Study on the relationship between agglomeration of service industry and economic growth in Yangtze River Delta based on spatial econometric models

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Abstract. Based on the panel data of 26 cities in the Yangtze River Delta from 2007 to 2016, this paper studies the impact of service industry agglomeration on economic growth in the Yangtze River Delta urban agglomeration. We construct a series of spatial econometric models, and use the maximum likelihood estimation method to estimate the parameters. Our results present notable regional differences of economic growth between cities and there exists significant spatial autocorrelations of economic development within Yangtze River Delta. Meanwhile, we find that agglomeration of services will depress economic growth in the surrounding areas. Based on this, some policy suggestions are put forward to adjust and optimize the spatial distribution of the service industry in the Yangtze River Delta region and to promote regional economic levels.

1. Introduction

In 2017, the increment value of China’s service industry has reached ¥42,703.2 billion, accounting for 51.6% of GDP and surpassing the secondary industry by 11.1%, which has become the largest industry in China. Yangtze River Delta urban agglomeration is an important intersection of "One Belt and One Road" and Yangtze River economic belt. The service industry in the Yangtze River Delta has been developed rapidly, and the proportion of the service industry has increased constantly since the reform and opening up 40 years ago. It is easier for the services to produce obvious agglomeration characteristics.

The relationship between industrial agglomeration and economic growth has attracted more and more interests among worldwide scholars. Ottaviano and Martin (2001) have proved that there exists a circular causation between economic growth and agglomeration, i.e. growth brings agglomeration while agglomeration boosts growth [1]. Ellison et al. (2010) has verified Marshall’s agglomeration theory by studying the industrial agglomeration effect in some neighbouring regions with the state of solidification [2]. Sarach (2015) has proposed and executed the suggested methodology of collaboration analysis; and it’s been found that industrial agglomeration improves the efficiency of industrial production and cooperation [3]. Fan and Scott (2003) have discussed the relationship between industrial agglomeration and economic growth by kinds of statistics survey in developing countries in East Asia, which confirms that there exists a positive relationship between industrial agglomeration and economic performance for many manufacturing sectors in China [4]. The proportion of the service sector in the economic structure, the number of people employed and labor
productivity are increasing instantly. Liu et al. (2017) has found that there are both significant positive global spatial autocorrelation and local spatial agglomeration effects on urban energy efficiency in China, however, agglomeration is not always positive [5]. Jin et al. (2011) has pointed out that the agglomeration level of modern services industries reflects the economic level unilaterally, where cities with low agglomeration level of modern service industry may have higher GDP [6].

Being one of the industry agglomerations, the service industry agglomeration refers to a process in which the service industry is highly concentrated in a specific geographical region and capital elements are continuously gathered within the spatial scope. Can such city-level agglomeration boost local economic growth and produce spatial effects on adjacent areas? It is of great importance to study the internal influencing mechanism of the service industry agglomeration and regional economic growth in the Yangtze River Delta as well as the spatial spillover effect. So far, there are not many studies of spatial econometrics on service industry agglomeration for the Yangtze River Delta. Traditional econometric analysis ignores the spatial correlation of variables, which may reduce the accuracy of the explained variables. Baudino (2016) has investigated the impact of physical and human capital accumulation on economic growth in China by different spatial panel specifications [7]. Liu et al. (2017) has used an improved spatial econometric model to analyze the impact of China's urbanization level and other related factors on energy consumption [8]. Ye et al. (2018) has replaced spatial adjacency matrix with economic weight matrix and studied the impact of financial agglomeration on China's urbanization with a spatial Durbin model (SDM) [9].

With the rapid development of science and information, more and more scholars have studied the methods of spatial econometric model. In general, a spatial econometric model can be characterized as Gaussian, non-Gaussian or generalized stochastic with random effects [10]. Wang et al. (2018) has introduced network autocorrelations into the spatial econometric model, which eliminates the influence of spatial autocorrelations on the estimation of distance attenuation [11]. Arbia et al. (2019) has investigated what limits they can achieve for accurate estimates of spatial econometric models when dealing with enormous data sets, and has found that the calculation time not only increases non-linearly with a raise of sample size but also is related to the density of weight matrix [12]. Zhang and Yu (2017) have used a Mallows type criterion to come up with a new model selection method for the chosen of an optimal weights matrix [13].

