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SPECIALTY SECTION

This article was submitted to
Environmental Economics and
Management,
a section of the journal
Frontiers in Environmental Science

RECEIVED 29 September 2022

ACCEPTED 28 October 2022

PUBLISHED 10 November 2022

CITATION

Li T, Gao H and Yu J (2022), Analysis of
the spatial and temporal heterogeneity
of factors influencing CO₂ emissions in
China's construction industry based on
the geographically and temporally
weighted regression model: Evidence
from 30 provinces in China.
Front. Environ. Sci. 10:1057387.
doi: 10.3389/fenvs.2022.1057387

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Analysis of the spatial and temporal heterogeneity of factors influencing CO₂ emissions in China's construction industry based on the geographically and temporally weighted regression model: Evidence from 30 provinces in China

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With the rapid economic development in recent years, China has increased its investment in infrastructure construction, and the construction industry has become a significant contributor to China's carbon dioxide (CO₂) emissions. Therefore, carbon emission reduction in the construction industry is crucial to achieving the goal of "carbon peaking and carbon neutrality" as soon as possible. However, few studies have investigated the factors influencing CO₂ emissions from the construction industry in terms of spatial and temporal differences. To address this gap, we first improve the calculation method for the construction industry's life-cycle assessment (LCA). The geographically and temporally weighted regression (GTWR) model is then utilized to provide insight into the spatio-temporal heterogeneity of the various factors influencing CO₂ emissions across other regions and times. The results show that: 1) CO₂ emissions from the construction industry in China increased rapidly from 576.5 million tons (Mt) in 2004–3,230 Mt in 2012 and then gradually decreased to 1998.51 Mt in 2020; indirect CO₂ emissions accounted for more than 90% of the total CO₂ emissions after 2008. 2) There is a solid global positive correlation between CO₂ emissions from the construction industry in China during most of the time, and the spatial distribution of CO₂

Abbreviations: AMDI, arithmetic mean divisor index; CO₂, carbon dioxide; GDIM, generalized dividing index method; GTWR, geographically and temporally weighted regression; GWR, geographically weighted regression; IDA, index decomposition analysis; OLS, ordinary least squares; LCA, life cycle assessment; LMDI, logarithmic mean division index; RSS, residual sum of squares; SDA, structural decomposition analysis; SA, sensitivity analysis; VIF, variance inflation factor; SD, system dynamics; SDM, spatial Durbin model; TWR, time weighted regression.

emissions shows a northeast-southwest pattern, with the center of gravity gradually shifting from central China to the southwest. 3) Economic output and industrial agglomeration are positive factors for the increase of CO₂ emissions from the construction industry; and urbanization level, production efficiency, and energy efficiency are inhibiting factors for the increase of CO₂ emissions from the construction industry. But the contribution and trend of each influencing factor differed significantly across time and regions, showing substantial spatial and temporal heterogeneity. Our findings provide a scientific basis for the Chinese government to implement a regional carbon reduction strategy for the construction industry.

KEYWORDS

CO₂ emission, construction industry, LCA, GTWR, spatial-temporal heterogeneity, influencing factor

1 Introduction

Global warming caused by greenhouse gases is a global environmental problem that has become a significant threat to the survival of humans and other species (Lu et al., 2020). Among the many greenhouse gases, CO₂ accounts for about 70% (Li and Chen, 2020) and is the most important anthropogenic greenhouse gas in the environment (Li et al., 2021). To fight global warming, it is necessary to ensure that countries worldwide effectively reduce CO₂ emissions (Lu et al., 2020). With rapid urbanization and economic growth, China's CO₂ emissions are enormous and continue to grow, nearly doubling those of the United States and reaching one-third of the world's emissions (Lu et al., 2016; Ma et al., 2019; Zhang et al., 2022). The Chinese government is taking active measures to control CO₂ emissions (Du et al., 2018). Chinese President Xi Jinping pledged at the UN General Assembly and Climate Summit in 2020 that China will increase its autonomous national contribution and introduce more robust policy measures to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (Mallapaty, 2020; Normile, 2020). Therefore, economic restructuring and low carbon development are one of the country's most essential tasks at the moment (Chuai et al., 2015).

Previous studies have shown that the construction industry accounts for more than 40% of the world's energy consumption and 36% of the world's CO₂ emissions (Li et al., 2021). It is an important pillar industry of China's national economy and a resource-intensive industry (Wang and Feng, 2018). Huge resource and energy consumption generate a large amount of CO₂ emissions, accounting for 30% of the national CO₂ emissions (Li and Jiang, 2017). This is a great challenge for China achieving its goals of carbon peak in 2030 and carbon neutrality in 2060 (Li B. et al., 2020). Today, the contradiction between the development of China's construction industry and emission reduction is becoming increasingly prominent. Energy consumption and CO₂ emissions in the construction industry have become increasingly important issues in China's sustainable development (Zhang X. and Wang F., 2016). Therefore,

researches are desired which analyze the mechanism behind various factors influencing CO₂ emissions in the construction industry and provide policy suggestions of regional carbon emission reduction and decarbonization development in the construction industry (Wang and Feng, 2018). Because such research works can not only contribute to the sustainable development of China's economy but also the successful realization of "carbon peak and carbon neutrality" goals (Ma et al., 2020; Shi et al., 2020).

Many existing studies have investigated the influencing factors of CO₂ emissions in the construction industry using methods such as the structural decomposition analysis (SDA) (Shi et al., 2017), logarithmic mean divisia index (LMDI) (Jiang and Li, 2017), etc. However, they do not reflect the spatial and temporal differences of the influencing factors among provinces. The relationship between variables and the structure of the model often change with geographical location. And the spread of CO₂ in the atmosphere needs to be considered (Wang et al., 2018).

Therefore, it is necessary to consider the spatial effect of CO₂ emissions from the construction industry. In this paper, we first improved the method to simplify LCA, and then innovatively introduced the GTWR model to explore the influence mechanism of different factors on CO₂ emissions in the construction industry from two dimensions of time and space, so as to make up for the deficiency of existing research in this aspect. Finally, our analysis results provide a theoretical basis for realizing the low-carbon transformation and development of construction industry in various regions of China and regional carbon emission reduction. To the best of our knowledge, this paper is one of the first studies to analyze the influence mechanism of different factors on CO₂ emissions in the construction industry from the perspective of spatial and temporal differentiation.

The rest of this paper is structured as follows: Section 2 provides a review of the relevant literature. Section 3 provides the data sources and research methodology. Section 4 analyses the data and provides key results. Section 5 discusses the results of the study and develops policy recommendations. Section 6

summarizes the research work and proposes future research directions.

2 Literature review

There are two types of CO₂ emissions from the construction industry: direct and indirect CO₂ emissions (Chen et al., 2017). Direct CO₂ emissions are those caused by on-site combustion activities (Onat et al., 2014). Indirect CO₂ emissions are CO₂ emissions from other related industries induced by the construction industry (Feng and Wang 2015). Indirect CO₂ emissions from the construction industry account for a significant proportion of total CO₂ emissions. Two main methods for calculating CO₂ emissions from the construction industry are the input-output analysis (Hung et al., 2019) and the LCA (Lu et al., 2016). Influenced by Zhang and Liu (2013), the input-output analysis method is valid and commonly used for analyzing indirect CO₂ emissions from the construction industry (Chen et al., 2017; Shi et al., 2017). For example, Du et al. (2019b) used an input-output model to investigate the carbon emissions from the construction industry in Chinese provinces in 2006, 2009, 2012, and 2015 and found that the economic development level of most provinces was positively correlated with carbon emissions. However, China publishes a basic or extended input-output table every 2 or 3 years (Qi and Zhang, 2013), making the input-output analysis method unsuitable for in-depth and timely study (Wu et al., 2018). In contrast, the LCA method conducts a more timely and in-depth study of CO₂ emissions in the construction industry through the statistical data updated every year. Therefore, the LCA has been widely adopted in recent years. The complete life cycle of a building consists of six stages, namely the manufacturing phase of building materials, the transportation phase of building materials, the construction phase, the operation phase, the demolition phase, the waste disposal phase and the recycling phase (Zhang Z. and Wang B., 2016). Due to incomplete dataset, the simplified LCA method proposed by Feng and Wang (2015) considered CO₂ emissions from five construction materials (cement, steel, glass, wood and aluminum) produced by the relevant industries as indirect CO₂ emissions. Many researches assessed the carbon emissions of the construction industry using this simplified LCA, including Zhang et al. (2021), Chi et al. (2021), Wang et al. (2022) and Wen et al. (2020). Among them, Chi et al. (2021) pointed out that indirect carbon emissions from the construction industry accounted for about 95% of the total carbon emissions.

