiplier (LM) test and robust LM test were employed to determine whether the spatial effect exists in the econometric model for the estimation [41,72]. The results show that the SLM and SEM passed the LM test at the 1% significance level whilst the SEM was significant at the 10% level in the robust LM test. This fact demonstrates that it is essential to integrate spatial effects into the econometric models otherwise panel OLS modelling will lead to bias estimations. Furthermore, R^2 represents the fitting degree of the model and is usually used as a reference to select an approximate regression model. As shown in Table 7, both the SLM (0.880) and SEM (0.895) are superior to the panel OLS (0.772). Thirdly, as LeSage and Pace [71] suggested, the SDM should be considered if the LM test has rejected the non-spatial traditional panel model. The parameters of the SDM needed to be estimated by the Wald test and the joint likelihood ratio (LR) test. The two null hypotheses are H_0: ϕ ¼0, and H_0: ϑ þ $\delta\theta$ ¼0, respectively. If the results reject these two null hypotheses, the panel data is more applicable for the SDM. In contrast, the SDM should be simplified into the SLM if the null hypothesis that H_0: ϕ ¼ 0 is accepted.

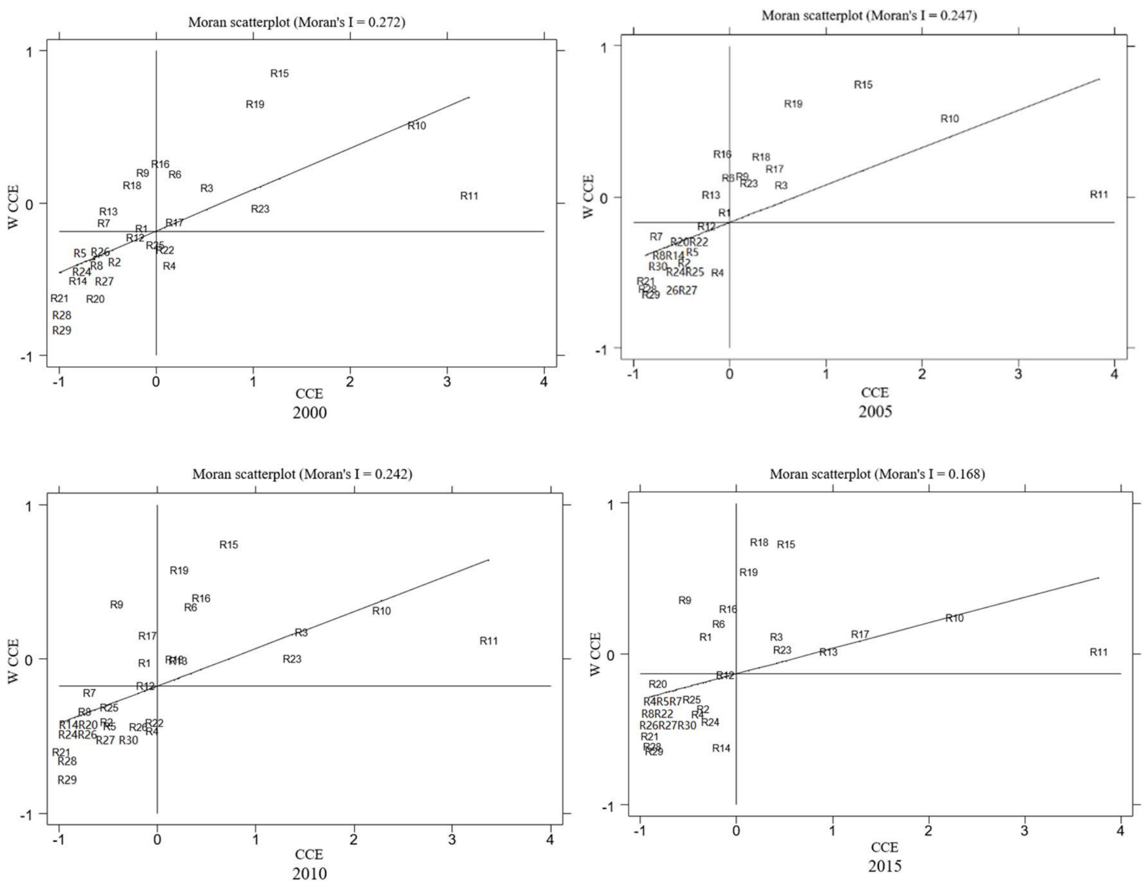

Fig. 2. Local Moran's I scatter plots of China's province-level CCE for selected years.

