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The heterogeneous drivers of CO_2 emissions in China's two major economic belts: new evidence from spatio-temporal analysis

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Abstract

CO_2 emissions have become increasingly prominent in China, and the primary emitters are economic belts that are spread throughout China. Two major economic belts, i.e., the Yangtze River Economic Belt (YTREB) and the Yellow River Economic Belt (YREB). Combined with stochastic impacts by regression on population, affluence and technology model, the spatial Durbin model under the space-and-time fixed effect and the Geographical and Time-Weighted Regression are employed to explore the spatio-temporal distribution characteristics and heterogeneous drivers of CO_2 emissions in the two economic belts. The results are as follows. First, CO_2 emissions exhibit obvious spatial correlation features in the YREB, but no such obvious spatial correlation is found in the YRETB. Second, in the YREB, the magnitude of the total influencing factors on CO_2 emissions follows an order where affluence (*A*) is the biggest driver, followed by energy intensity (*EI*), technology (*TEC*) and openness (*OP*), while the biggest driver in the YRETB is industrial structure supererogation (*ISS*), followed by population (*P*), energy intensity (*EI*), and affluence (*A*). Both direct and spatial spillover effects of the drivers are observed in the two economic belts. Third, the CO_2 emissions show a notable temporal lag effect in the YREB, but not in the YRETB. Fourth, the effects of the CO_2 emission drivers illustrate significant spatio-temporal heterogeneity in the two economic belts.

Keywords Heterogeneous drivers · CO_2 emissions · Spatial spillover effect · Geographical and time-weighted regression · Spatial Durbin model

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1 Introduction

Continuously growing energy consumption has caused a serious problem of CO_2 emission in China, which has aroused extensive public concern (Chen et al., 2020a, b, c, d; Zhang et al., 2017). China's energy consumption is less efficient than that of many developed countries, and therefore, the international community has long demanded China to reduce its CO_2 emissions (Li et al., 2020; Ma et al., 2019a, b). Building on the commitments of the Paris Agreement, the Chinese government has established a significant and ambitious goal to cut down the CO_2 emission intensity by 60–65% of 2005 levels and to reach peak CO_2 emissions by 2030 (Anderson et al., 2020; Rogelj et al., 2019). Facing the challenge posed by domestic CO_2 pollution and for the purpose of fulfill its climate commitment to the world, the Chinese government has placed a high priority on solving the problem of CO_2 emissions (Lu et al., 2020; Ma et al., 2021; Wen et al., 2020; Yan et al., 2020).

The growing problem of CO_2 emissions in China has attracted much scholarly attention in the past decade (Shahbaz et al., 2020). Yet, many studies in this field have been conducted on a national or administrative region basis (e.g., a province) (Wang et al., 2021a, b, c, d; Yang et al., 2020; Zheng et al., 2019), and merely a limited number of studies have focused on economic belts consisting of multiple administrative regions or urban clusters. As economic belts have become the major geographical unit producing the most CO_2 emissions, recent studies have gradually shifted their interests to various economic belts (Ahmad et al., 2021a, b; Ma et al., 2019a, b; Wang & Zhang, 2021). For example, Xu and colleagues investigated spatio-temporal differences and sources of CO_2 emissions in the Pearl River Delta from 2008 to 2012 (Xu et al., 2019). Zhou et al. (2021) analyzed land use data from 13 cities in the Beijing-Tianjin-Hebei (BTH) urban cluster and determined the Environmental Kuznets Curve (EKC) relationship between urbanization and land use CO_2 emissions. They found that levels of urbanization influenced the time when a city reached its peak of CO_2 emissions. However, most of these studies focused on a single perspective in one region, and few have conducted comparative analyses and time series comparisons across economic belts, especially between developed and underdeveloped economic belts. According to the EKC theory, there is an inverse U-shaped relationship between economic development and environmental pollution. Therefore, as the gap between north and south China in terms of their economic development, it is necessary to investigate the issue of carbon pollution in regions with different economic development levels separately. The Yangtze River Economic Belt (YTREB) in southern China and the Yellow River Economic Belt (YREB) in northern China are both major national strategies that rely on large rivers. Yet, there is an apparent disparity between these two economic belts in their levels of economic growth and sustainable development, as the former represents developed regions and the latter represents underdeveloped regions. From a cross-regional perspective, the current study compares the spatial correlation features and drivers of CO_2 emissions of these two major economic belts.

Supported by its highly developed economic foundation, the YTREB is a primary region leading the green economic development in China (Chen et al., 2020a, b, c, d; Liu et al., 2020). Despite being less developed than the YTREB, the YREB still exerts a potential effect on CO_2 emissions nationwide (Jiang et al., 2021). In the context where China aims at building an ecological civilization, the YREB has become a strategically essential ecological barrier, and controlling its CO_2 emissions is vital for China's sustainable development (Jiang et al., 2021). In September 2019, the Chinese government proposed a significant development policy of ecological protection and high-quality development of the YREB, which is deemed to be as crucial as the YTREB Development Plan (Gao et al., 2021). In addition, new demands for balancing CO_2 emission reduction and economic development have emerged in recent years (Adedoyin et al., 2020). To reduce CO_2 emissions in these two major economic belts, several questions still deserved an in-depth investigation: (1) What are the characteristics of CO_2 emissions in different Economic Belts? (2) Which spatial econometric models could be applied to measure the CO_2 emission drivers' direct and indirect effects? (3) How to recognize the heterogeneity of the drivers of CO_2 emissions in two major economic regions?

By exploring these questions, this paper has several primary contributions: (1) panel data of 56 cities in the YREB and 108 cities in the YTREB of China from 2008 to 2019 are applied to examine the spatio-temporal distribution characteristics and heterogeneous drivers of CO_2 emissions in these two economic belts respectively, providing empirical evidence for comparing low-carbon development level in different economic belts. (2) the local Moran's I is applied to demonstrate the spatio-temporal characteristics of CO_2 emissions of the two economic belts and identify the similarities and differences between them; (3) the spatial Durbin model (SDM) is combined with the expanded Stochastic Impact by Regression on Population, Affluence and Technology (STIRPAT) model, i.e., an integrated SDM-STIRPAT model, to weigh the effects of each driver on CO_2 emissions. Moreover, the differences between each driver in their influences on CO_2 emissions in the two economic belts are compared, rendering the analysis more reliable and convincing; (4) a method combining Geographical and Time-Weighted Regression (GTWR) and the STIRPAT model, is adopted to explore the spatio-temporal heterogeneity of drivers' impacts on CO_2 emissions in the two interested regions. All these findings will facilitate administrative departments and policy makers to make policies according to local conditions. The rest of the paper is structured as follows: Sect. 2 reviews the relevant literature and proposes arguments. Section 3 presents the data and methodology, elaborating on the spatial regression, STIRPAT model, variable definition and data collection. Section 4 reports the evidence-based results and discussion. Section 5 summarises key findings and provides some policy implications.

2 Literature review

With the promotion of low-carbon economy, many scholars are concerned with economic growth and the surge of CO_2 emissions. The drivers of CO_2 emissions in regions with different economic development levels is a critical and urgent issue. Most of the existing studies on CO_2 emissions can be divided into three main categories: estimation of CO_2 emissions, influencing factors of CO_2 emissions, and spatial distribution of CO_2 emissions.

First, the methods for estimating CO_2 emissions have local specificity due to the subtle heterogeneity of different countries and regions in the energy division, economic development model, data statistics, and policy system. In general, these methods include the CO_2 emissions inventory approach, Input–Output estimation model (I-O), Life Cycle Assessment (LCA), and Particle Swarm Optimization-Back Propagation (PSO-BP) algorithm, among which the CO_2 emissions inventory method is extensively applied in previous studies (Yang et al., 2020). This approach can be divided into top-down and bottom-up calculations. Most studies use the top-down approach based on aggregate energy consumption data. For instance, Wang et al. (2017) used the top-down approach given by the Intergovernmental Panel on Climate Change (IPCC) Guidelines for greenhouse gas (GHG) inventory to estimate the CO_2 emissions in Xinjiang from 1952 to 2012. However, the statistics for a given city cover both urban and rural regions. so the energy consumption data required for this top-down approach is only applicable to a few large-scale regions where the weak influence of rural areas can be ignored. This limitation prevents the top-down approach from providing local governments with sufficient evidence to formulate feasible initiatives to mitigate CO_2 emissions. Fortunately, the defect can be avoided by the bottom-up approach, which divides the carbon accounting boundary into three ranges based on energy consumption data: direct GHG emissions, indirect GHG emissions, and other life-cycle emissions (Cai et al., 2017). Qin et al. (2019) adopted data calculated by a bottom-up approach for 171 cities, combining direct and indirect CO_2 emissions to reveal the influencing factors of CO_2 emissions, suggesting that this method facilitates the calculation of CO_2 emissions between multiple cities. In recent years, as the remote sensing technology becomes increasingly popular, night-time lighting data can well reflect the human socio-economic activities which generate large amounts of CO_2 emissions. Some scholars have applied night-time lighting data to compensate for the lack of energy consumption data in the prefecture-level cities. Chen et al., (2020a, b, c, d) used the PSO-BP algorithm to uniform the scope of DMSP/OLS and NPP/VIIRS images from 1997 to 2017 and obtained county-level energy CO_2 emissions data by downscaling the provincial CO_2 emissions based on the night-time lighting data. However, generally, studies that use night-time lighting data to calculate CO_2 emissions have mainly centred on the global or national level, and economic belts have barely attracted much researchers' attention.