Currently, there are two common decomposition analysis approaches to study factors influencing CO₂ emissions in the construction industry, namely the index decomposition analysis (IDA) and SDA (Chen et al., 2019b). SDA is mainly used with input-output models, which have been extended to help reveal changes in energy consumption or CO₂ emissions in the economy (Chen et al., 2019a). For

example, Liu et al. (2022) used SDA method to find that the industrial structure optimization after 2015 has a significant inhibitory effect on CO₂ emissions in the construction industry, and the final demand plays an absolutely dominant role in improving CO₂ emissions. IDA is mainly used by researchers aiming to understand better the factors influencing energy consumption and CO₂ emissions in specific industries, such as construction. IDA can be further divided into arithmetic mean divisor index (AMDI) methods, LMDI and other forms (Lu et al., 2016). It is worth noting that most researchers prefer to use the LMDI to decompose CO₂ emissions (Gong and Song, 2015; Li D. et al., 2020). The LMDI calculation process is reversible, with no residuals or zero values in the decomposition (Li D. et al., 2020); and it can be developed more flexibly and requires less data than SDA (Shi et al., 2017). In addition, other studies applied models such as the Kaya model (Qi and Zhang, 2013; Shang et al., 2018; Lai et al., 2019), the generalized dividing index method (GDIM) (Li B. et al., 2020), the SDA and the sensitivity analysis (SA) combined model (Chen et al., 2019a), to decompose the factors influencing CO₂ emission changes in China's construction industry. The extended STIRPAT model further takes into account the impact of technological progress. The existing studies have explored the factors influencing CO₂ emissions in the construction industry by constructing extended STIRPAT models and combining them with fixed effects ordinary least squares (OLS) (Zhang et al., 2021), ridge regression (Cong et al., 2015; Zou et al., 2016; Peng, 2019), panel quantile regression (Wang et al., 2020a; Li and Chen, 2020). In addition, some scholars have carried out the structural path of carbon dioxide emissions in the construction industry to discover the impact of different structural paths on carbon dioxide emissions in the construction industry (Wang et al., 2020b; Chen et al., 2022).

Based on the above literature review, we can find that the existing research assumes that different regions are independent of each other, focusing on analyzing the influencing factors of CO₂ emissions in the construction industry from a global perspective, and ignoring the significant spatial interaction effects. Although the spatial Durbin model (SDM) (Lu et al., 2020; Wen et al., 2020) has been used to take the spatial weight matrix into account, no research has studied the different factors influencing the CO₂ emissions from the construction industry in various regions from the perspective of temporal and spatial differentiation (Shen et al., 2020). Therefore, it is necessary for us to explore the influence of different factors from the perspective of temporal and spatial differentiation. The main contributions of this paper are as follows: existing research ignored the fact that the CO₂ emission coefficients of power and heat in different provinces of China are different, and improved the simplified LCA in consideration of these two kinds of energy, so as to make the CO₂ emission estimation of the construction industry more accurate. Then, this paper reveals the spatial and temporal

heterogeneity of the impact of different factors on CO₂ emissions from the construction industry. Comparing the traditional research methods of influencing factors reflects the space-time characteristics of the influencing mechanism. The research results provide a reference value for the government to formulate carbon emission reduction policies for the regional construction industry.

3 Materials and methods

In order to study CO₂ emissions from the construction industry in a more timely and in-depth manner, this paper adopts a simplified LCA method to estimate CO₂ emissions from the construction industry in China; then the dynamic evolution characteristics of spatial pattern in CO₂ emissions at the provincial level are analyzed using a combination of global Moran's *I* and standard deviation ellipse. Finally, we use the GTWR model to explore the formation mechanism behind the dynamic evolution of the spatial CO₂ emission patterns. The specific research methods are described as follows.

3.1 Simplified life-cycle assessment

In this paper, we improve the simplified LCA approach proposed by Feng and Wang, (2015) to divide CO₂ emissions from the construction industry into two parts: direct CO₂ emissions and indirect CO₂ emissions, taking into full consideration the variability of thermal and electric power CO₂ emissions coefficients across regions in China. Direct CO₂ emissions are calculated by multiplying 13 primary energy consumptions such as raw coal, briquette, coke, gasoline, diesel, kerosene, fuel oil, lubricating oil, liquefied petroleum gas, and natural gas by the corresponding CO₂ emission coefficient, plus the secondary energy consumption is calculated by multiplying the related CO₂ emission efficient. Indirect CO₂ emissions are calculated by multiplying the consumption of different building materials (cement, steel, glass, wood and aluminum) by the corresponding CO₂ emission and recovery factors. Through the above methods, we established Eqs 1–3 to calculate the total CO₂ emissions from the construction industry:

$$CO_2 = CO_{2,D_1} + CO_{2,D_2} + CO_{2,I} \quad (1)$$

$$CO_{2,D_1} + CO_{2,D_2} = \sum_{i=1}^n E_i \times NCV_i \times A_i \times O_i \times \frac{44}{12} + \sum_{i=1}^n E_i \times CEF_i \quad (2)$$

$$CO_{2,I} = \sum_{j=1}^n M_j \times \beta_j \times (1 - \alpha_j) \quad (3)$$

Where CO_{2,D_1} represents the direct CO₂ emissions from primary energy in the construction industry, E_i represents the

consumption of the *i*-th energy, NCV_i represents the average low calorific value of the *i*-th energy, and A_i is the *i*-th energy. The carbon content per unit heat of a kind of energy, O_i represents the oxidation rate of *i*-th energy, 44/12 is the molecular weight ratio of CO₂ to carbon; CO_{2,D_2} represents the direct CO₂ emissions from secondary energy in the construction industry. CEF_i represents the CO₂ emission coefficient of electricity and heat by region; $CO_{2,I}$ represents the indirect CO₂ emission from building materials, M_j represents the consumption of the *j*-th building material, β_j represents the CO₂ emission coefficient of the *j*-th building material, α_j represents the recovery coefficient of the *j*-th building material.

3.2 Global Moran's *I*

We use global Moran's *I* to reflect the overall spatial correlation of CO₂ emissions from the construction industry in the whole study area (Wen et al., 2020). The calculation formula is shown in Eq. 4:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (4)$$

Where *n* is the total number of regions, X_i , X_j are the observed values of regions *i* and *j*, w_{ij} is the element of the spatial weight matrix, $S^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$ is the variance, $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$ is the mean, Moran's *I* ∈ [-1,1].

For Moran's *I*, the standardized statistic *Z* is usually used to test the significance of spatial autocorrelation. The calculation formula is shown in Eq. 5:

$$Z = \frac{I - E(I)}{\sqrt{VAR(I)}} \quad (5)$$

where $E(I)$ and $VAR(I)$ are the expected value and variance of the global Moran's *I*, respectively.

3.3 Standard deviation ellipse

In order to investigate the individual characteristics of CO₂ emissions from the construction industry, this paper uses the standard deviation ellipse to study the evolution characteristics of the spatial differences in CO₂ emissions. Standard deviation ellipse is one of the critical spatial econometric analysis methods used to measure regional economic factors' spatial differences and analyze economic factors' spatial distribution characteristics (Liu and Chen, 2016). The main elements include the center of gravity (center point), azimuth, major semi-axis, minor semi-axis, etc. Among them, the center of gravity represents the relative position of the spatial distribution of regional economic factors, and the calculation formula is shown in Eq. 6:

$$\bar{x}_w = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}, \bar{y}_w = \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i} \tag{6}$$

The azimuth angle θ is the angle formed by the clockwise rotation from the north direction to the long axis of the ellipse, which represents the main trend direction of the spatial distribution of economic factors. The calculation formula is shown in Eq. 7:

$$\tan \theta = \frac{\left[\sum_{i=1}^n w_i^2 x_i'^2 - \sum_{i=1}^n w_i^2 y_i'^2 \right]}{2 \sum_{i=1}^n w_i^2 x_i' y_i'} + \frac{\sqrt{\left[\sum_{i=1}^n w_i^2 x_i'^2 - \sum_{i=1}^n w_i^2 y_i'^2 \right]^2 + 4 \left[\sum_{i=1}^n w_i^2 x_i' y_i' \right]^2}}{2 \sum_{i=1}^n w_i^2 x_i' y_i'} \tag{7}$$

The long semi-axis reflects the degree of dispersion of economic factors in the main trend direction; the short semi-axis reflects the degree of dispersion of economic factors in the secondary direction. The calculation formula is shown in Eq. 8:

$$\delta_y = \sqrt{\frac{\sum_{i=1}^n (w_i x_i' \sin \theta \cos \theta - w_i y_i' \cos \theta)^2}{\sum_{i=1}^n w_i^2}}, \delta_x = \sqrt{\frac{\sum_{i=1}^n (w_i x_i' \cos \theta - w_i y_i' \sin \theta)^2}{\sum_{i=1}^n w_i^2}} \tag{8}$$

Where x_i', y_i' represent the relative coordinates from the center of gravity to the spatial location x_i, y_i . w_i represents the weight. θ is the azimuth of the standard deviation ellipse, and represents the clockwise rotation angle formed by the true north direction and the long axis. δ_x, δ_y represent the standard deviation on the X and Y axes, respectively.