Note: The horizontal axis of the scatter plot implies the provincial CCE concentrations, while the vertical axis implies the corresponding spatial lag.

Similarly, if the null hypothesis that *H₀: ϑ* þ *δβ* ¼ *0* is accepted, it is more valid to simplify the SDM to the SEM. The results show that the two null hypotheses are accepted at the 5% significance level by the Wald test and the LR test, which indicates that the SDM should be simplified into the SLM and SEM. Fourthly, the results of the LR test for examining the space and time effects concluded that there are both space- and time-fixed effects, namely two-way fixed effects (TWFE).

In conclusion, by employing the SLM and SEM with due consideration given to the TWFE, this study can estimate the relationship between carbon emissions and technical innovations in the construction industry.

3.4. Estimation results of spatial econometric models

It is noteworthy that the coefficients of the SLM and SEM are similar but different with the panel OLS. This is important to note because it further confirms that the non-spatial panel model may lead to the misestimation of the marginal effects of technical innovations on carbon emissions. Given that the SLM is superior in revealing spatial interactions of the provincial CCE than the SEM, the SLM is applied as main explanatory method in order to depict the spatial effects of the provincial CCE.

The spatial autoregressive coefficients are significantly negative at the 1% level, which implies that the CCE of a specific region is negatively affected by nearby regions due to spatial spillovers. Moreover, the spatial coefficient ρ (0.35) indicates that a 1% increase in the CCE of the geographically neighboring regions can cause a 0.35% reduction of CCE from the target region.

In Table 4, all the coefficients of explanatory variables are statistically significant except for PA. The coefficients of CGDP, PR, LP, ME, and TR are significantly positive to carbon emissions, whereas the coefficients of TE and TP are significantly negative.

CGDP, ME, and PR describe the economic performance of the construction industry and recorded coefficients of 0.093, 0.43, and 0.094, respectively, which concurs with the study of Zhang and Da [73]. According to the carbon Kuznets curve hypothesis, the relationship between economic development and carbon emissions varies in different phases. To date, the Chinese construction industry is still in an ascendency phase within the inverted U-shape curve. In fact, China's CGDP soared approximately 14-fold from 1.248 trillion yuan in 2000 to 17.467 trillion yuan in 2015 with a compound growth rate of 19.23%. Simultaneously, the national CCE rose from 252.18 million tons to 1090.67 million tons with an annual growth rate of 10.26%. ME reveals the mechanization level of the construction industry, and, as noted, this is a major source for fossil fuel consumption [50,51]. The positive effect of ME on CO_2 emissions emphasizes the importance of improving mechanical efficiency and the further promotion of clean energy use in the construction industry. In summary, China's economy development and urbanization processes place high requirements on infrastructure construction and housing building; both result in rising CCE.

As innovation performance indicators, TE, TP, TR and LP represent different impacts on CO_2 emissions. On the one hand, a 1% increase of TE and TP can lead to 0.253% and 0.136% carbon emission reductions with significance at the 1% and 5% level, respectively. Evidently, increasing TE can both reduce the number of manual workers and increase productivity, thereby improving energy use efficiency during construction processes [50]. TP measures the ability of knowledge creation and learning, which, undoubtedly, is beneficial for achieving technical progress aimed at securing