Second, to identify the main drivers of CO_2 emissions, many studies have applied the decomposition approach and multiple linear regressions, such as the IPAT model, extended-STIRPAT model, logarithmic mean divisia index (LMDI) and structural decomposition analysis (SDA). Among them, the STIRPAT model is the most commonly used. For instance, by using the STIRPAT model Zhang et al., (2021a, b) identified six drivers of CO_2 emissions, which are economic growth, population ageing, industrialization level, urbanization level, trade openness, and renewable energy investment. Their results suggested that the effect of renewable energy investment on CO_2 emissions varied across multiple investment stages. Liu and Xiao (2018) combined the system dynamics model and extended-STIRPAT model to investigate the drivers of CO_2 emissions under the EKC hypothesis, thus verifying the timing of peak CO_2 emissions in China under three scenarios. Another similar research also applied the extended-STIRPAT model to simulate the trajectory of CO_2 emissions and predicted CO_2 emissions of Qingdao (Wu et al., 2018). Nasir et al. (2021) analysed the determinants of the CO_2 emissions in Australia under an integrated framework of the STIRPAT model and EKC theory. They concluded that economic growth, industrialization, stock market development, and energy consumption have a short-term bidirectional cause-effect relationship with CO_2 emissions while financial development and openness have a long-term positive effect on CO_2 emissions. These studies on the drivers of CO_2 emissions tend to examine only the average effects. The spatio-temporal heterogeneity of the drivers of CO_2 emissions is rarely examined in previous studies, which, however, is possible through GTWR model measurement.

Third, since the economic belts have become influential contributor for low-carbon development, a strand of studies has focused on the spatial characteristics of CO_2 emissions and carbon reduction pathways in economic belts. In particular, studies on the YTREB's CO_2 emissions are proliferating. For example, Zhang and Chen (2021) discussed the effects of urbanisation and industrialisation on the carbon emission efficiency of the YTREB. Their study suggested that adjusting the industrial structure and innovating green technologies are the focus of improving the carbon emission efficiency of the YTREB. Similarly, Zhang et al. (2022) found that the carbon emission efficiency has remarkably improved in the YTREB, but the Matthew effect is prevalent across provinces. Li et al. (2021) adopted the Tapio decoupling model to investigate the decoupling effect between CO_2 emissions and economic development in the YTREB and put forward differentiated low-carbon development policies based on the urban decoupling types. Despite the proliferation of studies focusing on developed economic belts like the YTREB, only a few studies explored the spatial characteristic and carbon mitigation strategies in underdeveloped economic belts. By developing the cities' emission inventories, Tong et al. (2021) discussed that the heterogeneities in cities' characteristics will result in noticeable variations in carbon abatement policies. As another major national development strategy in China, the YREB plays a remarkable role in achieving the "dual carbon" targets. Therefore, it is necessary to explore the specific characteristic of CO_2 emissions in the YREB and to form a cross-sectional comparison with the YTREB.

The above-mentioned studies on CO_2 emissions have provided a solid theoretical basis and abundant empirical evidence for mapping CO_2 emissions and implementing specific carbon reduction measures. Nonetheless, there is still space for further exploration. First, most of the existing studies on CO_2 emissions focused on YTREB or the Yellow River Basin, while the YREB are relatively rarely involved in academic discussions. In other words, the carbon pollution problems in this underdeveloped economic belt have been neglected. Second, previous literature has mostly concentrated on a single region, while cross-regional comparisons between different economic belts have been rarely conducted. Third, previous studies mainly consider the effects of different drivers of CO_2 emissions but neglect the spatial and temporal heterogeneity of these drivers, making it difficult to develop locally appropriate strategies. Therefore, this study includes both the developed and underdeveloped economic belts into one study framework, conducts a comparative analysis of the CO_2 emission drivers, and compares their differences from the perspective of spatio-temporal heterogeneity. The findings are expected to provide valuable references for the development of a low-carbon economy in both the YTREB and YREB in a precise and localized manner.

3 Materials and methods

3.1 Study areas

The YTREB and YREB, spanning three main areas in eastern, central, and western China, are experiencing severe sustainability problems (Zou & Ma, 2021). Extending from the east coast of China to its central and western hubs, the YTREB includes the metropolitan areas of Shanghai and Chongqing and another nine provinces including Zhejiang, Anhui, Jiangsu, Jiangxi, Guizhou, Hubei, Hunan, Sichuan, and Yunnan. These areas account for more than 40% of the country's population and GDP, representing one of the most vibrant areas in China's economic development (Sun et al., 2018). Nevertheless, the YTREB has the largest proportion of energy-intensive industries in China, with 46% of the country's overall energy consumption and over 75% of the country's coal consumption (Zhang et al., 2021a, b). Thus, its carbon reduction strategy is a critical issue for the YTREB. Analogously, the most salient features of the YREB are the concentration of various resources throughout the basin and more than 20% of China's population and economy (Li et al., 2021). Since Sichuan province is normally categorised as part of the YTREB, the YREB here denotes the provinces around the Yellow River other than Sichuan (i.e., Qinghai, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong). Due to its wide expanse, the region varies significantly in terms of the environment, meteorological conditions, and socioeconomics (Ge et al., 2021). During the past two decades, the YREB has not only enjoyed significant economic productivity but also absorbed a large immigrant populations (Jiang et al., 2021). However, vulnerable ecosystems, severe ecological constraints, and CO_2 emissions resulting from industrialisation cannot be overlooked (Chen et al., 2020a, b, c, d). Following a low-carbon development path is an essential strategic orientation for the two economic belts. Here, 56 cities of the YREB and 108 cities of the YTREB are included in the study area. (Fig. 1).

3.2 Estimation of CO_2 emissions

CO_2 emissions could be calculated by aggregating various energy consumption according to the carbon conversion factor (IPCC, 2006) as follows:

$$CO_2 = \sum_{i=1}^{n} \left(E_i \times F_i \times 44/12\right) \tag{1}$$

where i refers to the i-th energy, $i = 1, 2, \ldots, n$; E_i is the depletion of energy i; F_i refers to the CO_2 emission coefficient of the i-th energy; 44/12 refers to the conversion coefficient between carbon and CO_2.

3.3 Variables selection

The IPAT model was proposed in 1970s to explore the environmental stress factors (Ehrlich & Holdren,1971), which can be expressed as:

$$I = P.A.T \tag{2}$$

where I represents CO_2 emissions, and P, A, T denote population, affluence, and technology, respectively. It is worth noting that the IPAT model assumes each driver is of equal

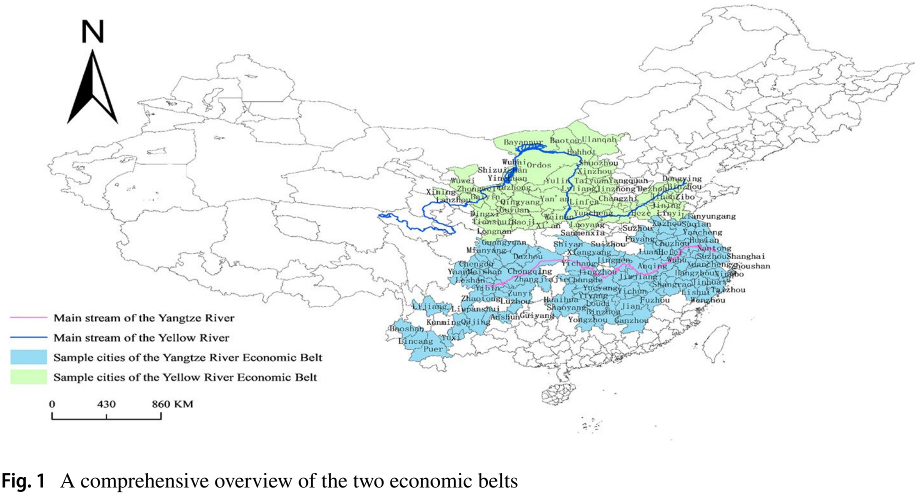

Fig. 1 A comprehensive overview of the two economic belts

weight on environmental pressure. To address this critical restriction, the following STIRPAT formula is adopted (Dietz & Rosa, 1997):

$$I = aP^bA^cT^de \tag{3}$$

where a represents the magnitude of the model; b, c and d denote the elasticity coefficients of population, affluence, and technology, separately; e denotes the error term. After logging, an equation of linear form is reformed as:

$$\ln I = a + b\ln P + c\ln A + d\ln T + e \tag{4}$$

Furthermore, other drivers, such as energy intensity, openness, and industrial structure, can be incorporated as the deciding drivers of CO_2 emissions as follows:

$$\begin{aligned}\ln CO_{2;i,t} = a + \beta_1 \ln PGDP_{i,t} + \beta_2 \ln P_{i,t} + \beta_3 \ln TEC_{i,t} + \beta_4 \ln EI_{i,t} \\ + \beta_5 \ln OP_{i,t} + \beta_6 \ln ISS_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where t refers to t-th year and i refers to the city i; CO_2 emissions (10^4 Tons) is calculated by Eq. (1); $PGDP$ refers to GDP per capita (Yuan); P refers to the year-end total population (10^4 persons); TEC represents technology and is calculated as a proportion of fiscal expenditure on science (%); EI denotes energy intensity and is measured as energy depletion per million GDP (Ton/10^4Yuan); OP represents openness and is estimated as a share of total imports and exports in GDP (%); ISS represents the industrial structure supererogation; μ_i, λ_t, and ε_{it} denote the space fixed effect, the time fixed effect, and the random error term, respectively.

