How urban agglomeration improve the emission efficiency？A spatial econometric analysis of the Yangtze River Delta urban agglomeration in China

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Abstract

Urban areas consume more than 66% of the world's energy and generate more than 70% of global greenhouse gas (GHG) emissions. With the world's population expected to reach 10 billion by 2100, and with nearly 90% of people living in urban areas, a critical question for planetary sustainability is how the size of cities affects energy use and carbon dioxide (CO_2) emissions. Are urban agglomerations more energy and emissions efficient than smaller cities? Does urban agglomeration exhibit gains from economies of scale concerning emissions? Here, we examine the relationship between urban agglomeration and CO_2 emissions for urban agglomeration in the Yangtze River Delta in China using a STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model considering the spatial effects. Also, it examines the influence of economic development, industrial structure, opening-up level, and technology on carbon emissions by exploring the spatial agglomeration and spillover effects. Our major finding is that urban size has had a negative correlation to carbon emissions, demonstrating that urban agglomeration is more emissions efficient. In addition, our results showed that carbon emission driving factors, such as technology progress, opening-up, population, have spatial dependence and spatial agglomeration effects. Technology progress, opening-up level, and population have a spatial spillover effect on carbon emissions. It means a city's carbon emissions are not only influenced by its own factors but also have an impact on neighboring cities. Therefore, cross-city or urban agglomeration policy, and actions of reducing carbon emissions, are necessary, whilst also developing a low-carbon economy by increasing the proportion of high-tech industry through technological progress and developing vigorous resource-saving and an environmentally friendly tertiary industry.

Keywords: Yangtze River delta, Carbon emissions, Urban agglomeration, Spatial effects

1 Introduction

Urbanization is a symbol of the modern world, characterized by the unprecedented growth of urban centers and substantial demographic changes(Kuriqi et al., 2019). By 2014, nearly 1000 urban agglomerations captured populations of 500,000 or greater. By 2050, the urban population is expected to increase by 2.5~3 billion, roughly equivalent to 64%~69% of the world population (IPCC, 2014). The positive effect of the growing urban size on prosperous economic growth has proved to be the central characteristic of modern urban economies (Glaeser and G. Resseger, 2010). Therefore, urban agglomerations have attracted wide attention among economists and urbanists, and have been promoted at the levels of theoretical research, experimenting, and policymaking. Inevitably, the process of urban agglomerations faces challenges, especially the impacts on environmental and climate change. Currently, urban areas are responsible for 71%~76% of CO_2 emissions from global final energy use and for 67%~76% of global energy use. In the future, the anticipated growth in urban populations will require further development of urban infrastructure, a major contributor to carbon emissions as urbanization advances (IPCC, 2014). Therefore, the process of urbanization that balances the growth of population and environmental conservation is a complicated issue and should be examined carefully.

China has experienced both industrialization and urbanization at a greater speed and on a greater scale than any other country in the world, during which process many new cities have arisen and grown (Zheng et al., 2019a, Zheng et al., 2019b). In China, the rate of urbanization increased from 19.72% in 1978 to 59.58% in 2018. Similar to any country with rapid urban growth, China has experienced environmental and climate pressure, and thus, has been actively seeking and implementing innovative practices to balance economic growth and sustainable development (Yang, 2013). The government has committed to reducing its carbon intensity—carbon dioxide emissions per unit of gross domestic product (GDP)—by 60%~65% of 2005 levels by 2020. Moreover, the government has also agreed to increase the country’s proportion of non-fossil fuel use in the energy consumption mix to approximately 20% by 2020 and proposed a peak in carbon emissions no later than 2030 (NDRC, 2015). For China to achieve its goal of tackling climate change and realizing national climate goals, it must achieve urban emission reduction targets and explore paths for emission reduction (Chen et al., 2016, Lee and Jung, 2018, Shan et al., 2017a).

It is not sufficient to simply consider reducing emissions at the national, provincial or city levels; it is also necessary to consider the urban environment as organically aggregated units. Extensive literature and data support the claim that large urban agglomerations are more conducive to productivity and innovation (Kuriqi et al., 2017). Yet some fear that a larger population will lead to higher CO_2 emissions.

Debate on the relationship between urbanization and CO_2 emissions has been under way for time. Some research suggest that urbanization would increase energy demand and boosts carbon emissions. Shahbaz et al. (2016) found that urbanization would initially reduce CO_2 emissions before it levels off in a later stage. Glaeser and Kahn (2010) showed that cities with larger populations are superior in terms of energy efficiency and CO_2 emissions. Martinez-Zarzoso and Maruotti (2011) analyzed the impact of urbanization on CO_2 emissions in developing countries from 1975 to 2003, and Shan et al. (2018) used data from China, to reach similar conclusions. Meanwhile, some studies drew opposite conclusions. For example, Poumanyvong and Kaneko (2010) suggest a positive impact of

urbanization on CO_2 emissions via cross-country analysis. Fragkias et al. (2013) discovered that CO_2 emissions proportionally scale with population size in metropolitan areas of the United States. Shi et al. (2018) found significant positive correlations between urban CO_2 emissions and urban population in China at multiple scales: from national scale, down to regional and urban agglomeration scales.
In light of the controversial standpoints towards this issue, this paper aims to answer the following research questions: are large agglomerations of cities more emission efficient than individual ones? How important is population size to carbon emission compared to other influencing factors? To answer these questions, it is essential to understand how the scale of an urban area correlates with CO_2 emissions and to distinguish the influence of population size from other factors on CO_2 emissions. Because one of the most prominent descriptors of urban size is urban population (Fragkias et al., 2013), population data are used in this paper to characterize urban size.