3.4 STIRPAT model

Thomas Dietz (1994) proposed the STIRPAT model based on the IPAT model incorporating the environmental impact of socioeconomic activities (He et al., 2017); the model is nonlinear and can estimate elastic coefficients (Zhang et al., 2021). Therefore, the STIRPAT model provides a broad framework for studying the environmental impact of various factors. The standard STIRPAT model is:

$$I = aP^{\alpha_1} A^{\alpha_2} T^{\alpha_3} e \tag{9}$$

where a represents a constant, α_1, α_2 and α_3 are the exponential terms of population size (P), affluence (A) and technology (T), respectively; e is the error term.

In order to fully and accurately explore the main influencing factors of CO₂ emissions from the construction industry, we

added several other important factors to the model (Du et al., 2017; Li B. et al., 2020; Wang et al., 2020a; Lu et al., 2020; Zhang et al., 2021) and expressed all variables in the logarithmic form to eliminate possible heteroskedasticity. The extended STIRPAT model is as follows:

$$\ln CO_2 = a + \alpha_1 \ln POP_{it} + \alpha_2 \ln PGDP_{it} + \alpha_3 \ln ECO_{it} + \alpha_4 \ln ENE_{it} + \alpha_5 \ln LP_{it} + \alpha_6 \ln URB_{it} + \alpha_7 \ln IA_{it} + e_{it} \tag{10}$$

where the CO₂ emissions from the construction industry are the dependent variable. We use year-end population (POP) to denote P. Per capita GDP (PGDP) and economic output (ECO) denote A. Energy efficiency (ENE) denotes T. Extending the STIRPAT model on this basis, we select urbanization level (URB), labor productivity (LP) and industrial agglomeration (IA) as other important factors affecting CO₂ emissions from the construction industry. The detailed definitions of these variables are shown in Table 1.

3.5 GTWR model

Although the geographically weighted regression (GWR) model considers spatial non-stationarity, GWR ignores temporal non-stationarity. In contrast, GTWR considers both spatial and temporal non-stationarity (Yuan et al., 2020). Therefore, we use this model to explore the temporal and spatial heterogeneity of the influence mechanism of different factors on the CO₂ emissions from China's construction industry. The core of GTWR is the selection of the spatial weight function. The spatial correlation of the data is realized through constructing the spatial weight matrix. In this paper, we use the Gaussian function method proposed by Huang et al. (2010) to combine the information from spatial and temporal dimensions.

Before GTWR builds the model, we use the multicollinearity test to check the collinearity of seven variables, including population, urbanization level, per capita GDP, economic output, energy efficiency, labor productivity, and industrial agglomeration. Through the variance inflation factor (VIF) test (as shown in Table 2), it is found that there is a serious collinearity between economic output, population, and GDP per capita. Economic output is closely related to CO₂ emissions (Du et al., 2019b; Lai et al., 2019). However, the spatio-temporal relationship between economic output and CO₂ emission in China's construction industry is far from clear. Understanding this relationship provides a valuable reference for comparing the 'quality' of economic growth in terms of carbon emissions with international counterparts (Wu et al., 2018). Thus, population and GDP per capita are excluded. We combined the STIRPAT model and the VIF test to establish the Eq. 11 of the GTWR model to study the influence of various factors on

TABLE 1 Statistical description.

Variable	Symbol	Definition
Population	POP	Population by province at the end of the year
Per capita GDP	PGDP	GDP to population ratio
Economic output	ECO	Gross output value of construction industry
Energy efficiency	ENE	Ratio of gross construction output to energy consumption
The level of urbanization	URB	Ratio of urban population to total population
Labor productivity	LP	The ratio of the total output value of the construction industry to the number of employees in the construction industry
Industrial agglomeration	IA	$IA_{ij} = (q_{ij}/q_j)/(q_i/q)$, where q_{ij} is the economic output of the i industry in the j region, q_j is the total economic output of the j region, and, q_i is the total output of i industry in the country, q is the country's total economic output

TABLE 2 VIF test.

Variable	VIF	Variable	VIF
POP	33.387	URB	4.348
PGDP	35.588	LP	4.322
ECO	83.596	IA	8.66
ENE	2.289		

CO₂ emissions from the construction industry from the perspective of temporal and spatial differentiation.

$$y_k = \beta_0(u_k, v_k, t_k) + \sum_{p=1}^q \beta_p(u_k, v_k, t_k)x_{kp} + \varepsilon_k \quad (11)$$

Where $\beta_0(u_k, v_k, t_k)$ are the regression intercepts; $\beta_p(u_k, v_k, t_k)$ are the regression coefficients of the variables p ; (u_k, v_k, t_k) are the space-time coordinates of the research unit, where u_k, v_k and t_k are latitude, longitude and time, respectively; $q = 5$; x_{kp} is the data of five variables such as URB, ECO, ENE, LP, and IA in the research unit k , ε_k is the error term for the study unit k .

3.6 Data sources

This paper takes 2004–2020 as the research period and takes the construction industry of 30 provinces in China (due to the lack of energy data, Tibet, Hong Kong, Macao and Taiwan are not included) as the research object. The above-required data are mainly obtained from the 2004–2020 *China Statistical Yearbook*, the *China Construction Statistical Yearbook*, the *China Energy Statistical Yearbook* and *IPCC Guidelines for National Greenhouse Gas Inventories*. The CO₂ emission coefficients of electricity and heat are derived from the studies of [Fan and Zhou \(2019\)](#), and [Li and Zhang \(2016\)](#), respectively. The CO₂ emission coefficients of building materials are derived from the studies of [Feng and Wang \(2015\)](#).

4 Results

4.1 Estimation of CO₂ emission from construction industry

[Figure 1](#) shows the total CO₂ emissions from China's construction industry from 2004 to 2020. From [Figure 1](#), we can see that CO₂ emissions increased from 576.5 Mt to 1998.51 Mt. Between 2004 and 2009, the national CO₂ emissions from the construction industry showed a slow increase with an average annual growth rate of 13.75%. Between 2010 and 2012, national CO₂ emissions from the construction industry increased rapidly, with an average yearly growth rate of 51.95%. Between 2013 and 2020, the trend shifted to a steady decline, with an average annual growth rate of -1.17%, in response to the economic recession triggered by the global financial crisis in 2008. The Chinese government launched the 4 trillion RMB stimulus package to address the challenges of this crisis, which invested mainly in infrastructure development ([Naughton, 2009](#)). This led to massive consumption of building materials in Jilin and Hebei, resulting in a rapid increase in CO₂ emissions from the construction industry from 2010 to 2012. After the 12th Five-Year Plan, China has increased efforts to restructure its industries, placing greater emphasis on energy conservation and emission reduction and curbing high energy consumption. By controlling the total amount of pollutants emitted in the production of building materials such as cement, steel and glass and the regional spatial layout of the building materials industry, indirect CO₂ emissions have been reduced ([Chi et al., 2021](#)). As a result, the total amount of CO₂ emissions from the construction industry has shown a decreasing trend. During the survey period, indirect CO₂ emissions accounted for about 90% of the total CO₂ emissions of the construction industry. In contrast, the proportion of direct CO₂ emissions is very small, ranging from 4.02% to 12.04%. During the period from 2004 to 2020, the direct CO₂ emissions of China's construction industry did not change much; The trend of indirect CO₂ emissions is

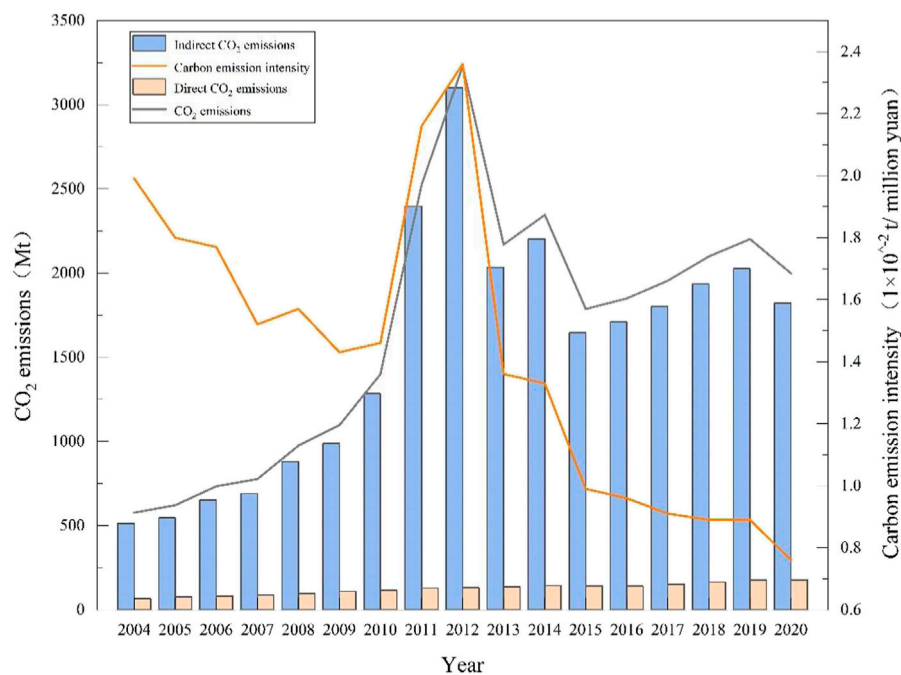


FIGURE 1
Estimation of CO₂ emissions from construction industry in China.