3.4 Data resource

Given the accessibility and consistency of data, the research used the data from the 164 cities of the two economic belts from 2008 to 2019. The original social and economic data are retrieved from China Urban Construction Statistical Yearbook (CUCSY, 2009–2020), China Regional Statistical Yearbook (CRSY, 2009–2020), and China Energy Statistical Yearbook (CESY, 2008–2020). Table 1 shows the descriptive statistics of variables.

Table 1 Descriptive statistics

Variables	Obs	Mean	S.D	Min	Max
CO_2 emission ($\ln CO_2$)	1968	6.150	1.204	3.246	8.923
Affluence (lnPGDP)	1968	10.253	0.709	8.698	11.967
Population (lnP)	1968	5.929	0.623	4.305	7.271
Technology (lnTEC)	1968	0.184	0.806	−1.548	1.949
Energy Intensity (lnEI)	1968	−2.485	0.806	−1.548	1.949
Openness (lnOP)	1968	1.819	1.395	−2.213	4.778
Industrial Structure Supererogation (lnISS)	1968	1.868	0.051	1.765	1.984

$\ln PGDP_{i,t}$=log of GDP per capita; $\ln P_{i,t}$=log of year-end total population; $\ln TEC_{i,t}$=log of the proportion of fiscal expenditure on science; $\ln EI_{i,t}$=log of energy depletion per million GDP; $\ln OP_{i,t}$=log of the share of total imports and exports in GDP; $\ln ISS_{i,t}$=log of industrial structure supererogation

3.5 Modelling methods

3.5.1 Exploratory spatial data analysis

To investigate the spatial correlation of CO_2 emissions and variances across areas, the global Moran's I is applied to describe the spatial distribution of CO_2 emissions throughout these areas, which can be measured as:

$$I = \frac{n \sum_i \sum_j w_{i,j}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_i \sum_j w_{i,j}\left(x_i - \overline{x}\right)^2} \tag{6}$$

where x_i refers to CO_2 emissions in city i, and x_j refers to CO_2 emissions in city j; $\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$; W_{ij} is the spatial weighting matrix. Based on previous studies, a 0–1 adjacency weight matrix (W_1) is constructed as follows:

$$W_{i,j} = \begin{cases} 1, & city\ i\ and\ j\ are\ adjacent \\ 0, & otherwise \end{cases} \tag{7}$$

The global Moran's I provides a general indicator that represents the whole spatial dependence across the study areas in the sample period. On the other hand, the LISA (Local Indicator of Spatial Association) agglomeration chart specifically visualizes the spatial distribution characteristics and changing trend of CO_2 emissions. Based on the 0–1 adjacency weight matrix (W_1), the index can then be calculated as follows:

$$LISA_i = \frac{n\left(x_i - \overline{x}\right)}{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2} \sum_{j=1, j \neq i}^{n} W_{i,j}\left(x_j - \overline{x}\right) \tag{8}$$

where $LISA_i$ refers to the Local Moran's I of city i in year t; W_{ij} denotes the Queen contiguity matrix, i.e., 0–1 adjacency weight matrix (W_1) above. There are five types of agglomerations in the LISA cluster map, including low-low clustering (L–L), high-low clustering (H–L), low–high clustering (L–H), high-high clustering (H–H), and insignificant areas. The H–H cluster and L–L cluster mean that the CO_2 emissions in city i is positively correlated with that in its neighboring cities, while the H–L cluster and L–H cluster indicate a negative correlation between the sample city and its adjacent cities about their CO_2 emissions.

3.5.2 Static spatial analysis

In case of a significant spatial correlation suggested by the above analysis, based on a series of diagnoses, a spatial Durbin model (Eq. 9) is established to examine both the direct effects and the indirect effects of drivers of CO_2 emissions:

$$\begin{aligned} \ln CO_{2;i,t} = {} & \beta_0 + \rho W \ln CO_{2;i,t} + \beta_1 \ln PGDP_{i,t} + \beta_2 \ln P_{i,t} + \beta_3 \ln TEC_{i,t} \\ & + \beta_4 \ln EI_{i,t} + \beta_5 \ln OP_{i,t} + \beta_6 \ln ISS_{i,t} + \theta_1 W \ln PGDP_{i,t} \\ & + \theta_2 W \ln P_{i,t} + \theta_3 W \ln TEC_{i,t} + \theta_4 W \ln EI_{i,t} + \theta_5 W \ln OP_{i,t} \\ & + \theta_6 W \ln ISS_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{9}$$

where β and ρ denote the coefficients of direct effects and indirect effects respectively; t and i refer to the *t-th* year and the city i, respectively; W refers to the spatial weight matrix.

3.5.3 Dynamic spatial analysis

In addition, CO_2 emissions in the past may potentially affect current CO_2 emissions. Therefore, the dynamic spatial Durbin model with dual fixed effects is adopted to explore the impacts of the explanatory variables as well as the explained variables. The equation is introduced as follows:

$$\begin{aligned} \ln CO_{2;i,t} = {} & \beta_0 + \rho W \ln CO_{2;i,t} + \tau \ln CO_{2;i,t-1} + \eta W \ln CO_{2;i,t-1} + \beta_1 \ln PGDP_{i,t} \\ & + \beta_2 \ln P_{i,t} + \beta_3 \ln TEC_{i,t} + \beta_4 \ln EI_{i,t} + \beta_5 \ln OP_{i,t} + \beta_6 \ln ISS_{i,t} \\ & + \theta_1 W \ln PGDP_{i,t} + \theta_2 W \ln P_{i,t} + \theta_3 W \ln TEC_{i,t} + \theta_4 W \ln EI_{i,t} \\ & + \theta_5 W \ln OP_{i,t} + \theta_6 W \ln ISS_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{10}$$

where α is the coefficient of the first order lagged term of CO_2 emissions; τ refers to the temporal lag auto-regressive coefficient of CO_2 emissions, η is the spatio-temporal lag auto-regressive coefficient of CO_2 emissions.

3.5.4 Geographically and temporally weighted regression model

The major drivers of CO_2 emissions in the two economic belts can be identified through the regression of the STIRPAT-SDM model. To explore the spatio-temporal differences of these drivers, the GTWR model is employed as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{d} \beta_k(u_i v_i, t_i) x_{i,k} + \varepsilon_i, \quad i = 1, 2, \ldots, n \tag{11}$$

where y_i denotes the value of point i; x_{ik} denotes the value of point i; β_k (μ_i, v_i, t_i) represents the unknown parameter of point i;ε_i denotes the error term that complies with the N (0, σ^2) distribution.

Since the observation points in different spatio-temporal dimensions have different influences, in order to measure the unknown parameters of the observation points (u_0, v_0, t_0), it is necessary to introduce the spatio-temporal weight matrix W_i (u_0, v_0, t_0) to observation points and find the optimal β_k (u_0, v_0, t_0) to minimize the objective function f. The procedure is shown as follows:

$$f = \sum_{i=1}^{n} \left[y_i - \beta_0(u_0, v_0, t_0) - \sum_{k=1}^{d} \beta_k(u_0, v_0, t_0) x_{i,k} \right]^2 \omega_i(u_0, v_0, t_0) \tag{12}$$

$$\begin{aligned} & W_i(u_0, v_0, t_0) = \operatorname{diag}\left[\omega_1(u_0, v_0, t_0), \omega_2(u_0, v_0, t_0), \ldots, \omega_n(u_0, v_0, t_0)\right] \\ & Y = (y_1, y_2, \ldots, y_n)^T \\ & X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1d} \\ 1 & x_{21} & \cdots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{nd} \end{bmatrix} \end{aligned} \tag{13}$$

$$\begin{aligned}\hat{\beta}_k(u_0, v_0, t_0) &= \left[X^T W(u_0, v_0, t_0) X\right]^{-1} X^T W(u_0, v_0, t_0) Y \\ \hat{Y} = X_i \hat{\beta}_k &= X_i \left[X^T W_i(u, v_0, t_0) X\right]^{-1} X^T W_i(u_0, v_0, t_0) Y = SY\end{aligned} \tag{14}$$