We also found that existing literature mostly focused on how urbanization rate and socioeconomic variables correlate to CO_2 emissions, while rarely considering the spatial factor, which is found to be critical in some studies. Liu et al. (2018) applied the KAYA model to analyze carbon emissions efficiency of 10 typical urban agglomerations from 2008 to 2015 in China. The results showed that the carbon emissions efficiency of China's urban agglomeration was generally not high and differed greatly from the efficiency of its counterparts at other spatial scales. Wang et al. (2016) examined the impact of urbanization quality on CO_2 emissions of 30 provinces in China and revealed significant temporal and spatial differences in the effects of urbanization quality on CO2 emissions. Makido et al. (2012) examined the relationship between urban form and CO_2 emissions considering 50 cities in Japan, and uncovered correlations between the spatial indices of urban form and sectoral CO_2 emissions for the residential and passenger transport sectors.

The Yangtze River Delta urban agglomeration, located at the lower reach of the Yangtze River in the eastern coastal part of China, covers approximately 211,700 km^2, or 2% of the country's territory. However, the 26 cities in this urban agglomeration, including Shanghai and the majority of the cities in Jiangsu, Zhejiang and Anhui Provinces, account for almost 20% of China's GDP (Ye and Ou, 2019). It is one of the most densely populated areas in China, exhibits the most rapidly-growing urbanization nationwide as well as a robust economy that is unequalled in China. This region is now the largest urban agglomeration in China, as well as the heart of China's economic development. Being the 'bellwether' of both urbanization and modernization within China, this region has garnered substantial attention about the role of urbanization as well as the subsequent effects of the urban areas on the environment. Throughout the globalized world, it is a common, even ubiquitous, practice for regional collaboration to support the growth and vitality of the world economy. Within China, a central source propelling the economy upwards and forwards is city agglomerations. In this paper, we conduct a comprehensive examination of the relationship between urban population size and urban CO_2 emissions, considering industrial structure, technology progress, and opening-up from the perspective of spatial interaction.

2 Material and Methods

2.1 Estimation of CO_2 emissions

Following the Intergovernmental Panel on Climate Change (IPCC) national GHG inventory guidelines, CO_2 emissions are estimated by fossil fuel consumption in physical units multiplied by an emission factor (IPCC 2006; Shan et al. 2018; Zheng et al. 2018):

$$CO2_{i,j} = AD_{ij} \times EF_{ij} \tag{1}$$

in which $CO2_{i,j}$ represents carbon emissions for energy type i used by sector j. AD_{ij} refers to the fossil fuels combusted measured in physical units, and EF_{ij} denotes the emission factors for fossil fuel i used in sector j. EF_{ij} could be further disaggregated into three components: net heating value of each fuel type i (TJ per t fuel); carbon content c of each fuel type i (tC per TJ); and oxidization rate o (percentage). Thus equation (1) can be rephrased as follows:

$$CO_2 = \sum\sum AD_{ij} \times n_i \times c_i \times o_{ij} \tag{2}$$

Emissions factors in this paper are derived from Liu et al. (2015), which significantly enhanced the accuracy of the emissions factors for China, based on previous work.

Generally, fossil fuel data can be derived from an Energy Balance Table (EBT) in a city's yearbook. However, EBTs are not always available from some cities' yearbooks, in which case fossil fuel data need to be estimated. We take the city-level emissions accounting methodology developed (Shan et al., 2017b) to estimate fossil fuel data by sector for all 25 cities. Different methods are adopted to construct cities' carbon inventory considering their data availability. Specifically, there are three ways trailed for different types of data sources, shown in Table 1.

Table 1 types of cities in terms of data availability

City Type	Description
Type 1	cities with EBT, for which all required data are directly provided in the yearbooks;
Type 2	cities without EBT but with energy transformation data
Type 3	cities without EBT and energy transformation data

By using the city-level carbon emissions accounting method, the carbon emissions for 25 cities in the studied urban agglomeration over the period 2005-2016 are calculated (**Figure 1**). It suggests that Ningbo, Suzhou, Shanghai, Nanjing, Hefei, Ma'anshan, and Wuxi were the top emitters and accounted for 60% of the total emissions of this urban agglomeration. The total carbon emissions in the studied area peaked in 2013. Investigating each city, we found that the top 16 cities of carbon emissions (defined as "peak city" in **Figure 1**) saw their carbon emissions peak during the study period, while the carbon emissions of the nine cities defined as "no-peak city" in **Figure 1** are still increasing.