TABLE 3 Global Moran's *I* test results.

Year	Moran's <i>I</i>	<i>p</i> -value	Year	Moran's <i>I</i>	<i>p</i> -value
2004	0.120	0.079	2013	0.020	0.287
2005	0.196	0.026	2014	0.025	0.272
2006	0.162	0.044	2015	0.202	0.027
2007	0.182	0.035	2016	0.233	0.023
2008	0.194	0.037	2017	0.272	0.014
2009	0.205	0.029	2018	0.289	0.009
2010	0.117	0.094	2019	0.409	0.003
2011	-0.028	0.338	2020	0.319	0.008
2012	-0.107	0.222			

basically consistent with that of the total CO₂ emissions of the construction industry.

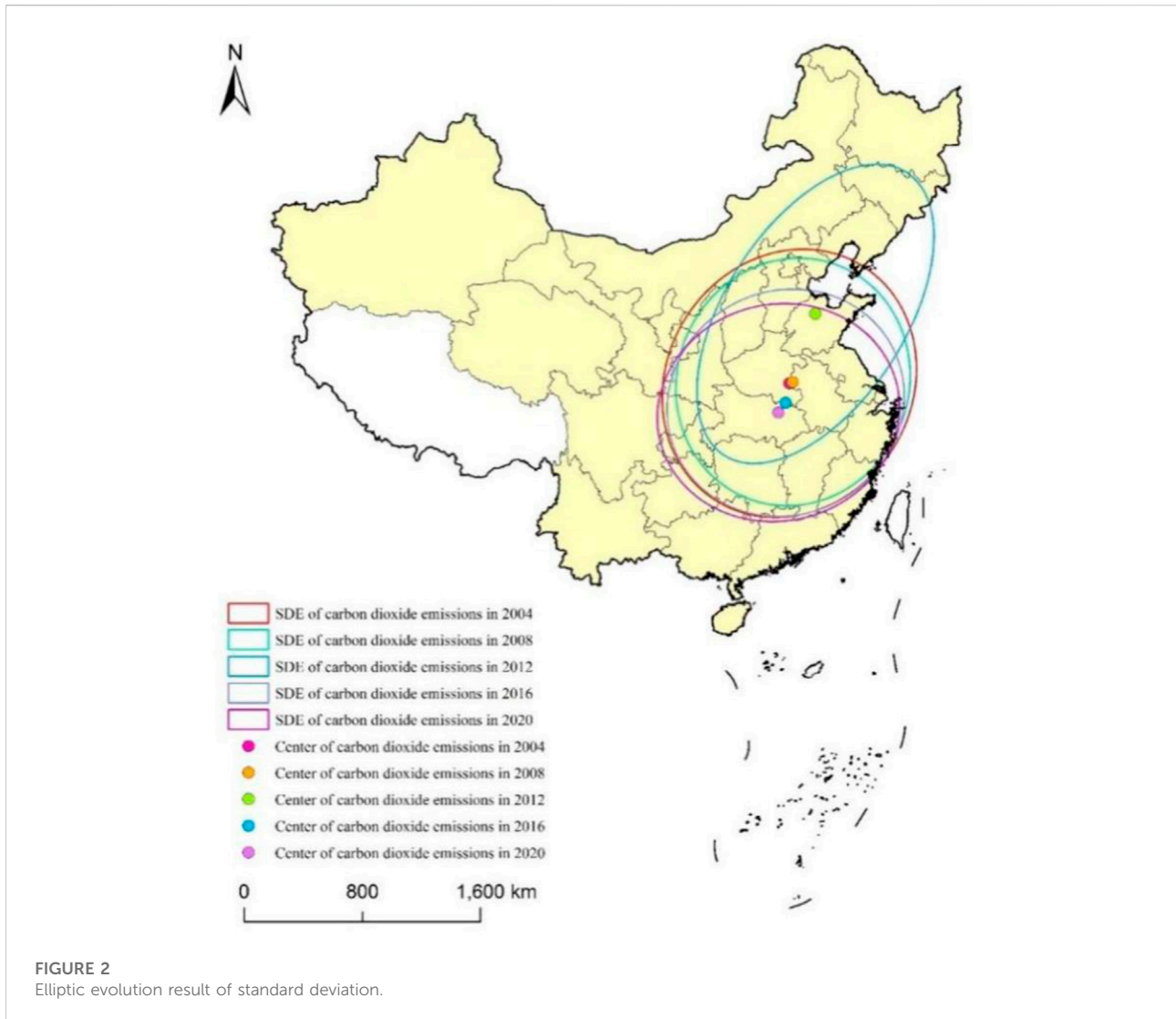
Figure 1 also shows the carbon emission intensity of China's construction industry (the ratio of CO₂ emissions to GDP). As can be observed, it declined from 1.988×10^{-2} t/million yuan to 0.758×10^{-2} t/million yuan between 2004 and 2020, with an average annual growth rate of -5.85%. It is noteworthy that the carbon emission intensity of China's construction industry declined in most of the surveyed years, except for 2008, 2010, 2011 and 2012. In particular, the carbon emissions intensity in 2020 decreased by 57.87% compared to 2005, exceeding the Chinese government's pledge at the Copenhagen Climate

Conference to reduce its carbon emissions intensity by 40–45% (Du et al., 2019a). This has laid a good foundation for the next phase of China's goal of achieving "carbon peaking and carbon neutrality".

4.2 Spatial autocorrelation test

This paper uses GeoDa software to calculate the global Moran's *I* of CO₂ emissions from the construction industry in China for the period 2004–2020. From the Table 3, we can see that the global Moran's *I* for most years of the study period show significant spatial autocorrelation with a statistical significance level below 0.05, which is consistent with the study of Lu et al. (2020). All of the global Moran's *I* with a significance level below 0.05 are positive, and the index is as high as 0.319 in 2020, indicating a strong positive spatial correlation between CO₂ emissions from the construction industry in China.

The global Moran's *I* only reveals the comprehensive global characteristics of CO₂ emissions from China's construction industry and fails to explain the individual characteristics of each region. Therefore, this paper combines the standard deviation ellipse to analyze further the local spatial evolution characteristics of China's construction industry's CO₂ emissions. Since the change of the standard deviation ellipse has a certain regularity, this paper selects a 3-year time interval to intuitively describe the movement trajectory of CO₂ emissions from the



construction industry, and the results are shown in Figure 2. It is shown that the standard deviation ellipse in 2012 deviates from the overall evolution trend. The main reason is that the cement consumption data of Jilin's construction industry during this period increased by more than 50 times compared with the previous year (Chi et al., 2021), resulting in a 55-fold increase in CO₂ emissions from Jilin construction industry. This shifted the ellipse significantly toward the northeastern region; therefore, year 2012 is not included in the description of the evolutionary trend. The standard deviation ellipse of CO₂ emissions from the construction industry from 2004 to 2020 covers most of the eastern and central regions and parts of the western region. The ellipse basically rotates in a clockwise direction, which shows that the trajectory of CO₂ emissions from China's construction industry is relatively regular, and the spatial differentiation pattern is relatively stable. From 2004 to 2020, the standard deviation ellipse of CO₂ emissions from the construction

industry covers most of the eastern and central regions as well as parts of the western region. Its center of gravity moves from Anhui to Henan and then to Hubei, gradually shifting to the southwest. As shown in Table 4, the ellipse rotates clockwise with azimuth θ changing from 31.359° in 2004 to 76.775° in 2020. It shows that the CO₂ emission in the eastern region has a more significant pulling effect on the western region. The azimuth changes to a balanced state, and the CO₂ emission distribution forms a northeast-southwest pattern gradually.

In the direction of the long axis of the standard deviation ellipse, the standard deviation of the Y-axis shortens from 939.809 km in 2004 to 824.947 km in 2020, indicating a spatial polarization of CO₂ emissions in the northeast-southwest direction. Specifically, the standard deviation on the Y-axis shortens from 939.809 km in 2004 to 849.783 km in 2008; the reason for this change is the weak economic base and slow economic growth in the southwest and northeast regions. This

TABLE 4 Statistical description of standard deviation results.