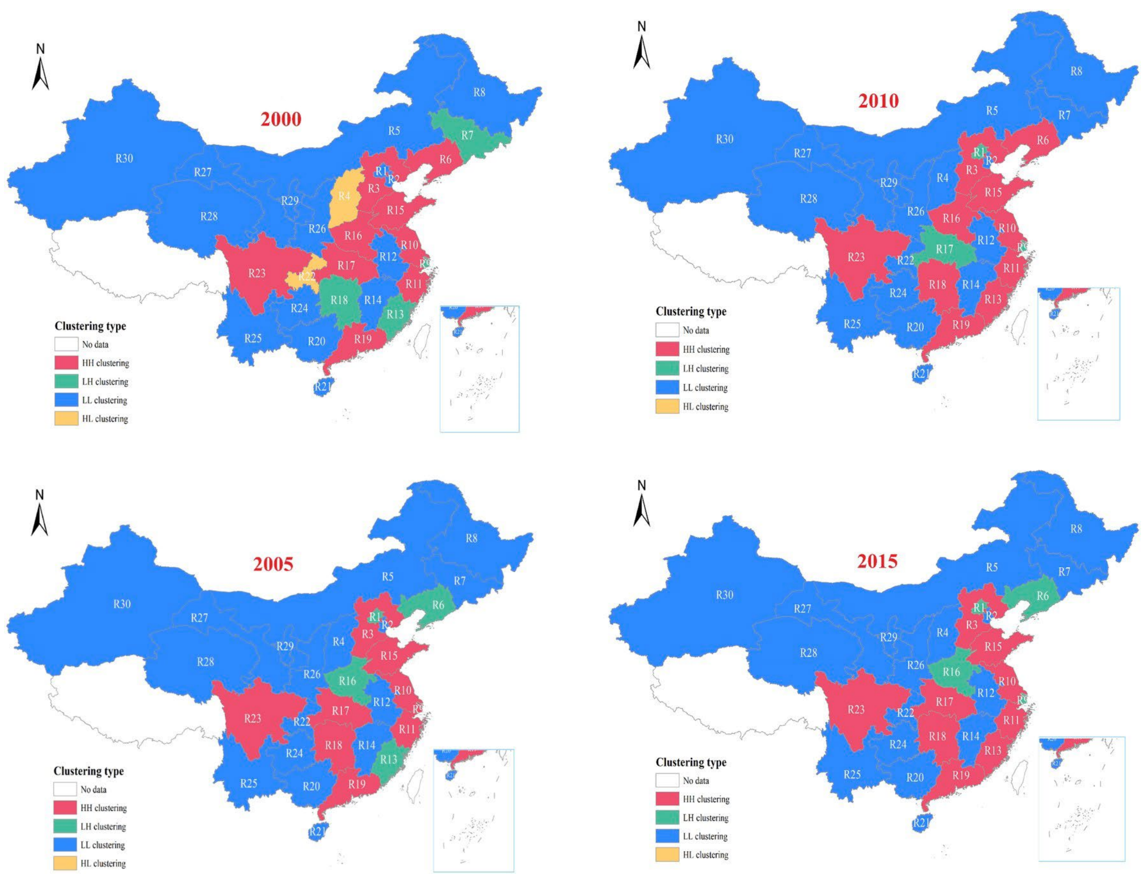

Fig. 3. Spatial clustering types of China's provincial CCE.

emission reductions. The coefficient of TP indicates that the effect of a large proportion of scientific researchers on the reduction of CCE is significantly effective, which is consistent with Zhang, Peng, Ma and Shen [18].On the other hand, TR and LP are statistically significant with coefficient values of 0.021 and 0.194, respectively. LP reflects the ability to create and transform value whilst TR describes technical investment. Both of these two indicators can depict the degree of innovation that is taking place [52]. However, the positive roles of TR and LP with regard to emission growth are contradictory when it comes to issues of economic expectation. This may be partially a consequence of the rebound effect. In other words, the improvement of technical inputs and productivity can minimize production costs and this may further stimulate additional demand for building construction. As a consequence, the massive carbon emissions induced by the growing construction scale trades off the savings stemmed from technical renovation and productivity improvement. Moreover, considering the labor-intensive nature of the construction industry, carbon emissions will continue to increase. To address this issue, it is necessary to enhance the use of technical equipment, as this

Table 6

The transitions of the regions in the Moran's scatter plots.

Year	Transition	2000–2005	2005–2010	2010–2015
Concentration	LH→HH	Shanghai (R9), Hunan (R18)	Liaoning (R6), Fujian (R13), Henan (R16)	
	HL→LL	Shanxi (R4), Chongqing (R22)		Hubei (R17)
	LH→LL	Jilin (R7)		
Deconcentration	LL→LH	Beijing (R1)		
	HH→LH	Liaoning (R6), Henan (R16)	Shanghai (R9), Hubei (R17)	Liaoning (R6), Henan (R16)

can facilitate the transformation of the construction industry from one that is labor-intensive to technique- and capital-intensive.

The number of technology patents measures innovation outputs in a direct manner [55]. However, PA fails to pass the significance test, and this therefore indicates that there is an insignificant spatial correlation between PA and CCE.

According to LeSage and Pace [71], the spatial effects induced by explanatory variables can be disaggregated into direct, indirect, and total effects. As Table 8 illustrates, all coefficients of the direct and indirect effects are statistically significant except for PA. It is worth noting that both CGDP and PR generate indirect but positive effects on emission reductions, which is the opposite with the direct impact effects. This is mainly because the strengthened economic performance of the local construction industry may attract capital and technical inputs which then cause industrial agglomeration and may subsequently trigger efficiency and productivity improvements. Similarly, the indirect impacts from TP and TE are also inversed with the direct impact, which is negatively correlated to emission reductions. In summary, all coefficients of the indirect effects are smaller than those of the direct effects, demonstrating the local-dominant features of factors leading to CO_2 emissions.