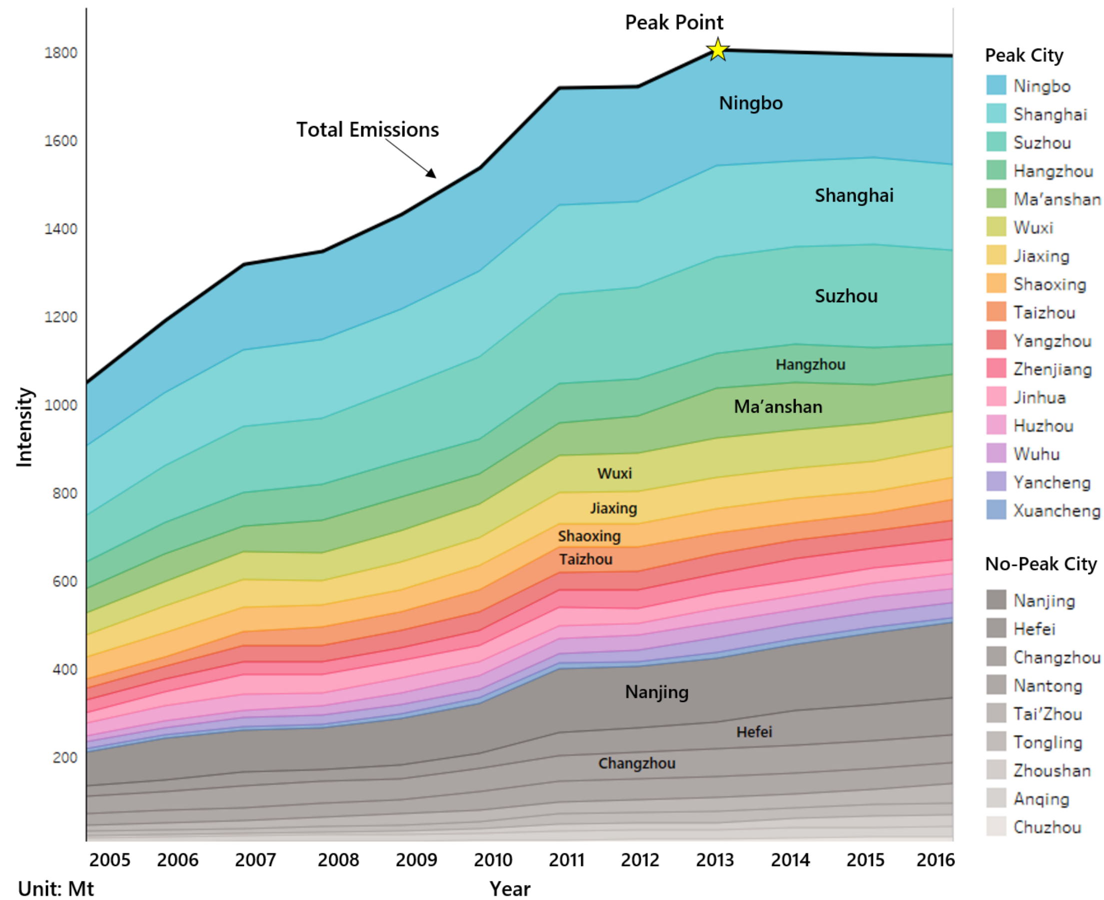

***Figure 1**. Carbon emission for 25 cities in the Yangtze River Delta urban agglomeration during 2005-2016*

Using the calculated carbon emissions for each city, carbon intensity (I) can be calculated applying the equation proposed by (Zheng et al., 2018):

$$I = \frac{CO_2}{GDP} \tag{3}$$

A map of carbon intensity change (%) for each city in the Yangtze River Delta urban agglomeration is shown in **Figure 2 (a)**. The percentage of change from 2005 to 2016 is divided into five groups based on quantiles: -70%~-64.98%, -63.47%~54.98%, -53.49%~41.99%, -30.05%~-24.18%, and a sole positive percentage value 21.19%. Across all 25 cities, only Zhoushan showed increased carbon intensity from 2005 to 2016, and Hangzhou, Huzhou, Shaoxing, Changzhou and Yangzhou were the leading cities with the most significant carbon intensity declines. The yearly carbon intensity is illustrated in **Figure 2 (b)**, showing the yearly change of carbon intensity for each city during this period. For all cities with decreased carbon intensity from 2005 to 2016, they generally experienced continuous decline each year, except for some cases such as Ma'anshan during 2008-2009 with a slight rise.

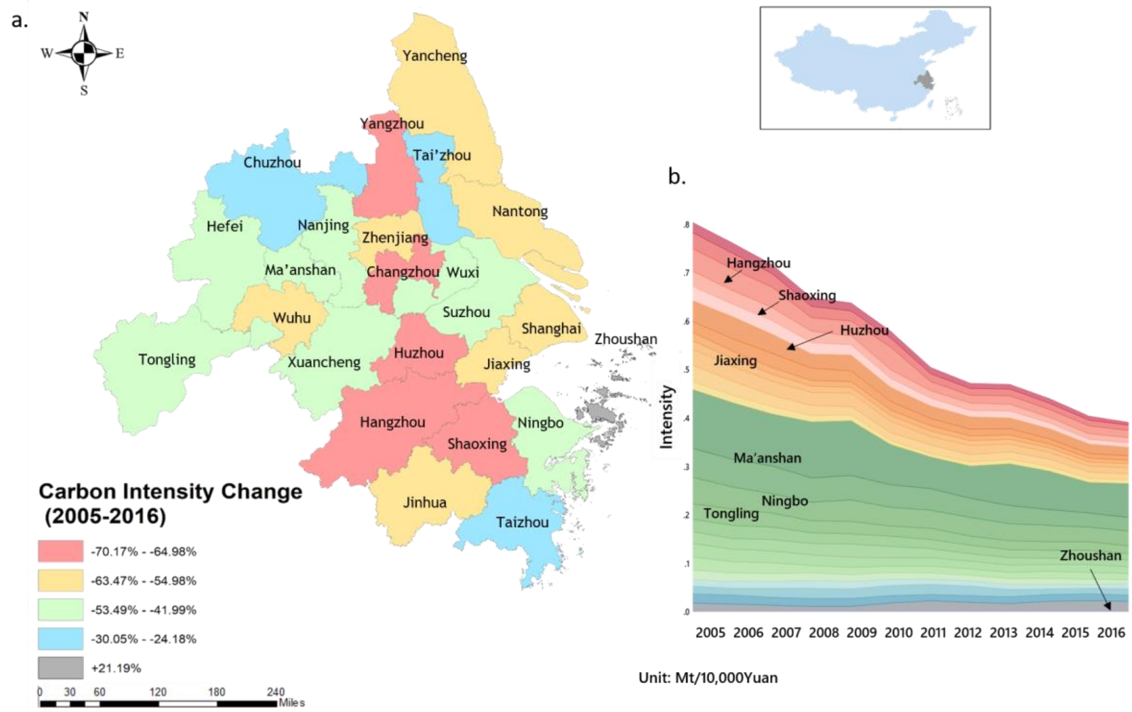

Figure 2. ***(a)*** *Carbon intensity change during 2005-2016; and* ***(b)*** *yearly carbon intensity of each city for the Yangtze River Delta urban agglomeration.*