These researches make the theory of spatial metrology more perfect. Our study adopts spatial econometric models to analyze the panel data of 26 cities in the Yangtze River Delta region from 2007 to 2016, which discusses the influence mechanism of service industry agglomeration on the economic growth of cities in that region and its spillover effect on surrounding areas. The rest of this study is organized as follows. In section 2, the setting of empirical model, data explanation and selection of measurement index are presented. Section 3 discusses the results of each spatial econometric model based on panel data. The main conclusion of our study and policy implications is included in section 4.

2. Settings of the empirical model, data explanation and selection of measurement index

2.1. Settings of the empirical model
It is assumed that the social production follows the cobb-Douglas production function. Based on the production mode of technology, capital and labor input, relevant internal factors of the economic effect of service industry agglomeration are taken into consideration. The model is established as follows:

\[ Y_{it} = AK_{it}^\alpha N_{it}^\beta \]  

(1)

where \( Y_{it} \) represents the output level (i.e. Per capita regional GDP (PGDP)) during period \( t \) of area \( i \). \( A \) represents the total factor productivity (or rate of technological progress), which reflects the role of technological progress in economic development and depends on the degree of agglomeration for service industry (AGG), service industry density (SDEN) and degree of opening-up [4]. We adopt foreign direct investment (FDI) to express the degree of economic development. \( K_{it} \) denotes the capital stock during period \( t \) of region \( i \), which is represented by the fixed asset input (FI). \( N_{it} \) denotes the
labor capital input during period $t$ of region $i$. $\alpha$ and $\beta$ are the elasticity coefficients of capital output and labor output respectively. In order to study the contribution rate of each input factor to regional economic growth, heteroscedasticity and violent fluctuation of data are eliminated and the variables are taken in the logarithmic form. The logarithmic model of production function obtained from equation (1) is presented as follows:

$$
\ln \text{PGDP}_i = \beta_0 + \beta_1 \ln \text{AGG}_i + \beta_2 \ln \text{SDEN}_i + \beta_3 \ln \text{FI}_i + \beta_4 \ln \text{FDI}_i + \beta_5 \ln N_i + \epsilon_i.
$$

(2)

2.2. Description of data

In this study, we adopt panel data of 26 cities (including Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, Taizhou of Jiangsu province, Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoyang, Jinhua, Zhoushan, Taizhou of Zhejiang province, Hefei, Wuhu, Ma’anshan, Tongling, Anqing, Chuzhou, Chiuzhou, Xuancheng of Anhui province) in the Yangtze River Delta region from 2007 to 2016 for empirical research. Data come from China City Statistical Yearbook and statistical yearbooks of Jiangsu, Zhejiang and Anhui provinces. We take the mean value for a given city to supplement for the sample variables with one-year data missing, i.e., for city A, when the value of FDI is missing for 2009, then the average value of 2008 and 2010 of that city is taken as the input value for 2009. Moreover, the linear interpolation is applied when meeting with more than one year of missing data.

2.3. The selection of measurement indicators

According to the Dividing Basis of Three Industries formulated by the national bureau of statistics based on the Classification of Industries In the National Economy (GB/T4754-2011), the tertiary industry is clearly defined as the service industry for the convenience of unifying the scope of service industry. Variables in this paper are described as follows:

- Explained variable - PGDP (calculated with resident population)

Using ArcGIS and GeoDa software, the PGDP of 26 cities in the Yangtze River Delta in 2016 was taken as the measurement index to draw a sextile map of the economic growth space of the urban agglomeration in the Yangtze River Delta (see Figure 1). It can be seen that the darker the color, the higher the level of economic development of the city. Meanwhile, there exist obvious regional differences in the economic growth level.