4. Discussion and policy implications

According to Fig. 4, CO_2 emissions in China's construction industry experienced rapid growth from 2000 and reached a peak in 2011. The increasing trend was a result of fiscal incentives which were initiated from 2008 onwards and were worth nearly four trillion Chinese Yuan. The whole stimulation plan covered a large volume of infrastructure construction and housing building; both inevitably generated large amounts of CO_2 emissions. For example, the amount of cement (2.84

Table 7

Estimation results of three panel data models and tests.

Variables	panel OLS		SLM		SEM	
	FE	RE	TWFE	RE	TWFE	RE
lnCGDP	0.120**	0.142***	0.093***	0.132***	0.096***	0.124***
	(-3.25)	(-4.13)	(-2.89)	(-3.91)	(-2.9)	(-3.7)
lnTP	0.137	0.0407	0.136**	0.062	0.131**	0.066
	(-1.93)	(-0.74)	(-2.08)	(-1.15)	(-1.97)	(-1.21)
lnPA	0.0127	0.031	0.024	0.043**	0.028	0.031
	(-0.61)	(-1.60)	(-1.21)	(-2.18)	(-1.39)	(-1.62)
lnPR	0.0930**	0.111**	0.094**	0.082**	0.093**	0.123***
	(-2.59)	(-3.24)	(-2.5)	(-2.34)	(-2.49)	(-3.5)
lnTE	0.190*	0.420***	0.253***	0.404***	0.230***	0.436***
	(-2.08)	(-6.85)	(-2.98)	(-6.69)	(-2.67)	(-7.06)
lnLP	0.469***	0.391***	0.194**	0.307***	0.183*	0.354***
	(-6.21)	(-5.86)	(-1.99)	(-4.35)	(-1.85)	(-5.02)
lnME	0.362***	0.629***	0.430***	0.604***	0.409***	0.642***
	(-3.78)	(-10.44)	(-4.9)	(-9.97)	(-4.6)	(-10.65)
lnTR	0.021	0.0318**	0.021*	0.034***	0.021*	0.031***
	(-1.63)	(-2.61)	(-1.82)	(-2.82)	(-1.73)	(-2.67)
cons	1.003	2.802***		2.469***		3.301***
	(-1.03)	(-3.74)		(-3.36)		(-4.32)
ρ			0.350***	0.188***		
			(-3.85)	(-3.13)		

λ					0.299***	0.255***
					(-3.11)	(-3.36)
σ2	0.097***	0.097***	0.073***	0.096***	0.074***	0.095***
R2	0.772	0.767	0.880	0.899	0.895	0.898
the joint LR test	Space fixed	85.06***	Time fixed	221.45***		

SDM with TWFE	Statistics	p-value
Wald test spatial Lag	14.23	0.0760
LR test spatial Lag	9.81	0.2789
Wald test spatial error	13.34	0.0642
LR test spatial error	14.34	0.0733

Notes: ***; **; * denote significant at 1%, 5%, 10% le vel of significance, res ectively. Numbers in brack ets are t-values.

Table 8

Direct, indirect, and total effects.

Variables	LR Direct		LR Indirect		LR Total	
lnCGDP	0.096***	(-2.85)	0.025**	(-2.37)	0.071***	(-2.77)
lnTP	0.140**	(-2.20)	0.037**	(-1.96)	0.104**	(-2.14)
lnPA	0.022	(-1.17)	0.006	(-1.12)	0.016	(-1.15)
lnPR	0.095**	(-2.55)	0.025**	(-2.23)	0.070**	(-2.5)
lnTE	0.254***	(-3.06)	0.067**	(-2.54)	0.187***	(-3.00)
lnLP	0.203**	(-2.06)	0.053*	(-1.86)	0.150**	(-2.02)
lnME	0.433***	(-4.86)	0.114***	(-3.32)	0.318***	(-4.65)
lnTR	0.020*	(-1.81)	0.005*	(-1.66)	0.015*	(-1.78)

Notes: ***; **; * denote significant at 1%, 5%, 10% level of significance, respectively. Numbers in brackets are t-values.