2.2 The spatial STIRPAT model

The Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model has been widely employed in social science research to evaluate the impact of the human activities on the environment, such as climate change or environmental pollution. In this study, we are interested in explaining the complex relationship between CO_2 emissions and social and economic factors, therefore, we adopted the STIRPAT model. Generally, the STIRPAT model is derived from the IPAT model, which has been widely applied in literature to analyze the influence of human impact on the environment. Environment has been an independent variable, the influencing factors have been the wealth, technology and population.

$$I = \alpha P^{\lambda_1} A^{\lambda_2} T^{\lambda_3} e \qquad (4)$$

In the IPAT model, where I is urban carbon emissions; α is a constant term; P is population size; A is per capita wealth; T is the technical level of energy utilization; and e is a random error term. According to Dietz and Rosa, theoretically, $\lambda_1 > 0, \lambda_2 > 0, \lambda_3 < 0$, that is, growth in population and per capita wealth contributes to carbon emissions while improving energy utilization technology reduces carbon emissions.

Based on the IPAT model, Dietz and Rosa (1994) developed the STIRPAT model as follows:

Compared to the IPAT model, the STIRPAT model is extended to incorporate more factors, which can be more flexible and can better capture the impact factors on the environment with specific needs. In this study, we modified the original STIRPAT model by incorporating new variables derived from the collected data. In our established STIRPAT model, technological progress ($TECH$), represented by the proportion of science and technology expenditure in local financial budget expenditure; industrial structure ($INDU$), represented by the proportion of secondary industry added value to GDP; and opening-up level ($OPEN$), represented by the proportion of total import and export trade to GDP, are introduced as explanatory variables to explore their influence on carbon emissions. As in equation (4), coefficients are used to reflect the proportional relationship between the explanatory variables and carbon emissions. Taking logs, the linearized STIRPAT model is as follows:

$$\ln CI_{it} = \alpha + \lambda_1 \ln POP_{it} + \lambda_2 \ln GDP_{it} + \lambda_3 \ln TECH_{it} + \lambda_4 \ln INDU_{it} + \lambda_5 \ln OPEN_{it} + \varepsilon_{it} \quad (5)$$

Where CI is carbon intensity, POP is the population, representing the urban size, α is a constant term and $\lambda_1 \sim \lambda_5$ are the elastic coefficients of variables.

From the above data analysis of each cities' carbon emissions in the Yangtze River Delta urban agglomeration, it exhibits a difference in the carbon intensity. Considering the CO_2 emissions are driven by different regional dynamics, it is necessary to investigate the emission pattern from a spatial perspective, and thus spatial correlation is conducted. A primary advantage of exploring spatial correlation is that it highlights the spatial dependence and neighborhood relativity of predefined variables (Anselin, 1988). Here, we apply the widely-adopted Moran's I (Moran's Index; (Moran, 1950) to measure the spatial relationship between a variable and its geographical neighbors.

Following Elhorst (2014), there are primarily three types of spatial econometrics models: Spatial Lag panel Model (SLM), Spatial Error panel Model (SEM), and Spatial Durbin panel Model (SDM). For a certain location, considering the hypothesized influence of CO_2 emissions from its neighboring regions due to spillover effects, the value of the dependent variable observed at this location is partially determined by the spatially weighted average of the dependent variables of its neighbors. Anselin (1988) first built an econometric model based on the aforementioned hypothesis and was followed by several other studies in diverse research fields such as environmental studies. Therefore, in this study, we chose the spatial STIRPAT model to estimate the impact of carbon emissions. The equation of the used spatial STIRPAT model is as follows:

$$\ln CI_{it} = \alpha + \rho \sum_{j=1, j \neq i}^{N} \omega_{ij} \ln I_{jt} + \beta \ln X_{it} + \theta \sum_{j=1}^{N} \omega_{ij} X_{ijt} + \mu_i + \vartheta_t + \varepsilon_{it} \quad (6)$$

$$\varepsilon_{it} = \gamma \sum\nolimits_{j=1, j \neq i}^{N} \omega_{ij} \varepsilon_{jt} + \mu_{it} \quad (7)$$

Where CI_{it} is the carbon intensity of a spatial unit i at time t, α is a constant term, ρ is the spatial lag factor of carbon intensity, ω_{ij} is the spatial weight matrix, β is the carbon emission efficient factor, X_{it} represents the explanatory variables, θ is the spatial autocorrelation coefficients of the explanatory variables, μ_i and ϑ_t are the regional and temporal effects, respectively, and ε_{it} is the error term. The error term is further explained in equation (7), where γ is the spatial autocorrelation coefficients of the error term. When $\rho \neq 0, \theta = 0, \gamma = 0$, the model is simplified to SLM; when $\rho = 0, \theta = 0, \gamma \neq 0$, the model is simplified to SEM; when $\rho \neq 0, \theta \neq 0, \gamma = 0$, the model is an SDM; when $\rho = 0,\ \theta \neq 0,\ \gamma \neq 0$, the model is a SDEM. To comprehensively analyze the correlation among the explained variable, explanatory variables, and residual terms, this paper applied the SDM to estimate the impact of urban size along with other influencing factors on CO_2 emissions.

2.3 Data source

The sample comprises the yearly data of the 25 cities in the Yangtze River Delta urban agglomeration from 2005 to 2016, excluding Chizhou city due to data unavailability. The data are mainly sourced from China's urban statistics yearbooks: *Jiangsu Province Statistical Yearbook*, *Zhejiang Province Statistical Yearbook*, *Anhui Province Statistical Yearbook* and the statistical yearbooks of the studied cities from 2004 to 2017. The price index of each province used for base period adjustment is derived from the *China Statistical Yearbook* since 2005. Data are prepared yearly because of the way they were collected, and also because the yearly frequency better reflects the relationship between city size, industrial structure, and carbon emission, compared to quarterly or monthly.