Year	Center of gravity coordinates	Directional angle θ	Standard deviation along the x -axis (km)	Standard deviation along the y -axis (km)
2004	115°10'12",33°07'33"	31.359	831.337	939.809
2008	115°24'30",33°09'08"	20.587	785.931	849.783
2012	118°14'21",37°11'48"	32.674	610.539	1,143.671
2016	114°40'19",31°52'59"	61.389	759.215	816.986
2020	114°04'11",31°18'52"	76.775	736.311	824.947

makes the increment of CO₂ emissions from the construction industry decrease. The standard deviation on the Y -axis expands from 849.783 to 960.939 km from 2008 to 2014, indicating that the spatial distribution of CO₂ emissions tends to diverge in the Y -axis direction, a trend that may be explained by the fact that in response to the economic crisis, the state increased its investment in infrastructure, and the northeast and southwest regions promoted the rapid development of the construction industry with the help of national policies, resulting in a surge in CO₂ emissions from the construction industry in the two regions. From 2014 to 2018, the standard deviation of the Y -axis shortened from 960.939 km to 801.559 km, and the spatial polarization of construction CO₂ emissions in the northeast-southwest direction intensifies; this results from the technological spillover effect of the construction industry in the eastern region, pulling the emission reduction efforts in the northeast and southwest regions. In period 2018–2020, it expands from 801.559 km to 824.947 km, indicating that the spatial distribution of the construction CO₂ emissions tends to be dispersed again. In the direction of the short axis of the standard deviation ellipse, the standard deviation along the X -axis continues to shorten from 831.337 km in 2004 to 736.31 km in 2020, indicating the spatial polarization of CO₂ emissions from the construction industry in China is increasing in the northeast-southwest direction.

4.3 GTWR test

4.3.1 Model fitting

The above analysis reveals the spatial autocorrelation and significant spatial variation of CO₂ emissions in China's construction industry through global Moran's I and standard deviation ellipses, showing that CO₂ emissions in China's construction industry have spatial autocorrelation and significant spatial differences. To further reveal the formation mechanism of the dynamic evolution characteristics of spatial differences in CO₂ emissions in China's construction industry, this paper uses GTWR to conduct a comparative analysis of five factors, namely urbanization, economic output, energy efficiency, industrial agglomeration, and labor productivity.

TABLE 5 Comparison of model test results.

Models	R ²	Adj. R ²	RSS	AICc
OLS	0.896	0.895	73.699	472.765
TWR	0.908	0.907	65.061	444.157
GWR	0.919	0.918	57.514	429.109
GTWR	0.939	0.938	43.588	387.100

To verify the applicability and accuracy of the GTWR model, calculations were performed using 17 years of spatial panel data from 2004 to 2020, and the GTWR results were compared with those of OLS, GWR and time weighted regression (TWR). The model-related parameters are shown in Table 5. R^2 and adjusted R^2 (Adj. R^2) reflect the degree of model fit; the residual sum of squares (RSS) reflects the model's accuracy. The AICc value can be used as another important criterion to assess the model's merit, with smaller values indicating higher accuracy (Ma et al., 2021). As can be seen from the table, the GTWR model has a maximum fit of 0.939. The AICc values between models are much greater than 3, with the minimum value being 387.1 for GTWR, indicating a significant difference in the performance among various models. The GTWR model has higher accuracy. Compared with other models, the regression coefficients of the GTWR model are non-stationary in time and space; therefore, it can better explain the spatial and temporal distribution of factors influencing CO₂ emissions in the construction industry Table 5.

4.3.2 Time evolution of influence degree

Figure 3 shows the time evolution characteristics of the five influencing factors of CO₂ emissions from the construction industry in China. We can see that economic output is the dominant factor in the increase of CO₂ emissions each year. The development of the economy has driven the development of the industry; the real estate boom continues to heat up. The increasing standard of living has increased the demand for infrastructure construction, housing construction and commercial and industrial land construction. With the continuous expansion of construction scale, the energy consumption of the construction industry increases, and the

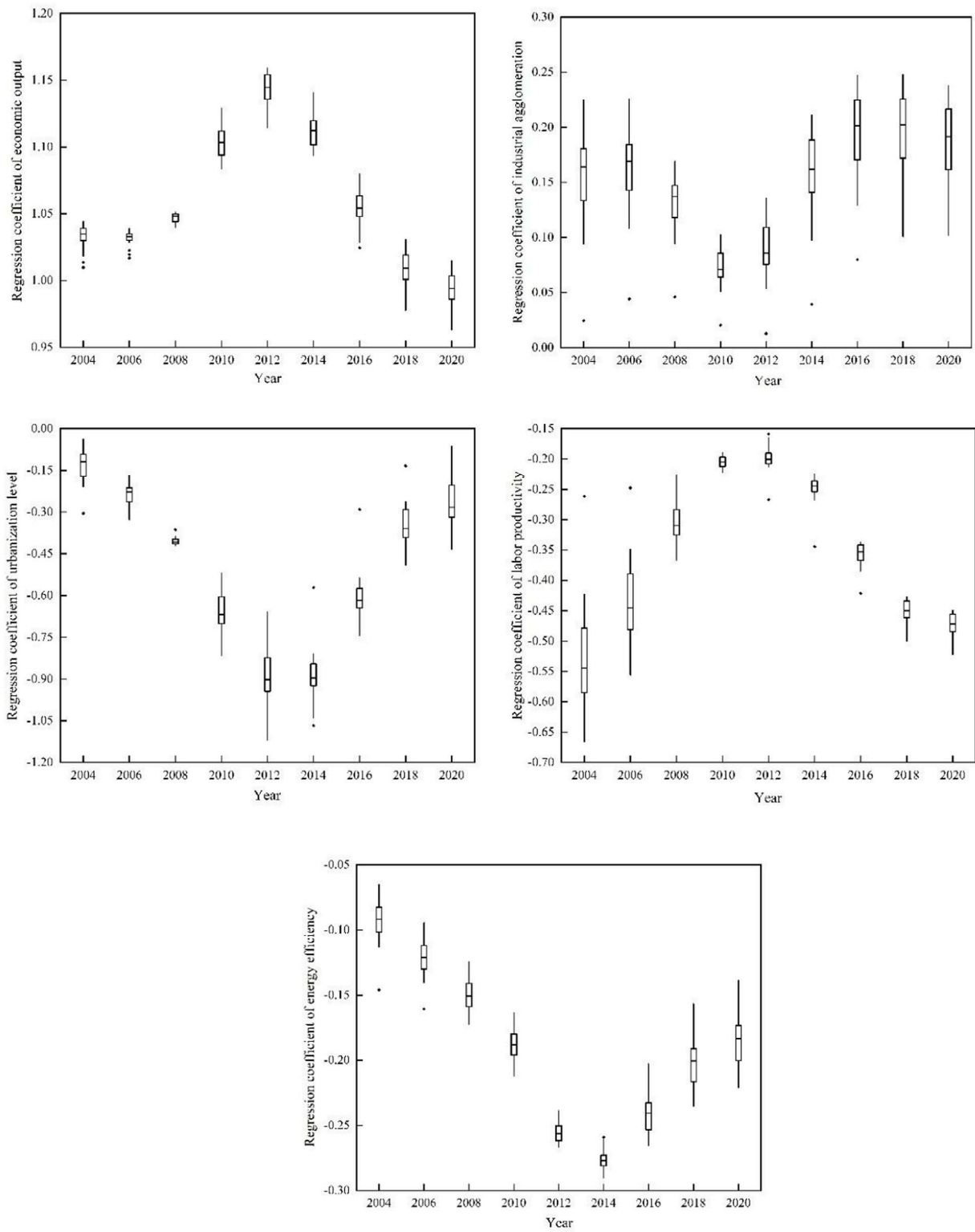


FIGURE 3
Time series trend of GTWR regression coefficients.

carbon emissions also increases accordingly. From 2004 to 2012, the contribution of economic output to the construction industry's CO₂ emissions increased, with the regression coefficient reaching its maximum value in 2012. The contribution of economic output to the construction industry's CO₂ emissions gradually weakened after 2012, and the regression coefficient reached its lowest level in 2020. With the improvement of the economic development level, the formulation of the low-carbon economy strategy and the introduction of carbon emission reduction targets, the development of a low-carbon economy strategy and the carbon emission reduction goal has made it possible to control the CO₂ emissions. Industrial agglomeration has contributed to the increase of CO₂ emissions in the construction industry in all years. On the one hand, industrial agglomeration increases economic activity and leads to more CO₂ emissions; on the other hand, industrial agglomeration may lead to specialization and technological innovation in the construction industry, resulting in a reduction of CO₂ emissions. Our results seem to imply that the 'growth effect' is greater than the 'reduction effect', which leads to an increase in construction CO₂ emissions (Li et al., 2021).