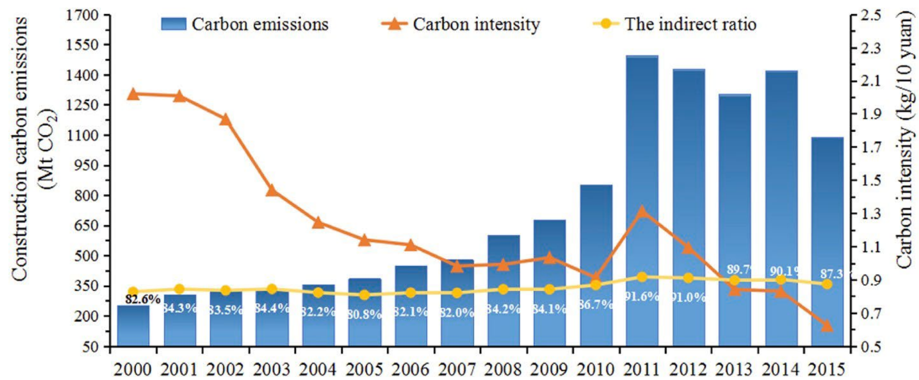

Fig. 4. CO_2 emissions, CO_2 intensity and the indirect ratio in China's construction industry during 2000–2015.

Note: the indirect ratio refers to the ratio of the indirect CO_2 emissions consumed from building materials to the total CO_2 emissions.

billion tons) and aluminum (38.3 million tons) consumed in 2011 was almost twice the level recorded in 2010. At the beginning of 12th Five Year Plan (2010–2015), the central government developed an ambitious emission reduction target system in response to the agreement made in the United Nations Climate Change Conference in Copenhagen. Against this backdrop, the amount of CO_2 emissions represented a declining trend after 2011.

The spatial characteristics of CCE followed the distribution of high in the eastern coastal areas and low in the northern and western inland areas, which is consistent with the distribution of economic development in China. In fact, the economic superiority of the eastern area can trigger population mobility and agglomeration. For instance, according to China's sixth population census in 2010, Guangdong (R19), Zhejiang (R11), Shanghai (R9), and Henan (R18), which are located in the eastern area and categorized into the HH clustering group, had the largest net inflows of population. In contrast, Anhui (R12), Hunan (R18), and Jiangxi (R14) which belong to the LL clustering group had the largest net outflows of population. Such intensive population gathering processes place high demands on infrastructure construction and house building which, in turn, contribute to high CO_2 emissions.

In most previous research, large construction scales and excessive construction activities are regarded as the main contributor responsible for large amount of CO_2 emissions [7,74]. However, an overview of the value of each coefficient reveals that the economy related performance indicators (e.g., CGDP and PR) caused smaller positive impacts on emission growth than the machinery- and labor-related factors (e.g. ME and TP). Therefore, realizing industrial upgrading and structural optimization are more effective than control economic output if one wishes to achieve emission reduction. The results of this study further emphasize the importance of embracing high level technology in order to achieve sustainable construction and emission reduction. It follows, that the construction authorities should devote their efforts to improving informationization and automation levels to maximize the efficiency of equipment, such as 3D printing and 5D-BIM (building information modelling) technology. In this study, patent application shows no statistical correlation with CO_2

emissions and its spillover effect within the construction industry. One possible reason for this is that patent application suffers from long acceptance periods and time-lagged effects. Moreover, the procurement system, social conditions, and energy consumption behavior of the construction industry is more localized than other economic sectors [75–77], this impedes technology transfer and knowledge spillover.

5. Conclusions

The construction industry is the primary contributor to China's present level of CO_2 emissions. Therefore, a systematic understanding of the role of technology innovations in CCE mitigation was of great

Appendix A

Table A1

CO_2 emission factors for 17 energy types

significance. This study has undertaken a spatiotemporal investigation of province-level CCE in China using panel data from 2000 to 2015. Spatial econometric models were employed to estimate the spatial spillover effects of CCE. The conclusions are as follows.

(1) The distribution of the provincial CCE showed remarkable spatial disparities, with high values of CCE concentrated on the eastern coastal area and low values distributed in the northern and western inland areas.
(2) The global Moran's I index indicates a significantly geographical autocorrelation of CCE among different regions. Further, over 80% of regions were in the HH and LL clustering groups; thereby exhibiting a spatial agglomeration trend of provincial CCE.
(3) Based on the estimate of two spatial econometric models (SLM and SEM), the results of spatial autocorrelation implied that the influence of the surrounding regions was positive on the CCE reduction of a specific region.
(4) The factors, including CGDP, PR, LP, ME, and TR, showed significant negative effects on the CCE mitigation. Specifically, the economy related performance indicators led to less positive impacts on emission growth than the machinery- and labor-related indexes. In contrast, TP and TE exerted positive effects on CCE reduction.