Urban scale, indicated by population size in this paper, is the core explanatory variable in this study. The primary purpose of this study is to investigate whether the degree of agglomeration and economic activities in the Yangtze River Delta urban agglomeration is conducive to reducing the CO_2 emission intensity. As many counties in rural areas are under the jurisdiction of prefecture-level cities in China, the prefecture-level municipal district can properly reflect the economic scope of the city, so this paper takes the total population of prefecture-level municipal districts at the end of the year as the basis to represent the size of each city. The descriptive statistics of the variables used in the regression model are shown in Table 2.

Table 2. Descriptive statistics of variables

Variables	Mean	STD. DEV	Min	Max
CI （tonnes/10^4 yuan）	0.0227	0.0176	0.0062	0.1212
POP （10^4）	491.7967	269.4067	72.2200	1450.0000
GDP （10^4 yuan）	6.0647	3.2243	0.7331	14.5556
INDU （%）	52.3261	7.6512	27.4689	74.7346
TECH （%）	3.3124	1.8199	0.4039	17.8454
OPEN （%）	52.0323	44.6959	2.7360	288.1898

A flowchart summarizing the methodological design is shown in **Figure 3**. Besides the abovementioned influencing factors and data sources, **Figure 3** also demonstrates the logical flow in regression analysis. Before estimating the parameters of all spatial panel data, we first estimate the general STRIPT models without regard to spatial effect, and use the Lagrange Multiplier method (LM) to test whether SEM or SLM should be used. If the LM-lag test is more significant than LM-err, the SLM or SDM model should be chosen; whereas if LM-err is more significant, SEM or SDEM should be used (Anselin and Rey, 1991). When the results of the two tests are both significant, robust LM-lag and robust LM-err tests are performed. If the robust LM-lag test is passed instead of robust LM-err, the SLM or SDM model should be chosen, whereas if robust LM-err is more significant, SEM or SDEM should be applied.

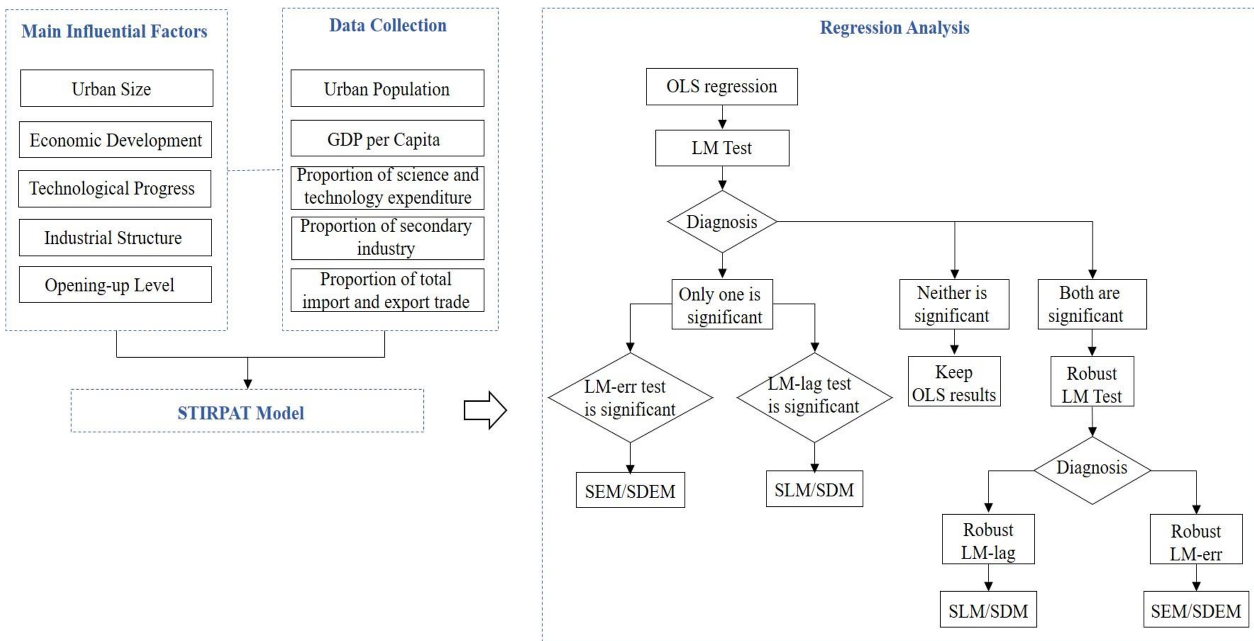

Figure 3. *Methodological framework.*

3 Results and Discussion

3.1 Unit Root Test

To reduce pseudo-regression, the first step in empirically testing the CO_2 intensity and the influencing factors is to find out whether the panel dataset has a unit root. The LLC test (Levin et al., 2002) and the IPS test (Im et al., 2003) are applied to examine the unit root of each variable. The test results show that the dataset used in this paper is stable, since significant values are presented for all variables in Table 3.

Table 3 Results of the panel unit root tests.

Variables	IPS		LLC	
	time trend	no time trend	time trend	no time trend
$\ln CARBON$	-3.20718**	-6.02023**	-9.8534**	-9.43684**
$\ln POP$	-6.46164**	-8.42846**	-12.9861**	-12.5995**
$\ln GDP$	-4.42713**	-6.06201**	-8.80465**	-7.71470**
$\ln INDU$	-1.52144*	-4.13955**	-7.19593**	-6.99959**
$\ln OPEN$	-4.21683*	-5.03705**	-9.48284**	-8.45349**
$\ln TECH$	-8.62312**	-11.2941**	-24.9292**	-22.8306**

Note: * and ** represent significance at the 5% and 1% levels, respectively.