The spatio-temporal distance between the observation point (*u0*, *v0*, *t0*) and (*ui*, *vi*, *ti*) and the Gaussian kernel function which is applied to measure the spatio-temporal weight matrix are as follows:

$$d_{0i} = \sqrt{\lambda\left[(u_0 - u_i)^2 + (v_0 - v_i)^2\right] + \mu(t_0 - t_i)^2} \tag{15}$$

$$\begin{aligned}W_i &= \exp\left\{-\left(\frac{\lambda\left[(u_0 - u_i)^2 + (v_0 - v_i)^2\right] + \mu(t_0 - t_i)^2}{h_{ST}^2}\right)\right\} \\ &= \exp\left\{-\left(\frac{(u_0 - u_i)^2 + (v_0 - v_i)^2}{h_S^2} + \frac{(t_0 - t_i)^2}{h_T^2}\right)\right\} \\ &= \exp\left\{-\left(\frac{(d_{0i}^S)^2}{h_S^2} + \frac{(d_{0i}^T)^2}{h_T^2}\right)\right\} \\ &= \exp\left\{-\frac{(d_{0i}^s)^2}{h_S^2}\right\} \times \exp\left\{-\frac{(d_{0i}^T)^2}{h_T^2}\right\} \\ &= W_{i0}^S \times W_{i0}^T\end{aligned} \tag{16}$$

in which h_S represents spatial bandwidth; h_T denotes temporal bandwidth, and h_{ST} represents spatio-temporal bandwidth.

The aforementioned methods are implemented with stata/SE version 16, GeoDa, and ArcMap 10.2. Figure 2 provides a schematic representation of the study.

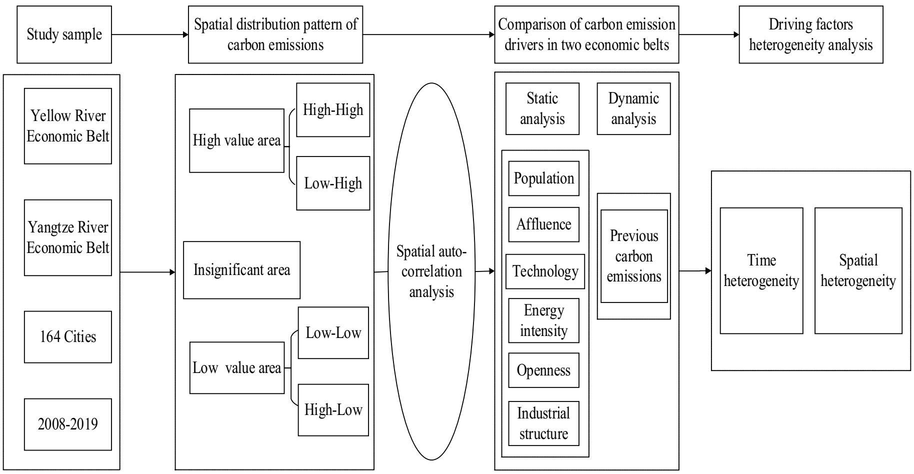

Fig. 2 A schematic diagram of the study

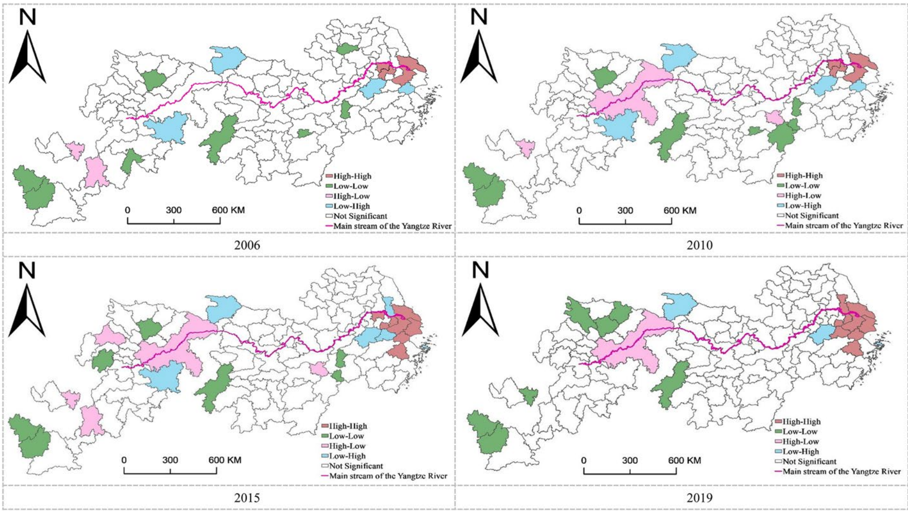

Fig. 3 Spatial clustering of CO_2 emissions in the YTREB

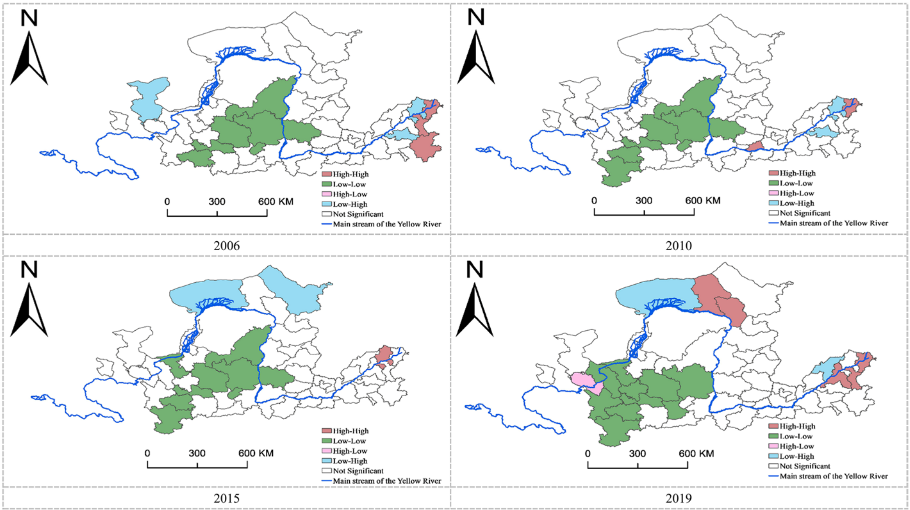

Fig. 4 Spatial clustering of CO_2 emissions in the YREB

4 Results and discussion

4.1 Spatial auto-correlation of CO_2 emissions

GeoDa is used to map the LISA cluster charts (Figs. 3 and 4), which illustrates the spatial auto-correlation distribution of CO_2 under 5% significance in the two study economic belts. Figure 2 shows the results for the YTREB. H–H clusters are mostly concentrated in the downstream region of the Yangtze River, distributed in cities including Suzhou, Nantong, Changzhou, and Zhenjiang, and they prevailed in 2015 and 2019. Relatively, L–L clusters are more scattered in this economic belt, mainly distributed in cities like Baoshan, Lincang, Huaihua, Nanchong, etc. Furthermore, the spatial clustering degree is small, indicating no obvious agglomeration of CO_2 emissions in the YTREB. The fact that there is no powerful spillover effect suggests gaps among cities regarding their CO_2 emissions.

Compared to the YTREB, the YREB shows more obvious and distinct features in its spatial distribution of CO_2 emissions, which can be easily observed in Fig. 3. Overall, L–L clusters show a polarization effect and exert less radiation to neighboring cities, while H–H clusters appear with a spatial spillover effect and the scope of agglomeration has expanded gradually. To be more specific, H–H clusters are primarily concentrated in Linyi, Dongying, Jinan, Zibo, and Binzhou, while L–L clusters are mainly concentrated in Yulin, Linfen, Pingliang, Qingyang, etc. The scope of H–H and L–L clusters have been expanded in the sample period, indicating an increased spatial auto-correlation of CO_2 emissions in the YREB.

In addition, a high-carbon "spillover effect" and a low-carbon "lock-in effect" are observed in the spatial distribution of CO_2 emissions in the YREB. The former refers to the spatial expansion of H–H clusters, that is, high-emissions areas spread from the east to the center, and the number of "H–H" cities have increased. The latter reflects the relative stability of L–L clusters with the scope gradually decreasing. In general, there is an apparent spatial dependence in CO_2 emissions between neighboring areas in the YREB.

4.2 Static spatial panel analysis

Table 2 reports the Hausman test, LM error test, LM lag test, and combined LR test. Hausman test is employed to determine the choice between a fixed or random effects model. According to the results of the Hausman test, the null hypothesis that individual effects are independent of the regression variables is rejected, and thus a fixed effects model is used. In addition, four different LM tests (i.e., LM spatial error, LM spatial lag, robust LM spatial error, and robust LM spatial lag) are applied to examine the null hypothesis of the absence of spatial error and spatial lag dependence. All results are significant, and thus the null hypothesis that there is no spatial auto-correlation error term or spatial lag term is rejected, and the SDM model is suitable for empirical analysis. Furthermore, LR tests are conducted to confirm that the SDM is nested in SEM or SLM and all the null hypotheses are rejected (Wang et al., 2021a, 2021b, 2021c, 2021d), so the spatial Durbin model with dual fixed effects is used in the current study.