The level of urbanization is the main inhibiting factor for the increase in CO₂ emissions from the construction industry. Urbanization has been shown to promote the concentration of production factors, accelerate technological development and promote cleaner production, thereby reducing CO₂ (Zhang et al., 2016; Wang and Zhao, 2018). The inhibition effect of urbanization level has been increasing from 2004 to 2012, with the regression coefficient reaching a maximum in 2012 and decreasing thereafter. Labor productivity is the second most important inhibiting factor for the increase of CO₂ emissions in the construction industry. The inhibition effect of labor productivity, which reflects the level of production technology in the construction industry, has shown a weakening and then increasing impact over time. In the years following the financial crisis, China increased investment in infrastructure construction, leading to relatively extensive operation and management which decreases the labor productivity and an increases the CO₂ emissions from the construction industry. It is worth noting that in some years, labor productivity had a stronger role in curbing construction CO₂ emissions than urbanization. Energy efficiency had a inhibition effect on the increase in construction CO₂ emissions in all years, but energy efficiency had little influence on reducing national construction CO₂ emissions (Wang et al., 2018). Energy efficiency is a measure of energy-efficient technologies in the construction industry, and the fragile inhibition effect of energy efficiency in 2004 suggests that the construction industry employs few energy-efficiency technologies in the early years. This inhibition effect slowly increases as the level of energy-efficient technologies develop in the construction industry Figures 4, 5, 6, 7, 8.

4.3.3 Spatial heterogeneity of influence degree

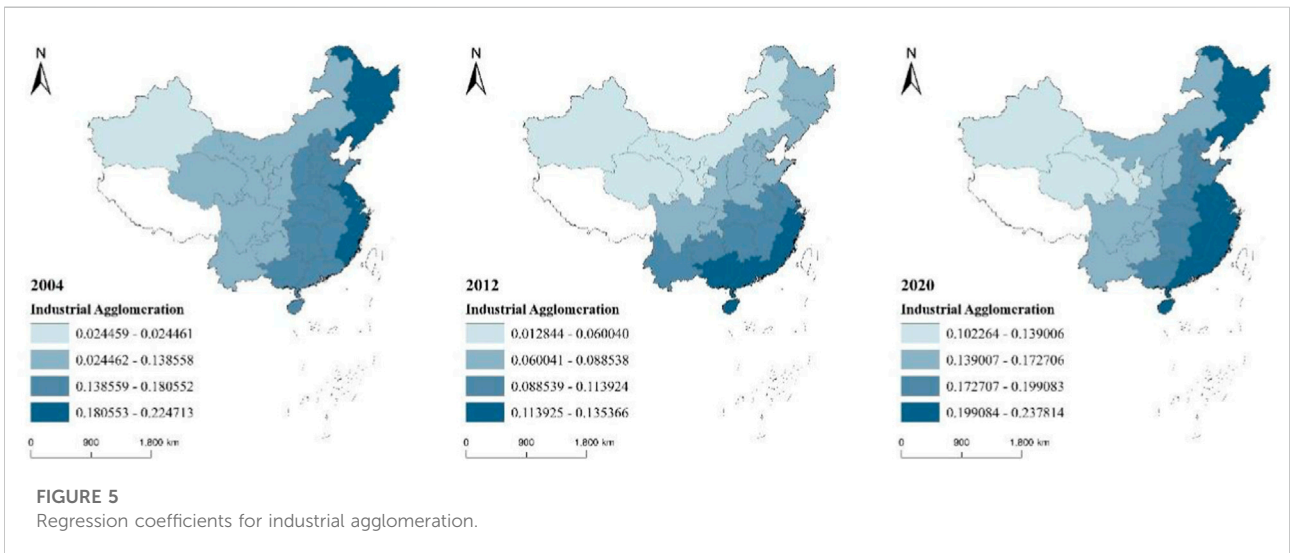
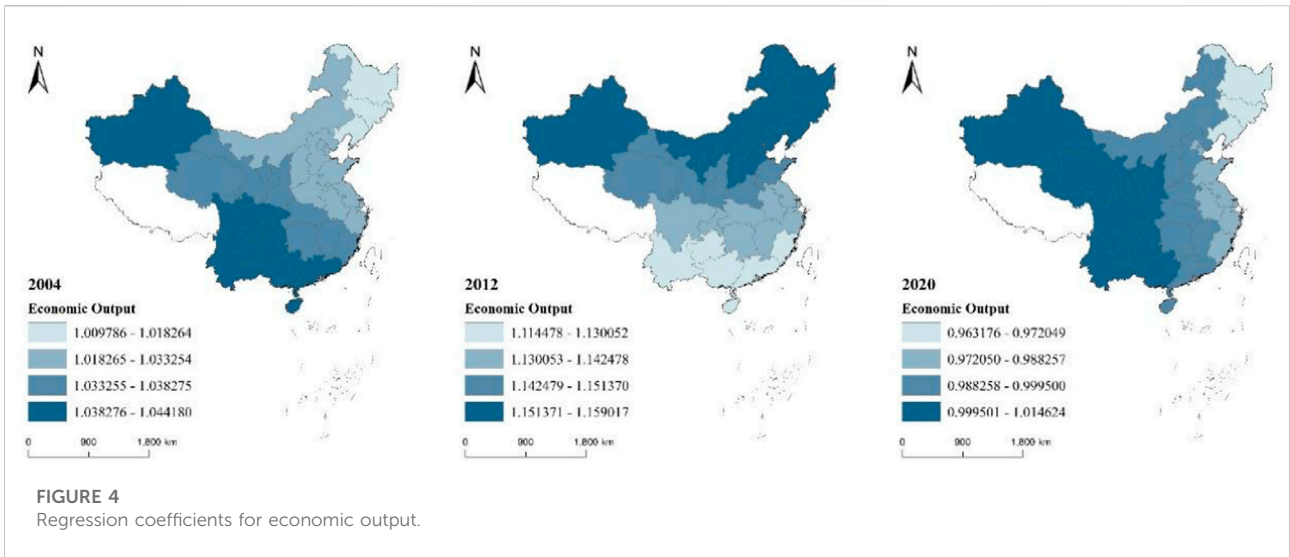
The GTWR model can calculate regression coefficients for different temporal and spatial influences and visualize them in ArcGIS 10.3. This aids to explore the various factors influencing carbon emissions in a local area. Results are visualized for 2004, 2012 and 2020 in this paper.

As shown in Figure 4, economic output yields higher influence on CO₂ emissions in the western provinces such as Xinjiang, Yunnan, Sichuan and Guizhou, mainly because these regions are relatively underdeveloped and lack of advanced technologies; they need to consume more energy and produce large amounts of CO₂ in exchange for the development of the construction industry. The provinces with higher regression coefficients of economic output in 2004 are located in the western regions, and in 2012 the provinces with higher regression coefficients shifted to the northeast and north central. The government has increased infrastructure investment to rapidly revive China's economy, leading to a significant construction boom in traditional industrial bases such as Heilongjiang, Jilin and Hebei, resulting in a sharp increase in CO₂ emissions from the construction industry. By 2020, the values with more significant regression coefficients for economic output gradually change to the western regions, led by Xinjiang, Yunnan, Sichuan and Guizhou.

As shown in Figure 5, from 2004 to 2020, the regions where industrial agglomeration has a more significant influence on CO₂ emissions remain unchanged and consistently distributed in China's eastern coastal and northeastern regions. By 2020, the provinces with larger coefficients are mainly located in Jiangsu, Zhejiang and Shanghai, Fujian, Guangdong and the three northeastern provinces, while the provinces with smaller coefficients are primarily located in the western regions, such as Xinjiang, Qinghai, Gansu, and Ningxia. This indicates that the construction industry in the eastern coastal and northeastern regions of China is more prone to agglomeration compared to the central and western regions; and this industry agglomeration is more likely to promote an increase in economic activities and energy demand in the construction industry, thus leading to the accelerated growth of CO₂ emissions.