- Core explanatory variable - AGG

Here, we take the location entropy of the service industry as the evaluation parameter, and evaluate it as the ratio between the proportion of the output value of a city’s service industry in the overall level of 26 cities in the Yangtze river delta and the proportion of the city’s population, namely,

$$
\text{AGG}_i = \frac{E_i}{E} \cdot \frac{H_i}{H}
$$

(3)
where \( E_i \) and \( H_i \) represent the output value and population of service industry for city \( i \) respectively. \( E \) and \( H \) represent the overall service industry value and population of the entire Yangtze River Delta region. The calculated location entropy of 26 prefecture-level cities in Yangtze River Delta from 2012 to 2016 is presented in Table 1. From Table 1, we can find that there are nine regions where the average location entropy of the service industry exceeds 1, which indicates that the service industry agglomeration appears among them. Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Zhenjiang, Hangzhou and Zhoushan are the eight cities whose location entropy always exceeds 1, revealing comparative advantages with higher degree of agglomeration over other cities. Obviously, there are notable regional differences in service industry agglomeration. For example, the degree of service industry agglomeration in Jiangsu province and Zhejiang province is relatively high while they are all less than 1 in all cities of Anhui province.

- Control variables – SDEN, FDI, FI, N

SDEN is obtained through dividing regional service industry income by regional area, and here we take the gross product of the tertiary industry as the service industry income. Per capita FDI is the actual utilized foreign direct investment that is converted into RMB at exchange rate that year. FI is presented with per capita year-end fixed asset investment stock in the region, which is a reflection of the long-term stable production material input, and measures the capital construction situation to a certain extent. N is reflected by education levels, which is defined by assigning values to the education years of each level (i.e. primary school, junior high school, senior high school, junior college and above), namely 6, 9, 12 and 16 years respectively; and calculate the sum of total number of students in each stage according to this weight and divide it by the total number of employees in the city.

| City      | 2012   | 2013   | 2014   | 2015   | 2016   | Avg. | City      | 2012   | 2013   | 2014   | 2015   | 2016   | Avg. |
|-----------|--------|--------|--------|--------|--------|------|-----------|--------|--------|--------|--------|--------|------|
| Shanghai  | 1.54   | 1.54   | 1.51   | 1.58   | 1.56   | 1.54 | Huzhou    | 0.68   | 0.67   | 0.68   | 0.70   | 0.68   | 0.68 |
| Nanjing   | 1.42   | 1.43   | 1.45   | 1.49   | 1.42   | 1.44 | Shaoxing  | 0.92   | 0.91   | 0.90   | 0.89   | 0.84   | 0.89 |
| Wuxi      | 1.59   | 1.54   | 1.46   | 1.42   | 1.39   | 1.48 | Jinhua    | 0.69   | 0.68   | 0.69   | 0.69   | 0.66   | 0.68 |
| Changzhou | 1.12   | 1.13   | 1.20   | 1.23   | 1.19   | 1.17 | Zhoushan  | 1.02   | 1.00   | 1.02   | 1.02   | 1.00   | 1.01 |
| Suzhou    | 1.52   | 1.52   | 1.51   | 1.51   | 1.43   | 1.50 | Taizhou   | 0.65   | 0.64   | 0.63   | 0.64   | 0.61   | 0.63 |
| Nantong   | 0.75   | 0.76   | 0.82   | 0.85   | 0.85   | 0.81 | Hefei     | 0.65   | 0.65   | 0.64   | 0.69   | 0.69   | 0.66 |
| Yancheng  | 0.50   | 0.50   | 0.52   | 0.54   | 0.53   | 0.52 | Wuhu      | 0.44   | 0.44   | 0.47   | 0.27   | 0.56   | 0.44 |
| Yangzhou  | 0.79   | 0.80   | 0.85   | 0.87   | 0.85   | 0.83 | Ma’anshan | 0.47   | 0.46   | 0.46   | 0.50   | 0.49   | 0.48 |
| Zhenjiang | 1.04   | 1.06   | 1.13   | 1.14   | 1.10   | 1.10 | Tongling  | 0.63   | 0.64   | 0.63   | 0.42   | 0.41   | 0.55 |
| Taizhou   | 0.70   | 0.71   | 0.76   | 0.79   | 0.79   | 0.75 | Anqing    | 0.23   | 0.23   | 0.23   | 0.26   | 0.25   | 0.24 |
| Hangzhou  | 1.36   | 1.35   | 1.37   | 1.43   | 1.44   | 1.39 | Chuzhou   | 0.21   | 0.21   | 0.21   | 0.23   | 0.23   | 0.22 |
| Ningbo    | 1.10   | 1.09   | 1.03   | 1.02   | 0.96   | 1.04 | Chizhou   | 0.32   | 0.32   | 0.34   | 0.34   | 0.34   | 0.33 |
| Jiaxing   | 0.75   | 0.75   | 0.73   | 0.74   | 0.71   | 0.74 | Xuancheng | 0.29   | 0.29   | 0.31   | 0.32   | 0.32   | 0.31 |

Note: all the results above are calculated according to equation (3) using data from China Statistical Yearbook, China City Statistical Yearbook and statistical yearbooks of each province and cities from 2012 to 2016.