3.2 The STIRPAT model

As stated above, before estimating the parameters of all spatial panel data, we first use the Lagrange Multiplier method (LM) to test whether SEM or SLM should be used in the STRIPT model, following the processing steps described in **Figure 3**. According to the Lagrange multiplier test results, SDM seems appropriate. Also, SLM is performed for comparison. Table 4 gives the results of the OLS (ordinary least square) and LSDV (least square dummy variables) methods for estimating the traditional mixed regression model and fixed-effect panel model.

Table 4 Estimation results of the nonspatial STRIPT model.

Variable	Pooled OLS coefficient	t-value	p-value	Fixed Effects LSDV coefficient	t-value	p-value
$\ln POP$	-0.3153	-7.7138	0.0000	-0.2638	-2.7096	0.0071
$\ln GDP$	-0.3593	-7.5372	0.0000	-0.4863	-15.6080	0.0000
$\ln INDU$	1.1018	7.0136	0.0000	0.5929	5.9402	0.0000
$\ln OPEN$	0.1934	5.8002	0.0000	0.0688	1.8033	0.0724
$\ln TECH$	0.0280	1.2930	0.1970	-0.0357	-1.2022	0.2303
R-squared	0.4421			0.6924		
Rbar-squared	0.4326			0.6882		
LIK	-156.9839			125.3791		
Spatial correlation						
Lagrange Multiplier (LAG)-LMLAG		5.8174	0.016		9.1324	0.003
Robust LM (LAG)-R-LMLAG		35.5546	0.000		13.8295	0.000
Lagrange Multiplier (ERROR)-LMERR		0.5466	0.460		2.5786	0.108
Robust LM (Error)-R-LMERR		30.2838	0.000		7.2756	0.007

With the presence of spatial correlation in a regression model, LeSage and Pace (2009) stated that the coefficients of the independent variables cannot accurately reflect the marginal effect. For example, when spatial lags of the variables occur in a model, the actual total effect on the dependent variable of a unit change in an independent variable – that is, the true partial derivative of the expected value of $\ln(CI)$ against $\ln(pop)$ - is not the same as the regression coefficient λ_1 in equation (5). The spatial correlation also captures spatial linkages and generates real-time feedback in the regression system, which can be separated into a direct (own-region) effect and an indirect (spatial spillover) effect (LeSage and Pace, 2009). The proper representation of the marginal effect is fused in the SDM in terms of individual cross-sections.

According to the Hausman test (Hsiao, 2003), we can further judge whether the SDM is based on a fixed-effect or random-effect estimation method. The result shows that the *p*-value of the Hausman test is 0.073. We cannot reject the original hypothesis that individual effects are related to the explanatory variables observed in the model, so an SDM with a random effect model is suitable. In the following, the estimation results of the SDM based on random effects are analyzed.

Table 5 Results of Spatial Durbin Model (SDM), numbers in parentheses denote significance

Variable	Fixed effect		Radom effect	
	SLM	SDM	SLM	SDM
$\ln POP$	-0.2063*	-0.1249	-0.2610**	-0.2214**
	(-2.0851)	(-1.1141)	(-3.2763)	(-2.7167)
$\ln GDP$	-0.3661**	-0.1729*	-0.3722**	-0.1526*
	(-8.9324)	(-2.1709)	(-9.2480)	(-2.0769)
$\ln INDU$	0.4982**	0.3482**	0.5166**	0.3810**
	(4.8362)	(3.0110)	(5.1055)	(3.4239)
$\ln OPEN$	0.0451	0.0352	0.0702*	0.0477
	(1.1725)	(0.9117)	(1.9643)	(1.3100)
$\ln TECH$	-0.0321	-0.0056	-0.0185	0.0147
	(-1.0693)	(-0.1620)	(-0.6578)	(0.4791)
ρ	0.2260**	0.1399*	0.2080**	0.0970**
	(3.8719)	(2.1686)	(3.5882)	(3.4824)
θ				0.1229**
				(5.0314)
$W * \ln POP$		-0.1243		-0.1848
		(-0.8839)		(-1.5998)
$W * \ln GDP$		-0.2269**		-0.2742**
		(-2.6540)		(-3.4225)
$W * \ln INDU$		0.0826		0.1084
		(0.6071)		(0.8196)
$W * \ln OPEN$		0.1464**		0.1442**
		(2.9320)		(3.1123)
$W * \ln TECH$		-0.0213		-0.0161
		(-0.5078)		(-0.4012)
Log-lik	130.5306	137.6636	-61703.6350	-121225.2400
R^2	0.9196	0.9225	0.9115	0.9144

Note: * and ** reflect significance at the 5% and 1% levels, respectively.

Results for the SDM are reported in Table 5. Notably, that the spatial autocorrelation parameter θ is statistically significant at the 1% level, indicating the existence of spatial dependence in the data. In other words, this result suggests that an increase in the CO_2 emissions of neighboring cities would drive an increase in CO_2 emissions in the focal city.

The spatial autoregressive coefficients (ρ) and spatial autocorrelation (θ) of each model are significantly positive at the 5% level. Further comparisons show that the estimated value of the spatial autoregressive coefficients (ρ) of the SDM model is significantly smaller than that of the SLM model. Taking fixed effects as an example, the estimated value of ρ in SDM is 0.0969, while that in SLM is 0.1399. It indicates that neglecting the spatial lag term of explanatory variables will lead to overestimation of the endogenous spatial interaction between the explained variables. In any case, the estimation results of the SLM and SDM models show that there are endogenous spatial interaction effects and random spatial interaction effects in the carbon emissions of cities in the Yangtze River

Delta urban agglomeration, i.e. significant spatial spillover effects in urban carbon emissions. This result suggests that for the Yangtze River Delta urban agglomeration to achieve energy conservation and emission reduction goals, it must promote the formation of a synergistic mechanism between regional policies of energy conservation and emission reduction.