First, the direct effect of the economy is positive at 1% significance level and its indirect effect is insignificant in the YREB, indicating a positive correlation between economic growth and local CO_2 emissions but no spillover effect of the economy on CO_2 emissions. The total effect of the economy is the largest, which means the economy has the largest impact and that economic growth would lead to serious CO_2 emissions problems in the YREB. Based on the static analysis results for the YREB, the coefficients in the YTREB are re-estimated to identify the influence of different levels of economic development on CO_2 emissions. By comparing the two economic belts, some basic findings can be concluded: (1) The direct effect of affluence is larger in the YREB than that in the YTREB, suggesting that the unit increment of the lagging economy brings more CO_2 emissions to the local area. (2) The indirect effect of affluence is insignificant in the YREB, but significantly negative in the YTREB. This means that the economic growth has a suppressive spatial effect on CO_2 emissions in the developed economic belt but no spillover effect in

Table 2 Static estimating results

Variables	YREB			YTREB		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
$\mathrm{lnPGDP}_{i,t}$	0.950***	−0.013	0.938***	0.890***	−0.309***	0.580***
	(8.508)	(−0.080)	(7.222)	(14.359)	(−3.394)	(5.684)
$\mathrm{lnP}_{i,t}$	0.777***	−0.360	0.417	0.996***	−0.063	0.934***
	(2.788)	(−0.801)	(0.800)	(12.057)	(−0.407)	(5.809)
$\mathrm{lnTEC}_{i,t}$	−0.048***	−0.098***	−0.146***	0.030***	0.003	0.033
	(−2.590)	(−2.806)	(−3.797)	(3.146)	(0.168)	(1.575)
$\mathrm{lnEI}_{i,t}$	0.901***	0.003	0.904***	0.967***	−0.054**	0.913***
	(28.307)	(0.084)	(16.824)	(45.416)	(−2.195)	(24.623)
$\mathrm{lnOP}_{i,t}$	−0.032**	−0.109***	−0.141***	−0.003	−0.029*	−0.032
	(−2.331)	(−3.701)	(−4.005)	(−0.262)	(−1.694)	(−1.509)
$\mathrm{lnISS}_{i,t}$	−0.789	−0.935	−1.724	0.717**	1.283**	2.000***
	(−1.234)	(−0.727)	(−1.236)	(1.967)	(2.130)	(3.110)
Spatial rho	0.008			0.110**		
	(0.123)			(2.211)		
sigma2_e	0.013***			0.005***		
	(4.295)			(8.084)		
Observations	672			1,296		
R-squared	0.888			0.959		
Moran's *I*-error	9.452***			8.881***		
LM-error	85.058***			77.228 ***		
Robust LM-error	69.471***			74.625***		
LM-lag	29.791***			26.070***		
Robust LM-lag	14.203***			9.203**		
Hausman	32.48**			20.27*		
LR-test (Assumption: sar nested in sdm)	26.57***			67.97***		
LR-test (Assumption: sem nested in sdm)	22.94***			60.63***		
LR-test (Assumption: sdm_time nested in sdm_both)	603.83***			1915.48***		
LR-tes t(Assumption: sdm_ind nested in sdm_both)	92.49***			305.42***		

(1) Robust z-statistics in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. (2) $\mathrm{lnPGDP}_{i,t}$ = log of GDP per capita; $\mathrm{lnP}_{i,t}$ = log of year-end total population; $\mathrm{lnTEC}_{i,t}$ = log of the proportion of fiscal expenditure on science; $\mathrm{lnEI}_{i,t}$ = log of energy depletion per million GDP; $\mathrm{lnOP}_{i,t}$ = log of the share of total imports and exports in GDP; $\mathrm{lnISS}_{i,t}$ = log of industrial structure supererogation

the underdeveloped economic belt. (3) The total effects of affluence are positive in both economic belts, but the significance is greater in the YREB. Meanwhile, compared with other drivers, the economic growth provides the strongest explanation for CO_2 emissions in the YREB. These results demonstrate that the lagging economy would lead to more CO_2 emissions, which may be linked to its unsound energy structure, and that the energy consumption driven by economic growth is the main contributor to CO_2 emissions in the YREB, which in accordance with the findings of Du et al. (2021) and Li et al. (2021).

Second, in the YREB, the direct effect of the population is positive at a 1% significance level, but both the indirect and total effects of the population are insignificant, suggesting that population growth contributes to CO_2 emissions in local areas but has no significant impact on neighbouring areas in the YREB. Similarly, the population exerts a significantly positive direct effect and an insignificant indirect effect on the YTREB. However, the total effect is positive at a 1% significance level in the YTREB. In other words, population expansion increases CO_2 emissions in the whole economic belt. This result is in line with Wu et al. (2019), who argued that the population size has exhibited a long-term trend of growth in most of China. Population expansion has driven a significant increase in demands for scarce resources, cement, a d energy to construct massive transportation infrastructure. The rising demand for energy in the industry and electricity sectors inevitably resulted in greater pollution and CO_2 emissions (Ribeiro et al., 2019). The implementation of the three-child policy will inevitably drive long-term population growth in the economic belts, with an accompanying increase in CO_2 emissions. Therefore, the two economic belts should learn from precious experiences in reconciling population growth and CO_2 emissions control. For instance, an evidence-based education system on emissions reduction should be widely disseminated in communities and schools to raise public awareness of low-carbon lifestyles.

Third, the direct and indirect effects of technological progress are significantly negative in the YREB. In other words, technological progress helps reducing CO_2 emissions in the YREB. Moreover, the indirect effect is more significant than the direct effect, suggesting that technological progress plays a better spatial spillover effect in the YREB. By contrast, in the YTREB, the direct effect of technological progress is significantly positive, while the indirect and total effects are insignificant, indicating a limited role from technological innovation to CO_2 emissions reduction in the YTREB. According to the evidence investigated by Li and Wang (2017), this result can be ascribed to the comparison of the positive and negative values expressed by the scale and intensity effect of technological progress on CO_2 emissions. Specifically, technological progress can contribute to CO_2 emissions abatement by improving the energy structure and optimizing the industrial structure. However, it can also expand the size of the economy while increasing the corresponding energy consumption, thus producing a rebound effect and increasing total CO_2 emissions. Generally speaking, the scale effect of technological progress on CO_2 emissions tends to be positive for developed areas, but for underdeveloped areas, this effect tends to continuously decrease until it becomes negative and then the intensity effect becomes the dominant (Vivanco et al., 2016; Wei & Liu, 2017). For the YTREB, the economic development driven by technological progress will consume additional electrical and thermal energy, resulting in considerable CO_2 emissions. In contrast, in the YREB where the economy is underdeveloped, the scale and rebound effects of economic development are negligible, and thus less CO_2 emissions are generated from technological progress compared to that in the YTREB.

Fourth, as for energy intensity, its direct and total effects are both remarkably positive, while its indirect effect is not notable in the YREB, indicating that an increase in energy intensity intensifies CO_2 emissions in specific cities and the entire YREB. Meanwhile, the three types of effects of energy intensity are all positive in the YTREB, suggesting a positive correlation between energy intensity and CO_2 emissions in the YTREB. Like Han et al. (2019) and Wang et al., (2021a, b, c, d), this study confirms that an increase in energy intensity contributes to higher total CO_2 emissions. Building on existing studies, this study reveals that the positive effect of energy intensity on CO_2 emissions is prevalent in both developed and underdeveloped economic belts. Reducing energy intensity and improving energy efficiency is an efficient method to reduce CO_2 emissions, especially to avoid the retaliatory rebound of CO_2 emissions post-COVID-19, which promotes an urgent demand for low-carbon technology progress (Wang & Wang, 2020).

Fifth, the direct effect of openness is negative at a 5% significance level in cities in the YREB, suggesting that foreign trade suppresses CO_2 emissions. Additionally, the indirect and total effects of openness are significantly negative, showing that the increase in foreign trade also curbs CO_2 emissions in the surrounding areas. This means that the development of trade openness is conducive to reducing rather than increasing CO_2 emissions in the YREB, which echoes the conclusions of Zhao et al. (2020) and Liu et al. (2018). In addition, the direct and total effects of openness are insignificant, while the indirect effect is significantly negative, demonstrating that only the indirect "Pollution Halo" effect of openness are transmitted in the YTREB (Tong et al., 2021). This result is different from that of Zhang and Chen (2021) who found the existence of pollution heaven effect in the YTREB. Overall, these results validate a "Pollution Halo" hypothesis rather than a "Pollution Heaven" hypothesis in the YREB and YTREB. Specifically, the "Pollution Halo" hypothesis argues that openness reduces local environmental pollution by the spatial effects of cleaner production technologies and superior management practices. The more advanced labour skills and pollutant treatment technology used by local enterprises through trade openness can positively impact the environment of host regions. The "Pollution Heaven" hypothesis, on the other hand, argues that due to tightening environmental regulations in developed regions, people tend to move energy-intensive industries to underdeveloped regions to avert expensive environmental treatment costs in developed regions. As a result, the environment of underdeveloped regions is further damaged (Ahmad et al., 2021a, b).