Overall, most of the results in this study illustrated the importance of technology innovations for CCE abatement and revealed the *status quo* of low technology innovation level in China's construction industry. The findings of this study systematically quantify the big saving potential of technology innovations, which can be regarded as a solid foundation for making stratified and specific emission reduction policies in the construction industry.

However, this study only glimpses the average effect of driving factors, which may cause inaccurate estimation given the high disparities in the economic development of China. Thus, future studies should investigate the spatial spillover effects of technical innovations on CO_2 emissions by dividing China into eastern, central, and western areas.

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	Energy types	NCV_i (PJ/10^4t, 10^8 m^3)	CC_i (Mt CO_2/PJ)	O_i (%)
1	Raw coal	0.20908	0.087464	88.535
2	Cleaned coal	0.26344	0.087464	88.535
3	Other washed coal	0.15393	0.087464	88.535
4	Briquettes	0.17796	0.087464	88.535
5	Coke	0.28435	0.104292	97.000
6	Coke oven gas	1.6308	0.071414	99.000
7	Other gas	0.8429	0.071414	99.000
8	Crude oil	0.41816	0.073284	98.000
9	Gasoline	0.43124	0.069253	98.000

(*continued on next page*)

Table A1 (*continued*)

	Energy types	NCV_i (PJ/10 t, 10 m)	CC_i (Mt CO_2/PJ)	O_i (%)
10	Kerosene	0.43124	0.071818	98.000
11	Diesel oil	0.42652	0.074017	98.000
12	Fuel oil	0.41816	0.077314	98.000
13	Liquefied petroleum gas (LPG)	0.50179	0.063024	99.000
14	Refinery gas	0.46055	0.073284	99.000
15	Nature gas	3.8931	0.056062	99.000
16	Other petroleum products	0.41816	0.074017	98.000
17	Other coking products	0.28435	0.091212	97.000

Note: Data are from CEADs.

Table A2

Descriptions of regions and CO_2 emission factors of electricity in each region of China

	Regions	Coefficient (tCO_2/MWh)
North China grid	Beijing, Tianjin, Hebei, Shanxi, Shandong and Inner Mongolia	1.0069
Northeast China grid	Liaoning, Jilin and Heilongjiang,	1.1293
East China grid	Shanghai, Jiangsu, Zhejiang, Anhui and Fujian	0.8825
Central China grid	Henan, Hubei, Hunan, Jiangxi, Sichuan and Chongqing	1.1255
Northwest China grid	Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang	1.0246
Southern China grid	Guangdong, Guangxi, Yunnan, and Guizhou	0.9987
Hainan grid	Hainan	0.8154

Data resource: Announcement on Baseline Emission Factor of China Regional Power Grid in 2009.

Table A3

CO_2 emission factors of electricity in each region of China (tCO_2/TJ).

	Region	Value		Region	Value
R1	Beijing	88	R16	Henan	124
R2	Tianjin	108	R17	Hubei	122
R3	Hebei	122	R18	Hunan	110
R4	Shanxi	116	R19	Guangdong	93
R5	Inner Mongolia	160	R20	Guangxi	153
R6	Liaoning	130	R21	Hainan	57
R7	Jilin	132	R22	Chongqing	98
R8	Heilongjiang	155	R23	Sichuan	105
R9	Shanghai	102	R24	Guizhou	292
R10	Jiangsu	109	R25	Yunnan	149
R11	Zhejiang	104	R26	Shaanxi	149
R12	Anhui	116	R27	Gansu	110
R13	Fujian	112	R28	Qinghai	245
R14	Jiangxi	134	R29	Ningxia	120
R15	Shandong	114	R30	Xinjiang	109

Table A4

The CO_2 emission factors and recycling coefficients of main building materials

	Cement	Glass	Steel	Aluminum	Timber
Carbon emission factors	0.8150	0.9655	1.789	2.600	0.8428
Recycling coefficient	0.45	0.7	0.8	0.85	0.2

Note: The unit of emission factor of Timer is kg CO_2/m^3 whilst the units of other emission factors are kg CO_2/kg.

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