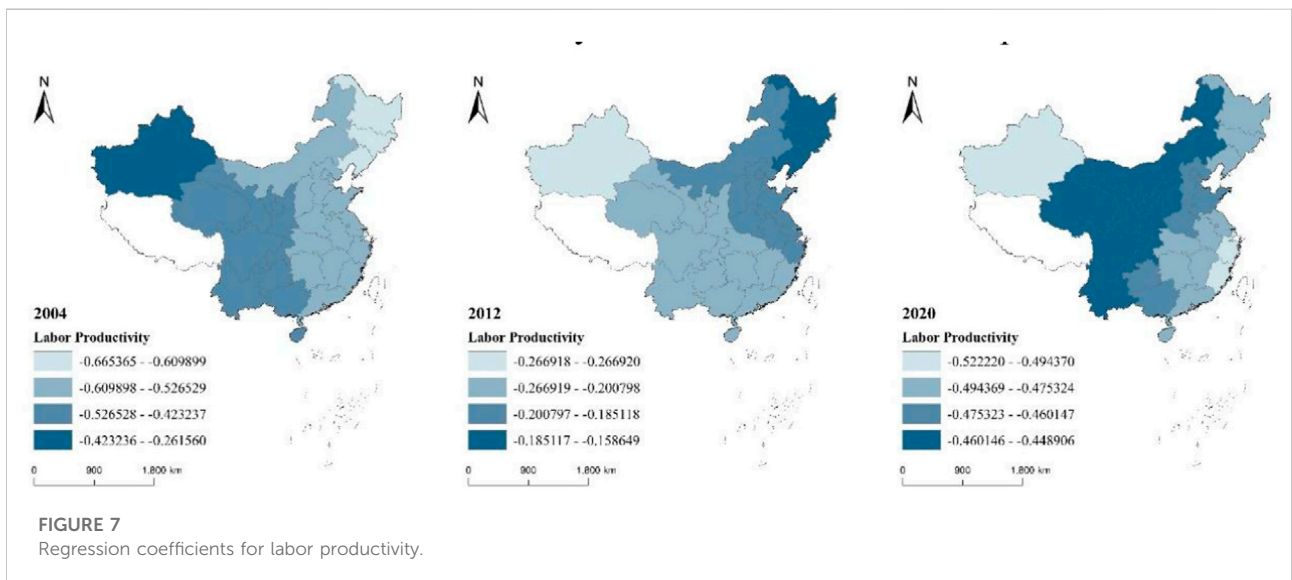
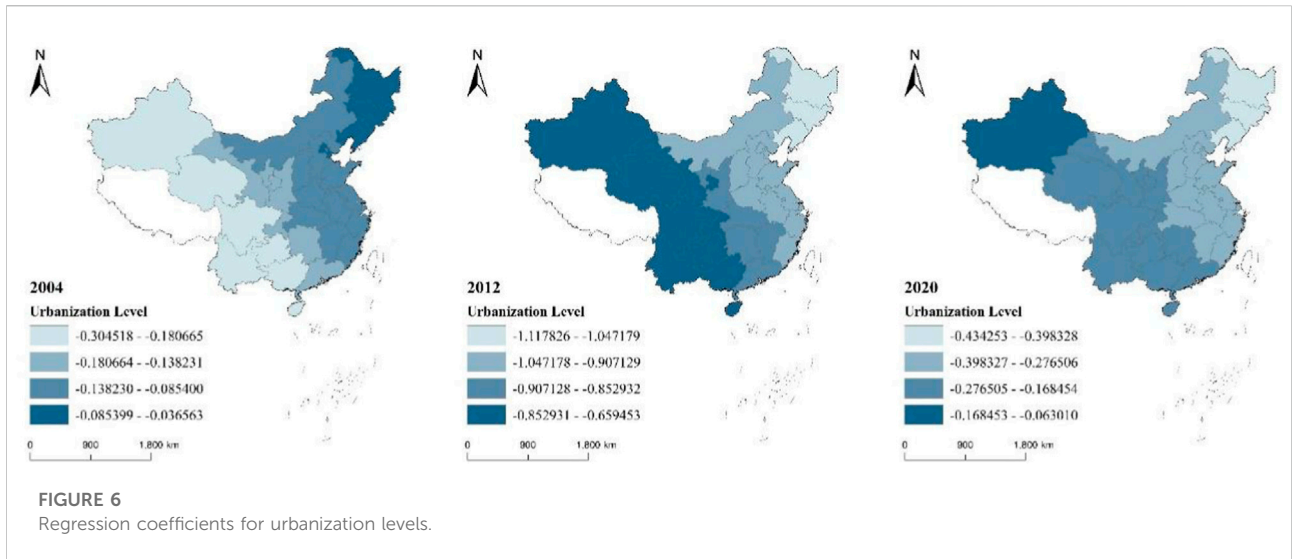
As shown in Figure 6, the level of urbanization inhibits the increase in CO₂ emissions from the construction industry in each province. In 2004, the inhibition effect was more significant in most of the western provinces. The inhibition effect of urbanization increased over time, and provinces with strong inhibition effect shifted from the west to the eastern coastal and north-eastern regions. By 2020, provinces with strong inhibition effect are distributed among the east, central and north-eastern China, and Xinjiang yielded the smallest absolute regression coefficients. This fully illustrates that the inhibition effect is more significant in regions with a high level of urbanization than in the urbanizing and non-urbanized regions (Zhang et al., 2021). The regression coefficients are the smallest in Xinjiang.

As shown in Figure 7, from 2004 to 2020, areas where labor productivity has less influence on CO₂ emissions gradually shifted to central and western China. In 2020, provinces with



large absolute values of coefficients were mainly distributed in the eastern coastal areas, including Shanghai, Zhejiang, Fujian and other regions. In contrast, provinces with small absolute values of coefficients are concentrated in the central and western regions. The influence of labor productivity on CO₂ emissions in eastern provinces is greater than that in central and western provinces. In recent years, the western region has paid attention to the introduction of excellent talents, promoting the increase in well-educated workforce. As a result, the labor productivity of many western provinces has exceeds that of some eastern provinces. This also implies that the improvement in production efficiency will gradually weaken the role of emission reductions in the construction industry in the central and western provinces.

As shown in [Figure 8](#), energy efficiency suppresses CO₂ emissions from the construction industry in each province, and the influence of technological progress on CO₂ emissions is relatively weak and unstable compared to the other variables. With its more significant inhibition effect shifting from the north of Qinling-Huaihe line to western China. From 2020, the provinces where energy efficiency have considerable influence on CO₂ emissions are Xinjiang, Gansu, Qinghai, Sichuan and Yunnan, which are located in central and western China. The main reason is that carbon emissions in less developed regions are vulnerable to technological advances (Du et al., 2017). The progress of energy efficiency technologies can contribute well to carbon emission reduction, while developed regions with higher technology levels and complex technological innovation are



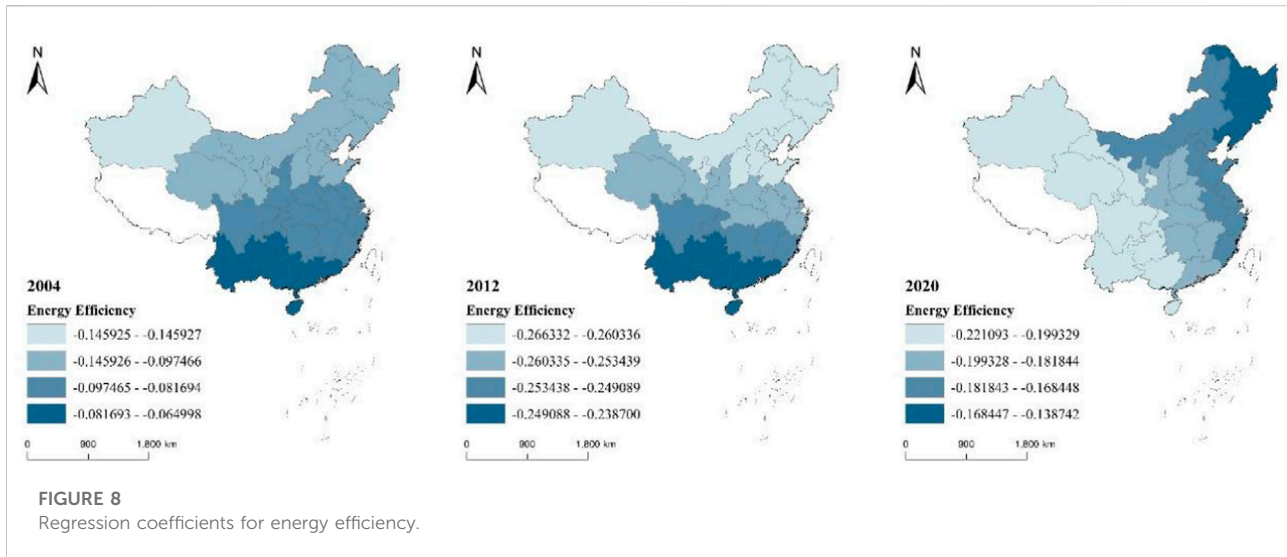
prone to encounter technical bottlenecks, making it challenging to improve energy efficiency further. This weakens its potential for CO₂ emission reduction in the construction industry.