Sixth, there is no direct, indirect, or complete significant effect of industrial structure supererogation on the YERB. Thus, the results provide no explicit clue to determine the influence of industrial structure supererogation on CO_2 emissions in this economic belt. On the contrary, the direct, indirect, and total effects of industrial structure supererogation are significantly positive in the YTREB. It is worth noting that its spatial spillover effect is stronger than the direct effect, suggesting that the industrial structure supererogation would aggravate the CO_2 emissions in the local area as well as the surrounding cities. This result is contrary to previous empirical findings (Wang et al., 2021a, b, c, d; Xiong et al., 2019) which support the "structural dividend hypothesis" that industrial structural upgrading can promote energy efficiency due to its high added value, thus mitigating the greenhouse effect and reducing CO_2 emissions. Instead, the current study reveals a "rebound effect" of industrial structure supererogation in the YTREB, which drives economic growth but also increases emissions at the same time. The reason may be that the YTREB is primarily manufacturing-oriented, and its resource allocation is not irrational (Zhao et al., 2022). The implication is that the YTREB cities should promote the mobility of factors and expedite the transition to a low-carbon industry structure.

4.3 Dynamic spatial panel analysis

The results based on the dynamic spatial Durbin model are reported in Table 3 and Table 4. Here some new findings can be derived. First, the coefficient of $\ln CO_{2t-1}$ is significantly positive in the YREB and insignificantly positive in the YTREB, indicating that previous CO_2 emissions have increased CO_2 emissions that are present in the YREB but not in the YTREB. Alternatively speaking, the snowball effect of CO_2 emissions exists only in the YREB. Second, in both economic belts, almost all coefficients of the explanatory variables are constant in their signs and significant in any term. Furthermore, the impact of drivers is stronger in the long term than in the short term, providing clear evidence for the construction of a cumulative effect of the cycle. Third, in the YREB, the coefficients of the economy are remarkably larger than those of the other drivers in any term. Moreover, the long-term effect of the economy is more obvious than its short-term effect, indicating that the backward economy can boost CO_2 emissions and that its influence is more significant than that of the other drivers. In addition, in the YTREB, the coefficient value for industrial structure supererogation is the largest among all drivers. This suggests that the industrial structure supererogation in the YTREB does not contribute to reducing CO_2 emissions in any term.

4.4 Analysis of the spatio-temporal heterogeneity of the drivers

Although the spatial economic analysis above provides the significance and influence of the drivers of the YREB and the YTREB, it is not sufficient to estimate the spatio-temporal heterogeneity of these drivers. Therefore, the GTWR model was introduced into the modelling process, and the results are mapped in Figs. 4 and 5. First, the values of AIC of the two models are −741.562 and −1326.37, and R_squared are 0.991 and 0.988 respectively, suggesting that the GTWR model is appropriate. Furthermore, most of the coefficients are significant, indicating the GTWR model is valid.

In Figs. 5 and 6, the coefficients of the economy as a driver are positive in both economic belts between 2008 and 2019. In addition, the spatial and temporal heterogeneity of the economy coefficients of the YREB is greater than that of the YTREB, indicating that there is a larger spatial and temporal variability in the impact of the economy in the YREB. Moreover, the spatial heterogeneity is more significant than the temporal heterogeneity, suggesting a lack of coordination between regional economies in terms of their effects on CO_2 emissions and the economy has a smaller effect for most cities in the middle cities of the YTREB and the western cities of the YREB. A larger effect exerted by the economy was observed in most western cities of the YTREB as well as the middle and the eastern cities of the YREB.

Figures 7 and 8 illustrate the heterogeneity of the population's effects. The specific impact of the population varies significantly across cities in these two economic belts. In the YREB, the contribution of the population to CO_2 emissions is larger in the middle cities and smaller in western cities. In the YTREB, the population on CO_2 emissions exerts greater impact in the middle cities than in the western and middle cities. Besides, in all the sample cities of the YTREB, the populations' contributions to CO_2 emissions share a common temporal feature, i.e., they have been increasing over the sample period.

Figures 9 and 10 suggests that the influence of technology on CO_2 emissions differs spatially and temporally across the two economic belts. Specifically, technological development promotes CO_2 emissions in Xi'an, Baoji, Xianyang, Pingliang, Qingyang, and some middle cities in the YREB. In addition, other cities where technological development increases CO_2 emissions include Jinzhong, Linfeng, Yangquan, Jincheng, Luoyang, Hebi, and Sanmenxia. In contrast, most cities in the YTREB enjoy an emission-reduction effect of technology, especially those in the eastern YTREB that exert a curbing influence of the population on CO_2 emissions during the later sample period.

Figures 11 and 12 present the results regarding energy intensity. Figure 9 demonstrates that the effect of energy intensity varies spatially and temporally in the YREB. Specifically, cities in the centre of the YREB are more vulnerable to the increase in energy intensity, indicated by a greater influence of energy intensity on CO_2 emissions in these cities. Most cities in the YTREB have experienced an increasingly positive impact of energy intensity on CO_2 emissions. Relatively, most middle cities and eastern cities of the YTREB are less sensitive to energy intensity, as energy intensity has a weaker influence in these areas. Unlike in the YREB, the heterogeneity of the impacts of energy intensity in the YTREB is mainly reflected in the temporal distribution but less in the spatial distribution. The effects of energy intensity have increased in almost all cities during the sample period.

Figures 13 and 14 show the effects of openness, i.e., foreign trade, on CO_2 emissions. In general, the heterogeneity of the effect of openness is reflected between cities, while it is primarily presented over time in the YTREB. Specifically, in the middle of the YREB, increased openness promotes CO_2 emissions. On the other hand, in cities where the openness level is relatively low, increased openness, instead, curbs CO_2 emission, and these cities are mostly located in the western part of the YREB, including Xining, Wuwei, Bayannur, Yinchuan, Shizuishan. Furthermore, many cities in the YTREB have seen a first upward and then the downward trend of the effect of openness, such as Chongqing, Zigong, Panzhihua, Luzhou, Deyang, Mianyang, Hefei, Bengbu, Huainan, Huaibei, Tongling, and Anqing.

Figures 15 and 16 show the differences in the impact of industrial structure supererogation, which suggests a remarkable variation across cities and years in both economic belts. In the YREB, industrial structure supererogation promotes CO_2 emissions in Luoyang, Zhengzhou, Kaifeng, Yan'an, Yulin, and Jiaozuo, but curbs CO_2 emissions in Jinan, Zibo, Jining, Liaocheng, Binzhou. Moreover, the effect of industrial structure supererogation has been increasing in the centre but declining in the west of the YREB. In the YTREB, industrial structure supererogation boosts CO_2 emissions in the western parts. Cities in the eastern parts of the YTREB have experienced a first boosting and then curbing effect of industrial structure supererogation on CO_2 emissions.

In conclusion, the spatio-temporal heterogeneity of the drivers of CO_2 emissions is supported in both underdeveloped economy and developed economy. Thus, the significance of tailoring policy measures based on local conditions cannot be ignored.

5 Conclusions and policy implications

5.1 Conclusions

With the SDM-STIRPAT model and the GTWR-STIRPAT model, this study analyses the drivers of CO_2 emissions in the two major economic belts at different development levels and their spatio-temporal heterogeneity during the period from 2008 to 2019. The results suggest that CO_2 emissions in the YREB demonstrate apparent clustering characteristics,

Table 3 Dynamic estimating results in the YREB

Variables	Main	$W{\cdot}X$	Short-term			Long-term		
			Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
$lnCO_{2;i,t-1}$	0.067**							
	(2.502)							
$W{\cdot}lnCO_{2;i,t-1}$	0.016							
	(0.505)							
$lnPGDP_{i,t}$	0.966***	−0.198	0.973***	−0.174	0.799***	1.043***	−0.168	0.875***
	(10.305)	(−1.207)	(10.861)	(−1.118)	(6.190)	(10.897)	(−0.991)	(6.144)
$lnP_{i,t}$	0.789***	−0.694	0.790***	−0.680	0.110	0.845***	−0.724	0.120
	(2.886)	(−1.367)	(2.853)	(−1.313)	(0.192)	(2.843)	(−1.280)	(0.192)
$lnTEC_{i,t}$	−0.048**	−0.084**	−0.048***	−0.089**	−0.137***	−0.052***	−0.098**	−0.150***
	(−2.535)	(−2.494)	(−2.690)	(−2.392)	(−3.281)	(−2.719)	(−2.401)	(−3.275)
$lnEI_{i,t}$	0.858***	−0.051	0.859***	−0.020	0.839***	0.922***	−0.002	0.919***
	(23.596)	(−0.732)	(24.349)	(−0.471)	(12.902)	(24.220)	(−0.051)	(12.638)
$lnOP_{i,t}$	−0.027	−0.099***	−0.028	−0.104***	−0.132***	−0.031	−0.114***	−0.145***
	(−1.582)	(−3.366)	(−1.569)	(−3.673)	(−3.802)	(−1.592)	(−3.696)	(−3.807)
$lnISS_{i,t}$	−1.568	0.071	−1.584*	0.135	−1.449	−1.698*	0.115	−1.584
	(−1.580)	(0.065)	(−1.657)	(0.115)	(−0.976)	(−1.656)	(0.089)	(−0.975)
Spatial rho				0.034				
				(0.488)				
sigma2_e				0.013***				
				(5.712)				
Observations				616				
R-squared				0.837				