3. Empirical analysis results

3.1. Spatial correlation analysis

PGDP of Yangtze River Delta from 2007 to 2016 is taken as the object to calculate Moran’s I and its statistics, and the results are shown in Table 2. The values of \( Z(I) \) fall between 2.789 and 4.863, both of which are greater than the critical value (1.96) under the 95% confidence interval. It shows that the original data have obvious clustering characteristics. P-values are all less than 0.01, indicating that the analysis results have significant statistical significances. All values of Moran’s I have passed the significance test, which indicates that the economic growth of the Yangtze River Delta urban
agglomeration has obvious spatial autocorrelations, and the strength of regional economic growth may be affected by the growth of adjacent regions.

3.2. Spatial weighted matrix
The general panel data model cannot accurately describe the impact of service industry agglomeration on economic effect due to the neglect of spatial correlations between different regions. Our study adopts the spatial panel model for analysis. In the spatial panel model, the spatial factors, namely the spatial weighted matrix, are introduced into the model to reflect the spatial correlation between variables, so as to conduct more accurate econometric analysis. Most studies usually use spatial proximity matrix for analysis where the distance of adjacent areas is assumed to be the same, which does not take into account the impact of different distances between cities. Generally, the spillover effect of economic activities is negatively correlated with the spatial distance between cities. Therefore, here the spatial weighted matrix is weighted through geographical distances, where $s_{ij}$ is calculated by the distance between city $i$ and city $j$. Then the spatial weighted matrix is defined as

$$w_{ij} = \begin{cases} \frac{1}{s_{ij}}, & i \neq j, \\ 0, & i = j. \end{cases}$$

(4)

Table 2. Global spatial correlation tests of per capita GDP in Yangtze River Delta from 2007 to 2016.

| Year | Moran’s I | E(I) | Sd(I) | Z(I) | P     | Year | Moran’s I | E(I) | Sd(I) | Z(I) | P     |
|------|-----------|------|-------|------|-------|------|-----------|------|-------|------|-------|
| 2007 | 0.085     | -0.040 | 0.036 | 3.453 | 0.001 | 2012 | 0.063     | -0.040 | 0.036 | 2.838 | 0.005 |
| 2008 | 0.082     | -0.040 | 0.036 | 3.353 | 0.001 | 2013 | 0.062     | -0.040 | 0.036 | 2.789 | 0.005 |
| 2009 | 0.079     | -0.040 | 0.036 | 3.300 | 0.001 | 2014 | 0.065     | -0.040 | 0.037 | 2.867 | 0.004 |
| 2010 | 0.055     | -0.040 | 0.036 | 2.617 | 0.009 | 2015 | 0.139     | -0.040 | 0.037 | 4.863 | 0.000 |
| 2011 | 0.068     | -0.040 | 0.036 | 2.962 | 0.003 | 2016 | 0.127     | -0.040 | 0.037 | 4.558 | 0.000 |

3.3. Spatial model selection
The spatial panel data models nowadays are mainly divided into three basic types: spatial autoregressive model (SAR), spatial error model (SEM) and spatial Durbin model (SDM) [14]. Formations are as follows (where $i$ represents the section dimension and $t$ is the time dimension; $j$ denotes different cities numbered from 1 to $N$; $w_{ij}$ is the elements of spatial weighted matrix; $y_{it}$ represents the vector of explained variable, namely $\ln PGDP$; $X_{it}$ is the matrix of explanatory variables; $\beta$ is coefficient vector, which is used to measure the impact of explanatory variables on the level of local economic growth; $\epsilon_{it}$ is a vector of error terms, where $\epsilon_{it} \sim N(0, \sigma^2 I_n)$):

- **SAR model:**

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it} \beta + \mu_i + \epsilon_{it},$$

(5)

where $\mu_i$ represents the individual spatial effect; $\delta$ is the spatial autoregressive coefficient, which measures the influence of the observed values in adjacent areas on the local observed values.