From Table 5, we can see that population size (POP) and GDP per capita (GDP), which represents the proxy of economic growth, presents a negative and significant effect on emissions. The driving factors of industrial structure ($INDU$), technology ($TECH$) and opening degree ($OPEN$) are positive.

A percentage change in the driving force produces an identical percentage change in impact. Coefficients >1.0 suggest an elastic relationship, indicating that the impact increases more rapidly than the driving force. The intensity of carbon emissions will be reduced by 0.22% for every 1% increase in the population size of the Yangtze River Delta urban agglomeration; that is, with the expansion of the urban scale, the carbon intensity will be reduced, yet there is less elasticity.

The carbon intensity will be reduced by 0.22% for every 1% increase in the population size. The coefficient of population size indicates that all else being equal, more populated cities produce lower emissions.

The coefficient of GDP per capita is negative. For every 1% increase in per capita GDP, the carbon intensity will be reduced by 0.15%. Meanwhile, the coefficient of $W * \ln GDP$ is negative at the 1% significance level, which indicates that the carbon intensity in neighboring cities will be decreased by 0.27% for every 1% increase in GDP per capita. This demonstrates that the economic growth of the focal cities will reduce the carbon intensity of the neighboring cities. The improvement of the economic development level is of great benefit to reduce the carbon intensity of the region and the surrounding areas.

At the 1% significance level, the coefficients of the industrial structure indicate that a higher share of secondary industry to GDP contributes to higher CO_2 emissions. This broadly aligns with our anticipation since it is commonly acknowledged that the development of the industry is closely related to energy consumption. For every 1% increase in the proportion of secondary production in the Yangtze River Delta urban agglomeration, the carbon intensity will rise by 0.38%, the highest increasing rate among all independent variables. Thus, the industrial structure is the most important factor affecting carbon emissions reduction in the Yangtze River Delta urban agglomeration. Industrial structure plays a significant role in controlling carbon emissions. To some extent, the evolution of economic industrial structure to a higher level helps to restrain carbon emissions and enhance carbon productivity, because the secondary industry is dominated by industry with high energy consumption, while the tertiary industry has higher added value and less energy consumption, which helps to improve carbon productivity.

The coefficient of opening-up level ($\ln OPEN$) is positive. The SLM model of the stochastic effect estimates that the intensity of carbon emissions will increase by 0.07% for every 1% increase in the degree of opening up of the Yangtze River Delta urban agglomeration. At the same time, the coefficient of $W * \ln OPEN$ is significantly positive at the 1% level, which indicates that in the sampled period, an increase in the opening-up level of a focal city will stimulate an increase in the carbon emission intensity of the surrounding cities; that is, the foreign trade of the focal city has a negative impact on the carbon emissions of the surrounding cities. Although some studies have shown that foreign direct investment (FDI) may bring advanced technology and management and enhance carbon productivity through technology spillovers (Zhu et al., 2016), results of this study show that the foreign trade of the Yangtze River Delta urban agglomeration has harmed CO_2 emission control. The improvement of carbon productivity caused by FDI has been weakened by the inflow of energy-consuming and high polluting industries from abroad. In the future, we should further optimize the structure of foreign trade, reduce the embodied carbon emissions, strengthening environmental regulations, and push enterprises for green technology innovation.

The coefficient of technological progress ($\ln TECH$) is positive but not significant, indicating that the technological progress of the Yangtze River Delta urban agglomeration has not played a significant role in CO_2 emissions in the sampled period. Previous studies have shown that if technological progress has a "green bias" feature, it will be conducive to energy conservation and emission reduction, but if it aims at improving productivity, it will be unfavorable to energy conservation and emission reduction by causing the expansion of production scale (Yang et al., 2011). **Figure 4** illustrates the relationships between the influencing factors and carbon emission within each region, as well as the interactions of carbon emissions among different regions.