(1) Robust z-statistics in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) $lnPGDP_{i,t}$ = log of GDP per capita; $lnP_{i,t}$ = log of year-end total population; $lnTEC_{i,t}$ = log of the proportion of fiscal expenditure on science; $lnEI_{i,t}$ = log of energy depletion per million GDP; $lnOP_{i,t}$ = log of the share of total imports and exports in GDP; $lnISS_{i,t}$ = log of industrial structure supererogation

Table 4 Dynamic estimating results in the YTREB

Variables	Main	*W·X*	Short-term			Long-term		
			Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
$\ln CO_{2;i,t-1}$	0.034							
	(1.545)							
$W\cdot\ln CO_{2;i,t-1}$	−0.022							
	(−1.538)							
$\ln PGDP_{i,t}$	0.882***	−0.296***	0.882***	−0.224**	0.657***	0.913***	−0.247***	0.666***
	(12.559)	(−3.368)	(12.718)	(−2.501)	(6.963)	(12.703)	(−2.685)	(6.958)
$\ln P_{i,t}$	0.995***	−0.117	0.993***	−0.011	0.982***	1.028***	−0.032	0.996***
	(11.151)	(−0.783)	(11.061)	(−0.079)	(6.000)	(11.056)	(−0.221)	(6.001)
$\ln TEC_{i,t}$	0.026***	−0.005	0.026***	−0.003	0.023	0.026***	−0.004	0.023
	(2.778)	(−0.270)	(2.973)	(−0.168)	(1.216)	(2.970)	(−0.198)	(1.216)
$\ln EI_{i,t}$	0.962***	−0.134**	0.960***	−0.040	0.920***	0.994***	−0.061**	0.933***
	(30.251)	(−2.395)	(30.351)	(−1.510)	(20.036)	(30.438)	(−2.293)	(20.028)
$\ln OP_{i,t}$	0.001	−0.023	0.000	−0.026	−0.025	0.001	−0.026	−0.026
	(0.064)	(−−1.465)	(0.042)	(−1.587)	(−1.254)	(0.053)	(−1.589)	(−1.254)
$\ln ISS_{i,t}$	0.533	1.244**	0.537	1.443**	1.980***	0.549	1.458**	2.007***
	(1.363)	(2.066)	(1.514)	(2.439)	(3.364)	(1.491)	(2.412)	(3.365)
Spatial rho				0.101**				
				(2.048)				
sigma2_e				0.005***				
				(7.708)				
Observations				1,188				
R-squared				0.969				

(1) Robust z-statistics in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.(2) $\ln CO_{2;i,t}-_1$ = log of one-period lagged CO_2 emissions; $\ln PGDP_{i,t}$ = logof GDP per capita; $\ln P_{i,t}$ = log of year-end total population; $\ln TEC_{i,t}$ = log of the proportion of fiscal expenditure on science; $\ln EI_{i,t}$ = log of energy depletion per million GDP; $\ln OP_{i,t}$ = log of the share of total imports and exports in GDP; $\ln ISS_{i,t}$ = log of industrial structure supererogation

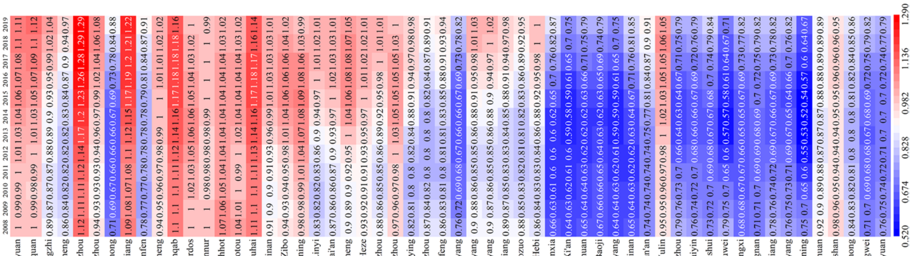

Fig. 5 Heat Map of economy coefficient of the YREB

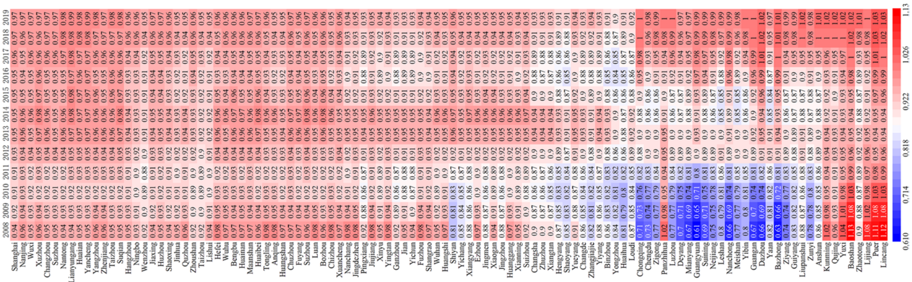

Fig. 6 Heat Map of economy coefficient of the YTREB

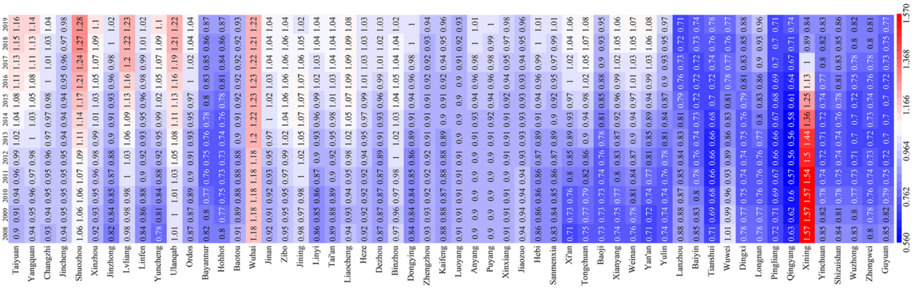

Fig. 7 Heat Map of population coefficient of the YREB

but such characteristics are not obvious in the YTREB. Both low-carbon "lock-in effect" and high-carbon "spillover effect" are found in the YREB. In addition, according to static panel analysis, in the YREB, the economy, population, and energy intensity exert significantly positive direct effects on CO_2 emissions, while the direct effects of technology and openness and indirect effects of technology and openness are significantly negative. In the YTREB, the direct effects of the economy, population, technology, energy intensity, and industrial structure supererogation are remarkably positive, while the indirect effects of the economy, openness, and energy intensity are significantly negative. The technological progress has a "scale effect" on CO_2 emissions in the YTREB, instead of YREB. In addition,

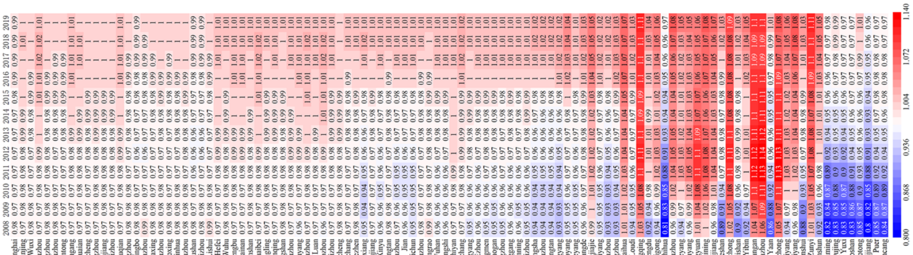

Fig. 8 Heat Map of population coefficient of the YTREB

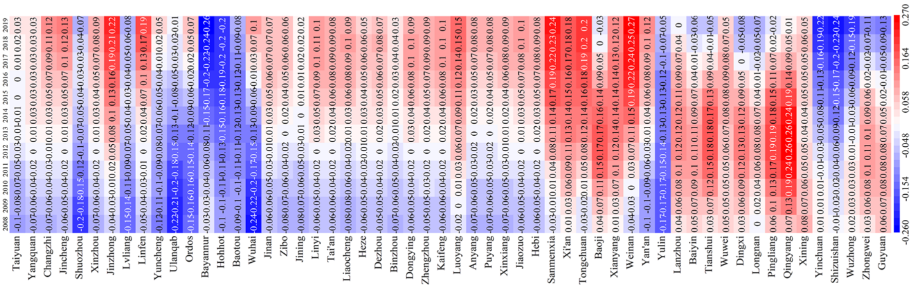

Fig. 9 Heat Map of technology coefficient of the YREB

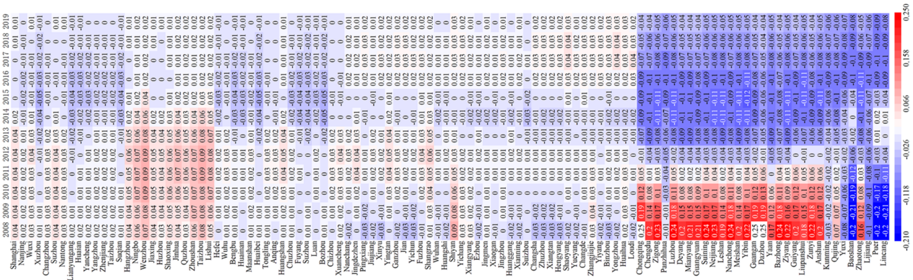

Fig. 10 Heat Map of technology coefficient of the YTREB

the dynamic analysis reveals that CO_2 emissions in the YREB exhibit an obvious temporal lag effect, but no significant temporal lag effect is observed in the YTREB. Meanwhile, the long-term effect of the drivers of CO_2 emissions is greater than the short-term effect, suggesting a snowball effect existing in these drivers. Finally, in both economic belts, there is remarkable spatio-temporal heterogeneity in the influence of different drivers of CO_2 emissions. Results obtained from this research enrich the low-carbon development theory and provide valuable empirical evidence for government to develop carbon reduction policies from the economic belt perspective.