- **SEM:**

$$\begin{align*}
\begin{cases}
y_{it} = X_{it} \beta + \mu_i + \varphi_{it}, \\
\varphi_{it} = \lambda \sum_{j=1}^{N} w_{ij} \varphi_{jt} + \epsilon_{it},
\end{cases}
\end{align*}$$

(6)

where $\varphi_{it}$ is the error term of spatial, and $\lambda$ is the spatial error autocorrelation coefficient that measures the influence of the error of the adjacent observation values on the local observations.

- **SDM:**

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it} \beta + \gamma \sum_{j=1}^{N} w_{ij} X_{jt} + \mu_i + \epsilon_{it},$$

(7)
where $\gamma$ is the vector of coefficients that measures the spillover effect of each explanatory variable on the level of economic growth in neighboring regions.

Based on the above models, by taking the influence of time and space factors on variables into comprehensive considerations, equation (2) is substituted into the above three spatial models. Our final models are as follows:

- **SAR model:**
  \[
  \ln PGDP_{it} = \delta \sum_{j=1}^{N} w_{ij} \ln PGDP_{jt} + \beta_1 \ln AGG_{it} + \beta_2 \ln SDEN_{it} + \beta_3 \ln FDI_{it} + \beta_4 \ln N_{it} + \mu_i + \epsilon_{it}.
  \]  

- **SEM:**
  \[
  \ln PGDP_{it} = \beta_1 \ln AGG_{it} + \beta_2 \ln SDEN_{it} + \beta_3 \ln FDI_{it} + \beta_4 \ln N_{it} + \mu_i + \varphi_{it},
  \]
  \[
  \varphi_{it} = \lambda \sum_{j=1}^{N} w_{ij} \varphi_{jt} + \epsilon_{it}.
  \]  

- **SDM:**
  \[
  \ln PGDP_{it} = \delta \sum_{j=1}^{N} w_{ij} \ln PGDP_{jt} + \beta_1 \ln AGG_{it} + \beta_2 \ln SDEN_{it} + \beta_3 \ln FDI_{it} + \beta_4 \ln N_{it} + \sum_{j=1}^{N} w_{ij} (\alpha_i \ln AGG_{it} + \alpha_j \ln FDI_{it} + \alpha_k \ln N_{it}).
  \]

These three models above involve different interaction effects of service industry agglomeration and economic growth. SAR model (8) focuses on studying the mutual influence of economic growth between neighboring cities. SEM (9) is suitable for capturing potential impacts that disturbance error terms of adjacent cities may have on the explained variable of local cities. SDM (10) not only studies the impact of local urban explanatory variables on economic growth, but also studies the spillover effect of explanatory variables.

### 3.4. Spatial panel model estimations

We choose SDM as the optimal one based on the goodness of fit test and natural logarithm function value test among these three models. Results are shown in Table 3, which includes the regression results of SAR model and SEM for comparisons.

| Table 3. Estimations of the spatial econometric model. |
|------------------------------------------------------|
|            | SAR       | Std.err. | SEM       | Std.err. | SDM       | Std.err. |
| ln AGG      | 0.7577*** | 0.0486   | 0.7812*** | 0.0436   | 0.8419*** | 0.0477   |
| ln SDEN     | -0.0025   | 0.0651   | 0.0096    | 0.0836   | -0.0097   | 0.0842   |
| ln FDI      | 0.1717*** | 0.0201   | 0.1701*** | 0.0342   | 0.1306*** | 0.0240   |
| ln FDI      | 0.5504*** | 0.0147   | 0.0461*** | 0.0138   | 0.0420*** | 0.0135   |
| ln FDI      | 0.0383    | 0.0453   | 0.0315    | 0.0433   | 0.0322    | 0.0416   |
| ln N        | -1.0920***| -0.0242  | 0.1097    | 0.0248   | 0.0139    | 0.0242   |
| ln N        | 0.7341*** | 0.0722   | 0.9689*** | 0.0137   | 0.8166*** | 0.0510   |
| R²          | 0.9656    | 0.9644   | 0.9646    | 0.9646   |