5 Discussion

5.1 Implications for theory

This paper provides a new perspective on the spatial and temporal analysis of CO₂ emissions from the construction industry in China. Existing studies mainly use SDA (Shi et al., 2017), IDA (Gong and Song, 2015) or STIRPAT combined with

panel regression (Zhang et al., 2021), which ignores the spatiotemporal heterogeneity in the degree of influence of different factors. This study investigates both the spatial and temporal non-stationarity of the influencing factors through GTWR. In order to make a more timely and in-depth study, this paper improves the simplified LCA method considering the regional differences of CO₂ emission coefficients of electricity and heat, and estimates the CO₂ emission of construction industry in China. Results show that indirect CO₂ emissions account for about 90% of the total CO₂ emissions from the construction industry in China, which is consistent to the results in Du et al. (2018), Feng and Wang (2015). Although we take into account regional differences in CO₂ emission efficient from



electricity and heat generation, they do not have a significant influence on the final results. Our work found a 57.87% reduction in the carbon intensity of the construction industry through the calculation of 2020 data. In this paper, we found a 57.87% decrease in carbon emission intensity in 2020, which is similar to the result of Du et al. (2019a) using system dynamics (SD) model to predict the optimal portfolio reduction. This indicates that the carbon emission reduction in China's construction industry is moving towards the optimal direction in recent years. The paper also utilizes global Moran's I and standard deviation ellipses to verify the spatial correlation and heterogeneity of CO₂ emissions from the construction industry (Lu et al., 2020). The results show the necessity to consider spatial and temporal heterogeneity when analyzing the mechanism behind the dynamic evolution characteristics of the spatial differences in CO₂ emissions in the construction industry. Therefore, in this paper, we apply GTWR to analyze the spatial and temporal heterogeneity of the influence of different factors on CO₂ emissions from the construction industry. We extend the STIRPAT model with common influencing factors (population, per capita GDP, economic output, energy efficiency, urbanization level) and test the spatio-temporal heterogeneity of the impact of labor productivity and industrial agglomeration on CO₂ emissions in the construction industry. The results indicate that economic output is the dominant factor in the increase of CO₂ emissions in the construction industry (Hu and Chu, 2015; Jiang and Li, 2017; Du et al., 2019b; Li B. et al., 2020). Industrial agglomeration is the second most important factor in the rise of CO₂ emissions in the construction industry, which are consistent with those of Li et al. (2021), Zhang and Lu (2015). The level of urbanization is the main inhibitory factor for the increase of CO₂ emissions from the construction industry, and the inhibitory effect of areas with a high level of urbanization is significantly greater than that of urbanizing and non-urbanized

regions (Zhang et al., 2021). Labor productivity is the second most important inhibiting factor. Although energy efficiency has a inhibition effect on the increase of CO₂ emissions, this effect seems to be weak and unstable (Li et al., 2012; Wang et al., 2018). This result also supports the findings of Liu and Lin (2017) and Lin and Liu (2015) that there is excellent potential for a decrease in energy intensity and an increase in energy efficiency in the Chinese construction industry (Wu et al., 2018). Overall, our results indicate that many factors have different effects on CO₂ emissions from the construction industry in other regions. This implies that local governments should strengthen inter-regional cooperation, promote cross-regional technology sharing and exchange, and collaborate on regional policies to reduce carbon emissions and work together to achieve the goal of "carbon peaking and carbon neutrality".

5.2 Implications for practice

Based on the above results and discussions, we can conclude that CO₂ emissions from the construction industry have obvious spatial effects, so this paper formulates emission reduction policies based on the spatial and temporal characteristics of the factors influencing CO₂ emissions in each region.

Economic output is the most crucial reason for the increase in CO₂ emissions from the construction industry in each region. However, the current extensive development model of the construction industry still exists; therefore, the government should set reasonable carbon emission reduction targets for each region according to local conditions, and synergistic emission reduction plans can be developed between neighboring provinces. First of all, the economically developed eastern provinces have a large volume of CO₂ emissions from the construction industry and should take on more CO₂ reduction

tasks. At the same time, the central and western regions should actively promote the transformation to a low-carbon economy. Second, a fair national carbon trading market and the legal system related to green buildings should be established and improved. The government should vigorously promote the low-carbon, green and high-quality development of the construction industry, and find a path for the coordinated development between the economic output of the construction industry and CO₂ emissions.

The government should promote the construction of a new urbanization model with a focus on green and high-quality development, and different regions should adhere to different urbanization strategies. Eastern regions should accelerate the coordination of urbanization development levels in central and western regions and jointly promote the green transformation of regional urbanization; central and western regions should continue to accelerate the urbanization of central cities (Li L. et al., 2020) and encourage the transfer of large and medium-sized cities to smaller cities in some regions, to form a mutually beneficial and win-win high-quality development model in the region and jointly curb the generation of CO₂ in the construction industry.

The emission reduction effect of energy efficiency is relatively weak and unstable. To achieve the emission reduction target of CO₂ emissions from the construction industry, it is necessary to improve energy efficiency while adjusting the industrial agglomeration pattern. Firstly, technological exchanges and cooperation across regions should be strengthened, promoting the technological achievements relating to energy efficiency and emission reduction from the east regions to the central and western regions. The eastern regions should increase investment in science and technology to achieve more technical breakthroughs on energy efficiency and emission reduction technologies while actively introducing advanced technologies from abroad. Secondly, the government should promote the active development of clean energy sources such as nuclear power, wind power, solar energy, tidal energy and green building materials such as eco-cement, fiber-reinforced composite materials and new green wall materials by relying on the favorable resources of each region.

Increased labor productivity plays an essential role in achieving carbon emission reduction targets. The government should raise environmental awareness among employees of construction companies at all levels, continue to strengthen policies for the introduction of construction talent in central and western regions, systematically train highly educated personnel in skill levels, and promote highly educated personnel to work on the front line as soon as possible; eastern regions should improve the overall quality of their construction teams to prevent the emergence of a general ageing construction workforce, further enhance labor

productivity in the construction industry, and promote regional carbon emission reduction.

6 Conclusion and limitations

6.1 Conclusion

This paper studies the spatial and temporal characteristics of CO₂ emissions from the construction industry in China at the provincial level, and investigates the mechanisms of different factors influencing CO₂ emissions from the perspective of spatial and temporal divergence based on the GTWR model. The findings of the study are as follows.

CO₂ emissions from the construction industry in China showed a trend of first increasing and then decreasing. It grew rapidly from 576.5 Mt in 2004–3,230 Mt in 2012, and then gradually decreased to 1998.51 Mt in 2020. After 2008, indirect CO₂ emissions account for more than 90% of total CO₂ emissions. Compared to 2005, the carbon intensity of the construction industry decreased by 57.87% in 2020. In terms of the spatial pattern, the empirical results show that there is a strong global positive correlation of CO₂ emissions from the construction industry in China during most of the concerned period. In terms of the standard deviation ellipse, the spatial distribution of CO₂ emissions from the construction industry in China shows a northeast-southwest pattern. The combination of the standard deviation of the long and short axes leads to a spatial polarization of CO₂ emissions in the northeast-southwest direction, and the center of gravity gradually shifts from central China to the southwest.

Due to the spatial and temporal heterogeneity of the different factors influencing provincial CO₂ emissions from the construction industry, the estimates from the GTWR analysis are more accurate than the classical econometric models. The regression results show that significant non-uniform linkage localization and spatial heterogeneity exist in the influence of various factors on CO₂ emissions from the construction industry. Economic output is the dominant factor, and its degree of influence strengthens before weakening in time and it increases spatially from east to west. Industrial agglomeration is the second most important factor, and its degree of influence weakens before strengthening in time and it decreases spatially from east to west. The level of urbanization is the most important inhibiting factor in the increase of CO₂ emissions from the construction industry, and its degree of influence strengthens before weakening in time and it decreases spatially from east to west. Production efficiency is the second most important inhibitor, with its influence decreasing in time and then increasing in space from southeast to northwest. Energy efficiency is the least essential inhibitor with its influence increasing in time and decreasing in space from northeast to southwest.

6.2 Limitations

Given the above studies, there are still some limitations in this paper. Firstly, we have not considered how the CO₂ emission coefficients for each energy source change with technological advances. Secondly, due to data limitations, this paper has adopted a simplified LCA model and lacks an assessment of the whole life cycle of the construction industry at stage 6. Thirdly, this paper has not quantified the differences that exist in CO₂ emissions from the construction industry. Future research can be improved as follows: firstly, the scope of activities in the six stages of the construction industry can be delineated in detail, and CO₂ emissions can be accurately assessed taking into account the changes in the emission factors of each energy source; then the Thiel index and Gini coefficient can be used to quantify the differences in CO₂ emissions in the construction industry in each region, and on the basis of the clarification of regional differences, a more accurate assessment of CO₂ emissions in the construction industry can be made in order to achieve the goal of “carbon peaking and carbon neutrality” as soon as possible. On the basis of clear regional differences, a more comprehensive regional carbon reduction policy for the construction industry will be formulated in order to achieve the goal of carbon peaking and carbon neutral” as soon as possible.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: <http://www.stats.gov.cn/>.

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Author contributions

The experiments and paper writing for this study were done by TL, HG provided the theoretical support. JY collected the data needed for the study.

Funding

This study was supported by a grant from the National Natural Science Foundation of China (Grant No. 42177336).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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