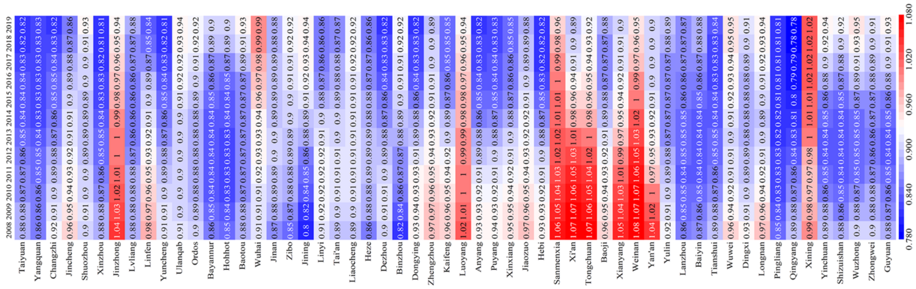

Fig. 11 Heat Map of energy intensity coefficient of the YREB

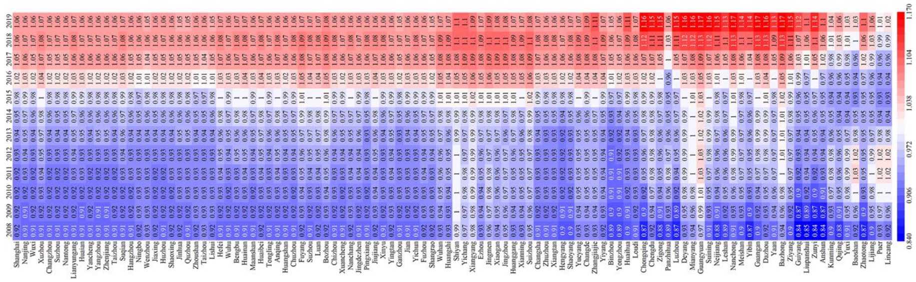

Fig. 12 Heat Map of energy intensity coefficient of the YTREB

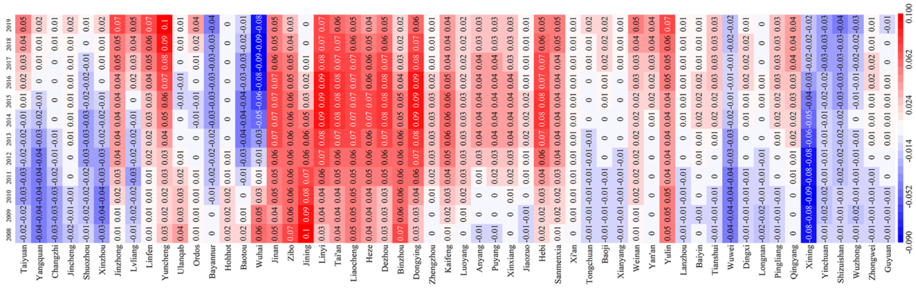

Fig. 13 Heat Map of openness coefficient of the YREB

5.2 Policy implications

On the basis of the above conclusions, policy suggestions for the YREB are proposed as follows: (1) The significant spatial auto-correlation of CO_2 emissions in the YREB indicates an agglomeration of CO_2 emissions at city level. As it is effective to disaggregate CO_2 emissions of economic belts into smaller urban CO_2 emissions, geographical configurations ought to be taken into account when making CO_2 emissions containment policies for the YREB. Specifically, cities in the L–L clusters should exert demonstrative effects

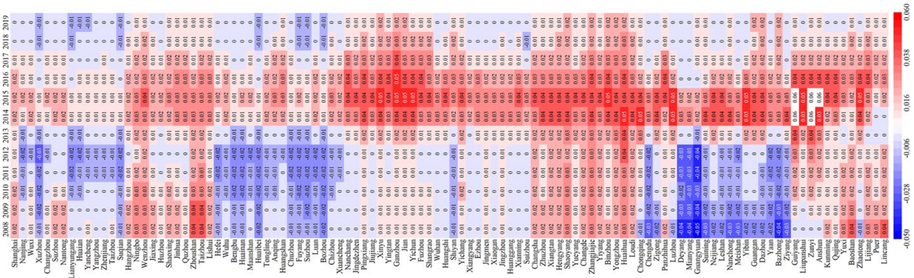

Fig. 14 Heat Map of openness coefficient of the YTREB

and prevent low-carbon lock-in effects. Cities in the H–H clusters should adopt strict control measures of CO_2 emissions to counteract high-carbon spillover effects and expand foreign trade and promote technological innovation (Li & Li, 2020). (2) High-quality development policies should be adopted, such as low-carbon technological innovation and opening to the outside world (Ding et al., 2019; Ganda, 2019; Sun et al., 2020), and the introduction of leading-edge technology should be integrated with the Belt and Road Initiative. (3) The cities in the centre and east of the YREB can curb CO_2 emissions with regard to economic development and population scale. Governments of cities in the western part of the YREB should focus more on improving the structure of foreign trade, rather than simply striving for quantity by environmental deregulation.

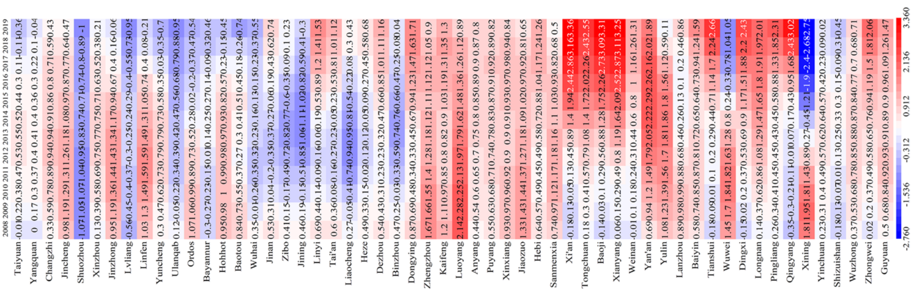

Fig. 15 Heat Map of industrial structure supererogation coefficient of the YREB

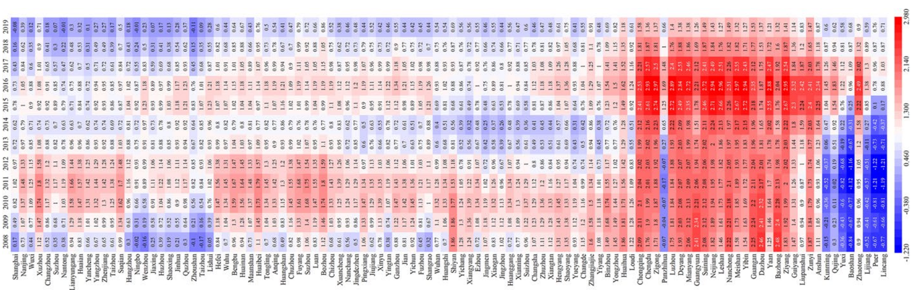

Fig. 16 Heat Map of industrial structure supererogation coefficient of the YTREB

In addition, in terms of the the YTREB, policy implications are provided as follows: (1) Considering the weak spatial dependence of CO_2 emissions in the YTREB, a low-carbon coordinated development strategy should be employed. The "race to the bottom" effect should be exerted in accordance with the "common but different" principle (Miao et al., 2019; Wu et al., 2020). (2) Economic development remains a crucial driver that affects CO_2 emissions, and a stable and sustainable economic development strategy is essential for the formation of a virtuous cycle of low-carbon development patterns. In addition, optimizing the population inflow structure and improving energy efficiency should be prioritized. The government should apply carbon emission tax to motivate lagging supply chains to escalate their low-carbon technologies and guide financial agencies to grant favourable loans to supply chains with inferior carbon technologies (Wu & Kung, 2020). (3) Cities in the eastern part of the YTREB should place more focus on the severe temporal trends of CO_2 emissions caused by energy intensity, whereas cities in the western part of the YTREB region should prioritize the industrial structures supererogation in their decision-making.

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Data availability The data used to support the findings of this study are available from the corresponding author upon request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

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