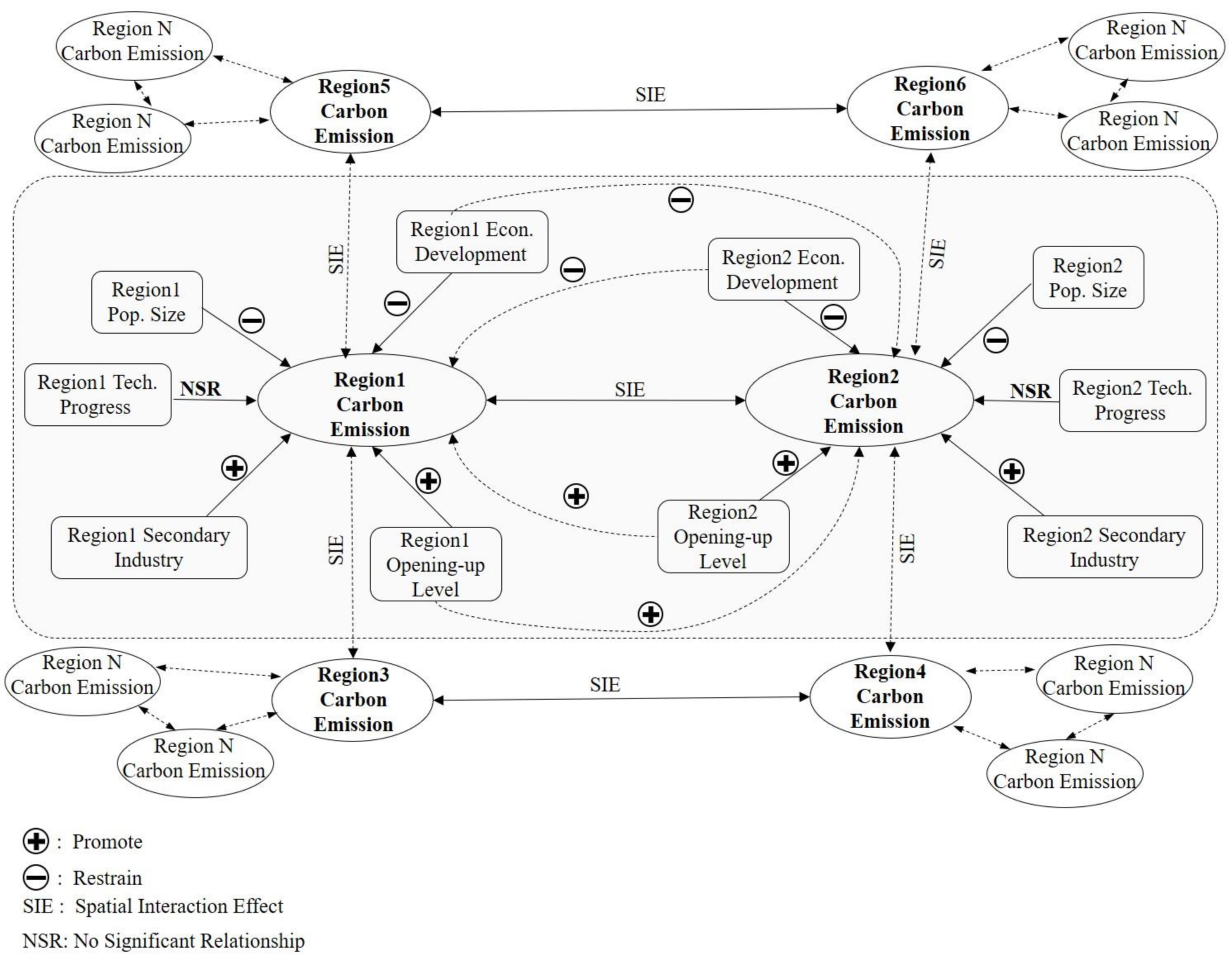

Figure 4*. Interactions between the influencing factors and carbon emission within and across regions.*

4 Conclusion and Policy Implications

Taking the Yangtze River Delta urban agglomeration as a case study, this paper adopts spatial econometric methods to explore the driving force of urban size, industrial structure, economic growth, technological progress and the opening-up on CO_2 emissions, taking into account the spatial interaction among cities in urban agglomeration.

We can conclude that the expansion of the urban scale contributes to reducing CO_2 emissions. As indicated in the results, a 1% increase of urban population would result in 0.22% reduction of carbon emission. Intuitively, this conclusion seems perplexing, due to the common belief that more population would directly or indirectly incur more energy consumption, and hence more CO_2 per capita. One possible explanation is that the aggregation of the population usually brings forth some agglomeration force that could improve production efficiency, leading to a reduction in CO_2 emissions per capita. The Yangtze River Delta region has one of the highest populations, the largest economic scale and the highest economic density in China. Its population, economic agglomeration effects, and scale and spillover effects are far higher than the national average level. In this agglomeration of a large number of high-quality populations, the sharing and spillover of knowledge, skills, and technology have significantly facilitated the carbon emission reduction.

The effects of a city's actions of CO_2 mitigation are not limited to its own, but also have an impact on the neighboring cities. The empirical results have demonstrated that economic growth and opening-up level play important roles in the change of carbon emission intensity, not only for the local but also for neighboring cities. More specifically, with a 1% increase of GDP of a city, the carbon emission of its neighboring cities would drop by 0.27%; when a city's opening-up level increases by 1%, the carbon emission of its neighboring cities would rise by 0.14%. However, against our expectation, technology progress and industry structure did not reduce the CO_2 for the focal or neighboring cities.

The conclusion of this study is of great significance to the carbon emission reduction policies of urban agglomerations. Considering the Yangtze River Delta urban agglomeration, cities of larger sizes are more emissions efficient. Thus, a national urban policy could encourage the development of large cities ceteris paribus. Meanwhile, there is a significant spatial interaction in terms of carbon emissions in the Yangtze River Delta urban agglomeration. It implies that city planning to reduce GHG should not only consider its own city, but also neighboring cities as well. Nowadays, with cities highly integrated within an urban agglomeration, it is important to develop a coordinated policy at the urban agglomeration level for addressing climate change. Although our study shows that technology has a limited impact on reducing CO_2 emissions, the government should promote a low-carbon economy by increasing the proportion of high-tech industry. Suggested approaches to the government include encouraging technological innovation, promoting cleaner production technology, and developing a vigorous resource-saving and environmentally-friendly tertiary industry.

Limited to the sampled data in this study, an optimal city size for energy efficiency maximization is hard to achieve. However, we are interested in approaching this goal through simulations using empirical knowledge. More specifically, we intend to examine the change of coefficients in the regression model by adjusting the "radius" that defines "neighboring region". In this way, different spatial scales can be simulated. Further, adopting our empirical knowledge, these different scales are incorporated into the spatial parameters used in the equations defining the spatial STIRPAT model. Then in the regression results, the change of a coefficient reflects the sensitivity of the corresponding explanatory variable as to CO_2 emissions. In addition, another improvement based on this study is to examine other urban agglomerations, to generalize universally applicable conclusions. Therefore, based on the further exploration of spatial scales, as well as extensive tests on other urban agglomerations, new and more thorough inferences are expected.

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