Note: *, ** and *** in the upper right corner of the regression coefficient represent the significance level of 10%, 5% and 1% respectively.
On the other hand, different model assumptions can be made according to the processing of time and individual effects for spatial panel models. We refuse the assumption of random effects under the significance level of 1% of Hausman test, and adopt the spatial panel data model of fixed effects. We conduct a robustness test on the results in Table 3 and found that LM-lag and Robust LM-lag tests both pass under a significance level of 5%, while LM-error and Robust LM-error tests both pass under a significance level of 1%. This indicates that the spatial econometric model adopted can better explain the relationship between service industry agglomeration and economic growth and as well as the spillover effect in the Yangtze River Delta urban agglomeration. The specific analyses are as follows:

As can be seen from Table 3, the estimated parameters of the service industry cluster level are all positive under the three models and pass the significance test of 1% level, which indicates that the service industry cluster has a significantly positive impact on the economic growth of the Yangtze River Delta region. Late economic geography states that often the wealth accumulates in central regions at the cost of backwardness in marginal regions. The regression coefficient of $W \cdot \ln AGG$ in Table 3 is significantly negative, which reveals that the service industry agglomeration in a city will hinder the economic growth of neighbouring cities in the Yangtze River Delta, and this further conforms to the theory of comparative advantage.

The regression results for both three models show that fixed asset investment and economic openness have passed significance tests under a significance level of 1% and have caused significantly positive effects on regional economic growth. Furthermore, the Yangtze River Delta regional economic growth is still a capital-motivated growth, whereas human capital exhibits positive but not notable effects on regional economic growth. Meanwhile, foreign direct investment does promote the local economy.

According to the new theory of economic growth, human capital leads to growth difference between cities but not the general direction of economic growth, the main reason may be attributed to the sources of data. For example, the data selected here for human capital variables are the number of students from primary schools, ordinary middle schools, ordinary colleges and universities rather than secondary professional schools, adult colleges or universities. The regression coefficient of $W \cdot \ln FI$ is significantly negative, indicating that the increase of fixed asset investment in a region will inhibit the economic growth in its neighbouring regions.

It’s worth to note that the service industry density has a negative impact with a small coefficient. This reflects that the service industry agglomeration may perform a crowded phenomenon. Long term of excessive agglomeration will cause negative net effect of agglomeration space, which further slower the growth of economic.

4. Conclusions

In this paper, spatial panel data of 26 cities in the Yangtze River Delta from 2007 to 2016 have been taken as samples to investigate the characteristics of spatial distributions for service industry agglomeration and economic growth, and to study the influence of service industry agglomeration on economic growth and its spillover effects. Main contributions of this work are as follows:

i) The economic growth of cities in the Yangtze River Delta region is characterized by significant regional differences. At the same time, the service industry has a remarkable agglomeration feature.

ii) There are significant spatial autocorrelation characteristics in the Yangtze River Delta region. In other words, the economic level of neighboring cities will affect each other.

iii) Increasing the degree of agglomeration of the service industry will promote the urban economic growth. The specialization and diversification brought by agglomeration will improve the production efficiency, and the proximity of space is conducive to the optimization of products and serves.

iv) The agglomeration of local service industry will inhibit the economic growth of its neighboring cities, and there may be vicious competition problems caused by unreasonable division of labor and collaboration. It is necessary to coordinate the development of service industry in various cities and dredge the channels of industrial agglomeration spillover.
Based on the above conclusions, we believe that agglomeration of service industry in central cities in the Yangtze River Delta region should be further promoted. Accordingly, our study puts forward the following policy implications: firstly, it’s essential to promote the integration process of the Yangtze River Delta urban agglomeration and the economic ties between cities and there is an urgent need to guide reasonable distributions of service industry and optimize the industrial structure; secondly, it’s better for the government to pay more attentions to the overall planning of the service industry and give full play to the positive effects of the service industry cluster; thirdly, it’s great to realize the coordinated development of regional service industry and promote the integration process of Yangtze River Delta region; finally, we believe that guiding the agglomeration cities to play a leading role in radiating and promoting the coordinated development of the Yangtze River Delta region is important.

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